Supplement to "Automobile Prices in Market Equilibrium with Unobserved Price Discrimination"

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Abstract

This paper gathers the supplementary material to D'Haultfœuille et al. (2017). We first present additional simulations and computational details. We then display additional material on the application.

1 Additional simulations and computational details

1.1 Effects of ignoring price discrimination

We use hereafter the DGP considered in Section 5.2 of the paper. We investigate the bias from ignoring price discrimination and compute the relative errors in estimated parameters and economic variables when the econometrician uses other prices instead of the true transaction prices. We consider the three examples of observed prices satisfying Assumption 2 discussed in the paper: maximal prices, (sales-weighted) average prices and one price observed for each product. As explained in the paper, ignoring price discrimination results in bias in the estimators because using the observed prices instead of the true prices constitutes a non-classical measurement error problem. The results of Table 1 quantify this bias.

The price sensitivity parameters always display substantial bias, with relative errors ranging between -6.4% and -11.2%, depending on the prices used and the group of consumers. The errors in the parameter of heterogeneity in price sensitivity σ^p lie between -17.4% and -19.2% of the true value. The intercept, which represent the utility of buying a product relative to choosing the outside good, displays very large bias from -115% to almost 70%. The signs of the bias vary with the group and the prices observed but we obtain similar bias when using average prices and one transaction price. The coefficients for the non-price characteristic are estimated with a very small bias under the first scenario while under the second and third models, the bias is of around -3% for all the groups of consumers. The parameters for the

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marginal cost equation are also estimated with large bias for the intercept, and smaller errors for the cost shifters.

Ignoring price discrimination has also large effects on economic variables because those are direct function of prices and parameters. We see indeed that price elasticities, mean consumer surplus, average mark-ups and marginal costs are estimated with large errors when using the observed prices instead of the true prices. Errors in price elasticities are between -6.8% and 7.7%. As expected, these errors are rather small for Group 1 when we use maximal prices, since Group 1 is then the pivot group, but the biases are large for the other groups and under Specifications (2) and (3). Again, errors in average surplus are small for the group for which prices are observed. On the other hand, the bias in average consumer surplus reaches 13.3% for the most price sensitive group in Specification (3). Biases in the estimated mark-ups are also substantial. We underestimate the mark-up for Group 1 and overestimate the mark-ups of all the other groups. The bias goes up to 78% for the most price sensitive group in Specification (3). Finally, the errors in estimated marginal costs are very small when the econometrician uses the average prices or one transaction price but they reach almost 6% when using the maximal prices. At the end, those simulation results show that the errors on variables of interest can be large and quite unpredictable as they depend on the consumer group and the prices used to estimate the demand.

	(1) $\widetilde{p} = \max_d p^d$	(2) $\widetilde{p} = \frac{\sum s^d \phi^d p^d}{\sum s^d \phi^d}$	(3) $\widetilde{p} = p^{d_j}$
Price sensitivities			
α^1	-6.4	-8.5	-7.8
α^2	-8.3	-10.4	-9.9
α^3	-8.8	-11	-10.2
α^4	-8.9	-11.2	-10.4
σ^p	-19.2	-17.6	-17.4
Intercept			
β_I^1	24.8	50.5	50.9
β_I^2	-0.8	66.9	69.8
β_I^3	-29.4	12.1	13.5
β_I^4	-115	-14.7	-11.3
Product characteristic			
β_X^1	-0.1	-3.5	-3.7
β_X^2	-0.1	-3.4	-3.6
β_X^3	1.2	-2.9	-3.2
β_X^4	2	-3.1	-3.4
Cost equation			
γ^I	18.5	-5.6	-8.2
γ^X	5.6	1.7	1.4
γ_1	0	1.9	2.1
γ_2	0	1.9	2.1
γ_3	0.1	2	2.2
Price elasticities			
ϵ^1	0.2	-6	-6.8
ϵ^2	2.5	-3.8	-4.6
ϵ^3	5.9	-0.6	-1.5
ϵ^4	7.7	1.2	0.3
Mean consumer surplus			
group 1	0.7	1.7	5
group 2	6.4	7.6	10
group 3	9.5	11	12.5
group 4	10.4	12.2	13.3
Average mark-up			
group 1	-19.2	-14	-13
group 2	8.3	15.3	16.6
group 3	35.7	44.5	46.2
group 4	65.6	76.3	78.3
Marginal cost	5.8	0.2	-0.3

Notes: All values are in %. Relative bias in parameter estimates are computed as the difference between the average estimated parameters and the true parameters divided by the true parameters. Bias in average price elasticities, mark-ups and consumer surplus are computed as the relative difference in the average variable over products, markets and simulations. We use the DGP presented in Section 5.2. The first column corresponds to the case where we observe the maximal prices. The second column corresponds to the case where only average prices are observed while in the third column only one transaction price is observed and it is drawn randomly using the sales as probability weights.

Table 1: Relative bias in the estimated parameterswhen ignoring price discrimination.

1.2 The logit and nested logit cases

We explore the computational aspects of the GMM in the logit and nested logit cases, for which we optimize on $(\alpha^1, ..., \alpha^{n_D})$ and $(\alpha^1, ..., \alpha^{n_D}, \sigma^1, ..., \sigma^{n_D})$, respectively. We consider nearly the same DGP as in Section 5.2. The utilities and marginal costs are set in the same way, except that because n_D varies hereafter, the coefficients of the characteristics are fixed in a slightly different manner. Specifically, the intercept and the coefficient of the non-price characteristic are equal to -0.75 and 2 for all groups, while the price sensitivity coefficient is set on an equally spaced grid ending at -1.5 and with a width of -0.5 (e.g., -3, -2.5, -2 and -1.5 with 4 demographic groups). As in Section 5.2, we consider 25 markets on which 4 firms sells 6 products each. In the nested logit, we consider 8 products per nest, and fix the coefficient of correlation of products within segment $\sigma^d = 0.5$ for each group d. We then make the number of firms vary from 4 to 16. Hence, the number of nests varies as we change the number of firms. We suppose that the econometrician does not observe transaction prices p_j^d but only the list prices, which are supposed to satisfy $\widetilde{p}_j = \max(p_j^1, ..., p_j^{n_D})$. Finally, we use product characteristics, cost shifters and the sum of the characteristics of the other products of the firm as instruments for the estimation. In the nested logit, we also rely on the additional instrumental variables defined as the sum of the characteristics of the other products in the segment.

To minimize the GMM function, we first have to choose a starting point. In each model (logit or nested logit), we choose the 2SLS estimator of that model, supposing that the transaction prices are equal to $\widetilde{p}$. Regarding the minimization itself, we use the BFGS quasi-newton algorithm. This choice may seem surprising, given that the objective function is not differentiable everywhere because of the maximum function appearing in the price equation. However, the algorithm works very well in practice and is much faster than the simplex algorithm. Such a good behavior is documented in the optimization literature, see e.g. Lewis and Overton (2013). To assess whether the algorithm converges to the global minimum, we draw randomly, for each simulation, 10 other initial points. We then consider to have reached the global minimum if for our preferred estimator, based on the initial 2SLS estimator, the value function is smaller or equal to the minimum of these other 10 optimizations, with a tolerance of 10^{-3}.

Table 2 reports the computational aspects of the optimization: the average time (in seconds) to compute our estimator based on the 2SLS starting point, and the proportion of simulations for which this estimator reaches the global minimum of the value function. The algorithm always converges. Moreover, in the vast majority of the simulations the estimator is the global minimum of the objective function according to the criterion above. Table 2 also reports the statistical properties of our GMM estimator. As expected, the root mean squared error (RMSE) decreases with the number of products in both models. We also observe that the estimator of α is more imprecise in the nested logit than in the logit model. Note however that

$\alpha/(1-\sigma)$, which is the main term of price elasticities, is much better estimated, with a RMSE comparable to the RMSE of α in the logit model. Intuitively, it is difficult to disentangle the effect of prices (α) from the effect of intra-group log market shares (σ) in the nested logit model, because the projections of these two variables on instruments are strongly correlated.

		$n_D = 2$				$n_D = 4$			
		Time	% reaching	RMSE		Time	% reaching	RMSE	
Model	J	(sec)	global min.	α	σ	(secs)	global min.	α	σ
Logit	24	0.014	100	0.02	–	0.29	100	0.03	–
	48	0.017	100	0.016	–	0.33	100	0.024	–
	96	0.022	100	0.012	–	0.39	100	0.016	–
Nested logit	24	1.4	100	0.53	0.16	9.3	95.5	0.24	0.062
	48	2.1	100	0.41	0.12	14	97.5	0.19	0.05
	96	7.0	100	0.27	0.08	190	99.5	0.17	0.042

Reading notes: 200 simulations for each setting. "Time" is the optimization time in seconds on our desktop computer (Intel® Core™, i3-4160, 3.6 GHz, 8Gb RAM) and using our preferred starting point. "% reaching global min." is the percentage of simulations for which the estimator reaches the global minimum of the value function. We display the average root mean squared errors (RMSE) of $\widehat{\alpha}^d$ and $\widehat{\sigma}^d$ across the different demographic groups d.

Table 2: Computational and statistical aspects of the GMM optimization for the logit and nested logit models.

1.3 Algorithm and simulations in the case of unobserved groups

We consider, for the model with unobserved groups studied in Section 4.1, an algorithm similar to the one developed for the model with observed groups. Namely, for each value of the vector of parameters θ, we compute $p(\xi, \theta)$ as the limit of the sequence $p_{n+1} = M_{s,\theta}(p_n)$, through the following steps:

1. Start from initial values for p_0^d, for each group d. We can use the observed prices $\widetilde{p}$ or previous transaction prices obtained for another θ.

2. Given the current vector of transaction prices p_n^d, invert Equation (14) to compute ξ_n, using the algorithm of Lee and Seo (2016). Compute the corresponding market shares $s_j^d(p_n^d, \xi_n, \theta)$, for all (j, d).

3. Compute p_{n+1}^d using Equation (16).

4. Repeat steps 2 and 3 until convergence of prices.

We evaluate the computational and statistical properties of our GMM estimator in this case through 200 Monte Carlo simulations. We generate market equilibrium for $T = 50$ markets with $J = 48$ products offered by 4 firms, each of them offering 12 products. The product characteristics are $X_{jt} = (1, X_{1jt})$ and an unobserved characteristic ξ_{jt}. The marginal cost equation is given by Equation (17), and all variables follow the same distributions as in the DGP of the simulations for our main model (see Section 5.2 of the main paper). We consider 4 groups of consumers that differ only in their price sensitivity parameter, and set $\alpha^d = (-1, -1.5, -2, -2.5)$. The preference for holding a car is set to $\beta_0 = -6$ and the preference for the characteristic X_1 is set to $\beta_1 = 3.5$. For each product, we suppose to observe the maximal price over the 4 consumer groups.

The proportion ϕ_t^d of each group varies across markets and is such that $\phi_t^d \sim \mathcal{U}(0.1, 0.3)$ for $d = 1, 2, 3$ and $\phi_t^4 = 1 - \sum_{d=1}^{3} \phi^d$. Though we could include the proportion ϕ^d in the vector of parameters θ, we assume here that they are known. This is the case when the econometrician knows the groups that are used for price discrimination and their proportion in the population, but does not observe their specific demand (e.g. male/female in our application, if there is price discrimination with respect to gender).

We estimate the model using demand-side moments only. We use an approximation of optimal instruments that follows Reynaert and Verboven (2014). We compute them using a numerical approximation of the Jacobian evaluated at the true parameter values. Finally, we use a tolerance of 10^{-16} in the inner loop where we compute ξ_n and a tolerance of 10^{-12} in the outer loop where we compute $p(\xi, \theta)$.

The simulation results are displayed in Table 3. As with our main model, and consistent with the result of Theorem 2, our algorithm always converges. Perhaps surprisingly, the average time to compute the estimator is much smaller than with our main model (27 seconds versus 214 seconds, see Table 3 in the main paper), despite a much larger average number of iterations (148 versus 31). This is because we have to perform the inner loop, where we compute ξ_n for given prices, only once rather than n_D times in our main model. Also, the optimization is easier because the dimension of θ is smaller than with our main model ($\dim(\theta) = 6$ versus 18). The estimator displays good performances and the average discounts are very precisely estimated.

	True	Estimation	
		Mean	Std. dev.
Price sensitivity			
Group 1	-1	-1	0.006
Group 2	-1.5	-1.5	0.01
Group 3	-2	-2	0.032
Group 4	-2.5	-2.5	0.055
Exogenous characteristics			
β_0	-6	-6	0.028
β_1	3.5	3.5	0.008
Mean objective function value		1.6×10^{-5}	
% simulations converging		100	
Number of iterations		148	
Time (sec)		27	
Average discount			
Group 1	0	0	0
Group 2	9.44	9.45	0.16
Group 3	13.65	13.64	0.22
Group 4	16.06	16.05	0.18

Reading notes: Mean and standard deviations of parameters for the converging replications of the 200 simulations. "Std. dev." stands for the standard deviation across simulations. "Time" is the optimization time in seconds using our preferred starting point and on our desktop computer using 6 parallel workers (Intel® Core™, 6-Core Xeon E5, 3.5 GHz, 16Gb RAM). "% simulations converging" is the percentage of simulations for which our algorithm converged.

Table 3: Simulation results for the model with unobserved groups.

As discussed in Section 4.1 of the main paper, Theorem 2 does not cover the case where average prices are observed. We nevertheless investigate through simulations whether our algorithm converges in this case. Using one synthetic dataset generated from the DGP described above, we assume that only the sales-weighted average prices are observed instead of maximal prices. We check that our algorithm still solves the system of equation in (ξ, p). For this, we draw 100 different values of $(\alpha^d)_{d=1,\dots,n_D}$ from $\mathcal{U}(\alpha^d/2, 3\alpha^d/2)$ and compute prices using $p_j^{0,d} = \tilde{p}_j$ as initial prices. We then compare these prices with those we obtain using 50 different sets of initial prices. Specifically, we draw independently across d and j the $p_j^{0,d}$, with $p_j^{0,d} \sim \mathcal{U}[1/2\tilde{p}_j, 2\tilde{p}_j]$. For each of the 100 different values of $(\alpha^d)_{d=1,\dots,n_D}$, we find that the 50 initial vectors of prices always lead to the same prices. This strongly suggests that Theorem 2 also applies to the case where average prices are observed.

2 Additional material on the application

2.1 Correction for null market shares

We first display the fraction of products with null market shares given the segmentation in 6 consumer groups we defined.

Group	Frequency of null sale
Age <40, Income $<$ 27,000	11.6%
Age <40, Income $\geq 27,000$	10.3%
Age $\in$ [40,59], Income $<$ 27,000	7.5%
Age $\in$ [40,59], Income $\geq 27,000$	4%
Age ≥ 60, Income $<$ 27,000	7.8%
Age ≥ 60, Income $\geq 27,000$	7.6%

Table 4: Fraction of products with null market shares in the final sample.

We now provide a rationale for the choice of our estimator $\widehat{s}_j^d = \frac{n_j^d+0.5}{N^d}$ of s_j^d, where n_j^d denoting the number of sales of product j in group d and N^d the number of potential buyers with characteristics d. The idea is to consider simple estimators of s_j^d of the form $(n_j^d+c)/N^d$, and fix c such that the expectation of $\ln((n_j^d+c)/N^d)$ is asymptotically unbiased. The reason we are looking for such a c is that $\ln(s_j^d)$ plays an important role at least in the logit or nested logit models. With an unbiased estimator of $\ln(s_j^d)$, we could estimate consistently and as usually the demand parameters. However, in our framework where individuals choose independently from each others, so that $n_j^d \sim \text{Binomial}(N_d, s_j^d)$, it is well-known that only polynomials of s_j^d of degree at most N_d can be estimated without bias. Our aim is then to find instead an estimator that is asymptotically unbiased at the first order.

For that purpose, we consider an asymptotic approximation where s_j is small but $\lambda_j^d \equiv N_d s_j^d \to \infty$. Let $Z_j^d = (n_j^d - \lambda_j^d)/\sqrt{\lambda_j^d}$. A second-order Taylor expansion of $(n_j^d + c)/N^d$ around s_j^d yields

$$\sqrt{\lambda_j^d}\left[\ln((n_j^d+c)/N^d) - \ln\left(s_j^d\right)\right] = Z_j^d + \frac{c}{\sqrt{\lambda_j^d}} - \frac{s_j^{d2}}{2\widetilde{s}_j^{d2}}\frac{1}{\sqrt{\lambda_j^d}}\left(Z_j^d + \frac{c}{\sqrt{\lambda_j^d}}\right)^2,$$

where $\widetilde{s}_j^d$ is between $(n_j^d+c)/N^d$ and s_j^d. The first order term, Z_j^d, is asymptotically standard normal and thus asymptotically centered. Now, considering the second-order term,

$$\sqrt{\lambda_j^d}\left\{\sqrt{\lambda_j^d}\left[\ln((n_j^d+c)/N^d) - \ln\left(s_j^d\right)\right] - Z_j^d\right\} = c - \frac{s_j^{d2}}{2\widetilde{s}_j^{d2}}\left(Z_j^d + \frac{c}{\sqrt{\lambda_j^d}}\right)^2.$$

Moreover, $s_j^{d2}/\widetilde{s}_j^{d2} \xrightarrow{\mathbb{P}} 1$ and $\left(Z_j^d + \frac{c}{\sqrt{\lambda_j^d}}\right)^2 \xrightarrow{L} \chi_1^2$. Hence,

$$\sqrt{\lambda_j^d}\left\{\sqrt{\lambda_j^d}\left[\ln((n_j^d+c)/N^d) - \ln\left(s_j^d\right)\right] - Z_j^d\right\} \xrightarrow{L} c - \frac{1}{2}\chi_1^2.$$

Choosing $c = 1/2$ therefore ensures that this second-order term is asymptotically centered around 0.

To examine the robustness of the estimation results to the correction of the null shares adopted. We re-estimate the nested logit model using the Laplace transformation of the market share equation used by Gandhi et al. (2013). This correction replaces the market share by:

$$\tilde{s}_j^d = \frac{N^d \widehat{s}_j^d + 1}{N^d + J + 1}.$$

As Table 10 in Section 2.3.1 below suggests, the estimation results are robust to the choice of a correction to deal with products with null market shares. The estimated parameters are very close using the two alternative corrections. As a consequence, subsequent results (not displayed here) on, e.g., discounts, are also close to each other.

2.2 Additional results

2.2.1 Differences with the uniform pricing model

We first present additional results on the difference between our model and the standard BLP. We display in Table 5 the relative differences between the main parameters of preferences. More specifically, we compute $(\theta^{unif} - \theta^{disc})/\theta^{disc}$, where θ^{unif} represents the vector of parameters estimated under the standard model and θ^{disc} the vector of parameters estimated with the price discrimination demand model. We observe that for all the groups except for the pivot group, the price sensitivities are underestimated with the standard BLP model. Conversely, the price sensitivity of the pivot group is overestimated. We also overestimate the importance of within group heterogeneity in price sensitivities. The coefficients of the intercept are underestimated for all the groups except the pivot group for which the difference in the parameters is very small (-1%). The differences in the preference for horsepower are very large and positive, except for the parameter for the group of old consumers with low income. Errors in the sensitivity to fuel cost can be up to 10.5%. The preferences for car models with three doors display also large differences while there is less differences in the parameters of preference for station wagon cars.

	Age < 40		Age ∈ [40,59]		Age ≥ 60	
	I = L	I = H	I = L	I = H	I = L	I = H
Price	-5.4	-4	-7.9	-5.7	-8.5	18.1
Std. dev. (σ^p)			8.2			
Intercept	-13.5	-9.6	-10.7	-7.7	-11.7	-1
Horsepower	44.7	49.8	21	20.5	-0.6	128.3
Fuel cost	10.5	10.1	5.4	3.7	1.6	5
Weight	-14.4	-11.9	-14.9	-11.7	-18.5	12.5
Three doors	-44.1	-364.9	28.4	11.7	-2.5	14.9
Stat. Wagon	-1.5	-0.1	-3.6	-0.7	-3.6	10.7

Reading notes: All values are in % of the estimated parameters under the price discrimination model, $(\theta^{unif} - \theta^{disc})/\theta^{disc}$.

Table 5: Relative difference in estimated parameters between the uniform and the price discrimination models.

Figure 1 displays the distribution of the differences in estimated marginal costs between the two models. We compute here the relative difference $(\hat{c}_j^{unif} - \hat{c}_j^{disc})/\hat{c}_j^{disc}$, where $\hat{c}^{unif}$ stands for the marginal cost of product j implied by the uniform pricing model and $\hat{c}_j^{disc}$ the one implied by the price discrimination model. The costs are always overestimated in the uniform pricing model, with an average difference of 9.5%. The relative cost difference even exceeds 18% for 2.9% of the products. These differences stem from the fact that, in the uniform pricing model, the marginal costs are deduced from the difference between the posted prices and the average mark-ups. In contrast, in the price discrimination model, the marginal costs are equal to the difference between the posted prices and the mark-ups of the pivot group. The pivot group mark-ups are higher than the average mark-ups estimated in the standard model, resulting in lower marginal costs. Ultimately, the errors in the estimation of marginal costs translate into errors in counterfactual simulation exercises.

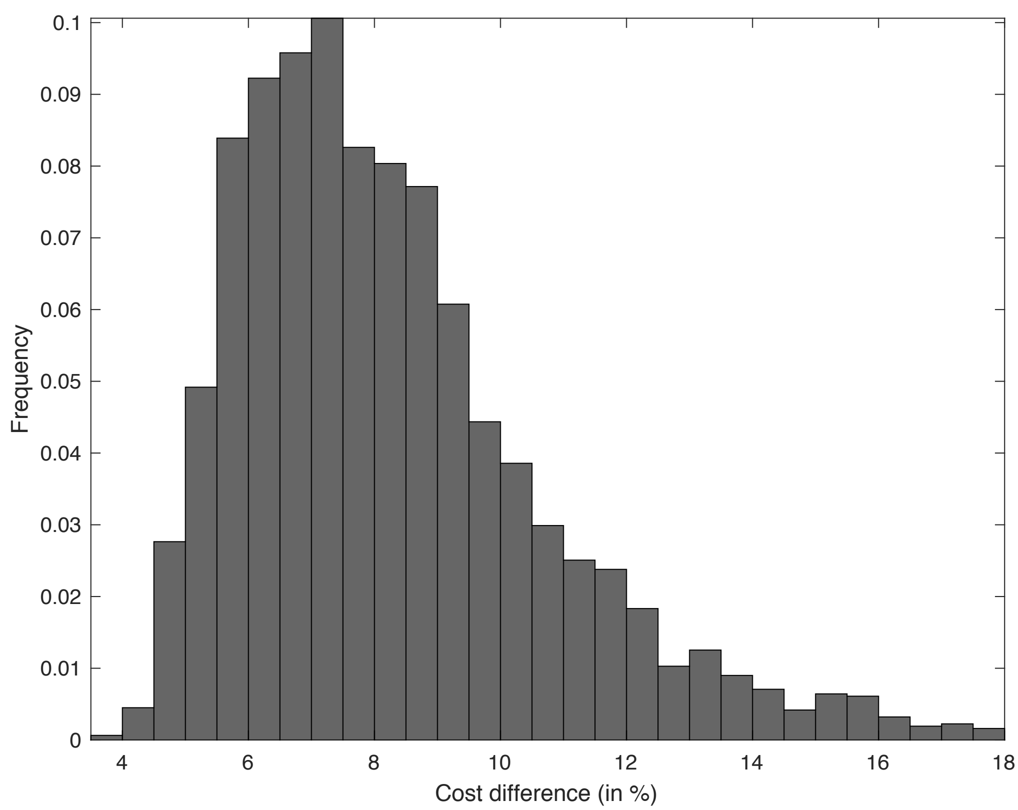

Figure 1: Distribution of the relative difference between estimated marginal costs.

2.2.2 Additional results on discounts

Figure 2 displays the resulting distribution of discounts across products for those having a discount lower than 20% (which represent 98% of the products). The corresponding average discount, averaged by product rather than by consumers, is equal to 9.6%, with some heterogeneity. For 10% of the products, the average discount is smaller than 6.7%, while for the 10% most discounted cars, the rebate is larger than 11.9%, and it even exceeds 32% for 1% of the cars. To understand better the source of this heterogeneity, we regress these discounts on the characteristics of the cars. The results are displayed in Table 6. Discounts increase with the list price and horsepower but decrease with weight and fuel cost. These results reflect both the differences in sales between consumer groups (e.g. products mostly sold to the pivot group tend to have a small average discount) and differences in the pricing strategy. Results with basked-weighted discounts are however similar, showing in particular that it is profitable for firms to offer large discounts for their most expensive cars.

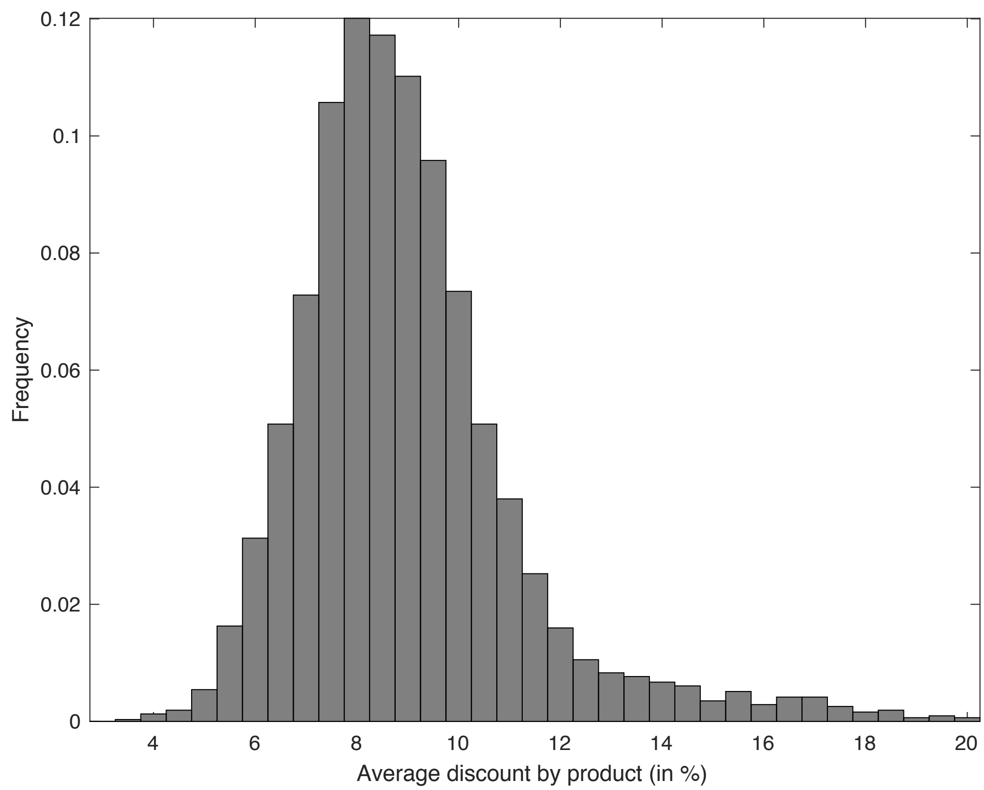

Figure 2: Distribution of estimated discounts across products

Variable	Parameter	Std-err
Intercept	13.59**	2.4
List price	3.99	7.94
Horsepower	2.63**	0.83
Fuel cost	-2.78**	0.39
Weight	-8.98	13.7
Three doors	0.77	0.47
Station wagon	0.26**	0.09
Executive	-6.21	7.7
Small Family	-2.57*	1.25
Large Family	-4.83	5.98
Small MPV	-1.34**	0.4
Large MPV	-1.65	1.01
Sports	-4.56	4.06
Allroad	-1.88	1.43
R^2	0.65	

Reading notes: the standard-errors are robust to heteroscedasticity and account for the first-step errors in the estimated discounts. Significance levels: †: 10%, *: 5%, **: 1%.

Table 6: Regression of average product discount on cars characteristics

2.3 Robustness checks

2.3.1 Nested logit model

We consider here the nested logit model as an alternative to the random coefficient models. We show that our results are basically confirmed with this approach. The nested logit approach requires to define a segmentation of the market in homogeneous groups of products. Our segmentation, based on the main use of the vehicle, is close to the one of The European New Car Assessment Program one (Euro NCAP). Table 7 displays the 8 segments that we consider and their market shares over the period. Note in particular that sports cars include all convertible cars as well as vehicles with a high ratio horsepower/weight, while the small multi-purpose vehicles (MPV) segment includes small vans such as Renault Kangoo. The entire classification is presented in Table 8.

Segment	Market shares (in %)	Segment	Market shares (in %)
Supermini	45.14	Small MPV	17.56
Executive	1.17	Large MPV	1.07
Small Family	17.01	Sports cars	5.11
Large Family	8.67	Allroad	4.77

Table 7: Segments and their market shares.

Table 8: Segmentation of the automobile market

Group	**Make**	Supermini	Small family	Large family	Executive	Sports car	Small MPV	Large MPV	Allroad/SUV
PSA	*Citroen*	C1, C2, C3, Saxo	Xsara	C5	C6	-	Berlingo, C4, Nemo, Xsara	C8	C-Crosser
	Peugeot	106, 107,1007,206, 207	306, 307, 308	406, 407	607	-	Bipper, Partner	807	4007
Renault	*Renault*	Clio, Modus, Twingo	Megane	Laguna	Vel Satis	-	Kangoo, Megane	Espace	Koleos
	Dacia	Sandero	Logan	-	-	-	-	-	-
B.M.W	*B.M.W*	-	1-Series	3-Series	5, 6, 7-Series	Z4	-	-	X3, X5, X6
	Mini	Mini	-	-	-	-	-	-	-
Chrysler	*Chrysler*	-	-	Sebring	300C, 300M, Crossfire	-	PT Cruiser	Voyager, G.Voyager	-
	Jeep	-	-	-	-	-	-	-	Compass, Cherokee, Commander, G.Cherokee, Wrangler
	Dodge	-	Caliber	Journey	Viper	-	-	-	Durango, Nitro
Daihatsu	*Daihatsu*	Cuore, Sirion, YRV	-	-	-	Copen	-	-	Terios
Daimler	*Mercedes*	-	A-Class	C, CLK-Class	E, CL, R, S, SL, CLS, SLR-Class	SLK-Class	B-Class, Vaneo	Viano	G, GL, GLK, ML-Class
	Smart	Fortwo, Forfour	-	-	-	Coupe, Roadster	-	-	-
Fiat	*Alfa Romeo*	Mito	147	156, 159, GT	166, Brera	GTV, Spider	-	-	-
	Fiat	500, Palio, Panda, Punto, Seicento	Bravo, Stilo	Croma	-	Barchetta	Doblo, Fiorino, Idea, Multipla	Ulysse	Sedici
	Lancia	Y	-	Lybra	Thesis	-	Musa	Phedra	-
Ford	*Ford*	Fiesta, Ka,	-	Mondeo	-	Puma	Focus, Fusion, T.Connect, Tourneo	Galaxy, S-Max	Kuga
	Jaguar	-	-	X-Type	S-Type, XJ, XK	-	-	-	-
	Land Rover	-	-	-	-	-	-	-	Freelander, Defender, Discovery, R.Rover
	Volvo	-	C30, V50	C70, S40, S60, V70	V40, S80	-	-	-	XC60, XC70, XC90
GM Europe	*Chevrolet*	Kalos, Matiz	Aveo, Lacetti, Nubira	Epica, Evanda	-	Corvette	Rezzo, Tacuma	-	Captiva, Tahoe
	Daewoo	Kalos, Matiz	Lanos	-	Evanda	-	Rezzo	-	Korando
	Opel	Corsa	Astra	Insigna, Signum, Vectra	Omega	Tigra, Speedster	Agila, Combo, Meriva, Zafira	-	Antara, Frontera
	Saab	-	-	9-3	9-5	-	-	-	-
Honda	*Honda*	Jazz	Civic	Accord	-	S2000	FR-V, Stream	-	CR-V, HR-V
Hyundai	*Hyundai*	Atos, Getz, I10	Accent, Coupe, I30	Elantra, Sonata	-	-	Matrix	Trajet	Tucson, Santafe, Terracan
	Kia	Picanto, Rio	Cee-d, Cerato	Magentis	-	-	Carens, Soul	Carnival	Sorento, Sportage
Lada	*Lada*	-	111, 112	-	-	-	-	-	Niva
Mazda	*Mazda*	2	3	6	RX8	MX5	5, Premacy	MPV	-
Mitsubishi	*Mitsubishi*	Colt	Lancer	Carisma	-	-	Spacestar	Grandis	Outlander, Pajero
Nissan	*Nissan*	Micra, Note	Almera, Qashqai	Primera	350Z, Maxima-Q	-	Almera	-	X-Trail, Murano, Pathfinder, Patrol, Terrano
Porsche	*Porsche*	-	-	-	911, Boxter, Cayman	-	-	-	Cayenne
Rover	*Rover*	25, Streetwise	45	75	-	-	-	-	-
Ssangyong	*Ssangyong*	-	-	-	-	-	-	Rodius, Stavic	Actyon, Korando, Kyron, Rexton
Subaru	*Subaru*	Justy	Impreza	Legacy	-	-	-	-	Forester, B9Tribeca
Suzuki	*Suzuki*	Alto, Ignis, Splash, Swift, SX4	Liana	-	-	-	Wagon-R	-	G. Vitara, Jimny, Samurai, Vitara
Toyota	*Toyota*	Aygo, IQ, Yaris	Auris	Avensis, Prius	-	Celica, MR	Corolla	Previa	RAV4, L.Cruiser
	Lexus	-	-	IS	GS, LS	-	-	-	RX
VW Group	*Audi*	A2	A3	A4, A5	A6, A8, R8	S3, S4, S6, S8 TT	-	-	Allroad, Q5, Q7
	Seat	Arosa, Ibiza	Cordoba, Leon	Toledo	-	-	Altea	Alhambra	-
	Skoda	Fabia	-	Octavia, Superb	-	-	Roomster	-	-
	Volkswagen	Fox, Lupo, Polo	Eos, Golf, Jetta, Newbeetle	Scirocco, Passat	-	Phaeton	Caddy, Touran	Sharan	Tiguan, Touareg

	(1) Uniform model Our correction		(2) Discrimination model Our correction		(3) Discrimination model Gandhi et al. correction	
	Parameter	Std-err	Parameter	Std-err	Parameter	Std-err
Price sensitivity						
Age < 40, I = L	-2.66**	0.061	-2.66**	0.061	-2.5**	0.058
Age < 40, I = H	-2.52**	0.06	-2.51**	0.06	-2.36**	0.058
Age ∈ [40,59], I = L	-2.21**	0.051	-2.21**	0.052	-2.08**	0.049
Age ∈ [40,59], I = H	-2.13**	0.053	-2.12**	0.053	-1.98**	0.048
Age ≥ 60, I = L	-1.93**	0.066	-1.95**	0.065	-1.77**	0.06
Age ≥ 60, I = H	-1.77**	0.07	-1.81**	0.067	-1.81**	0.063
Intra-segment correlation						
Age < 40, I = L	0.17**	0.039	0.18**	0.04	0.11**	0.039
Age < 40, I = H	0.29**	0.042	0.3**	0.042	0.22**	0.041
Age ∈ [40,59], I = L	0.21**	0.034	0.23**	0.034	0.17**	0.033
Age ∈ [40,59], I = H	0.28**	0.04	0.3**	0.04	0.19**	0.039
Intercept						
Age < 40, I = L	-6.53**	0.256	-7.08**	0.255	-7.5**	0.245
Age < 40, I = H	-6.47**	0.268	-7.06**	0.262	-7.44**	0.252
Age ∈ [40,59], I = L	-6.96**	0.245	-7.26**	0.243	-7.59**	0.233
Age ∈ [40,59], I = H	-6.54**	0.265	-6.88**	0.255	-7.41**	0.237
Age ≥ 60, I = L	-7.86**	0.313	-7.94**	0.296	-7.89**	0.287
Age ≥ 60, I = H	-8.2**	0.317	-8.21**	0.301	-8.29**	0.291
Horsepower						
Age < 40, I = L	5.74**	0.221	5.74**	0.219	5.38**	0.207
Age < 40, I = H	5.15**	0.198	5.13**	0.196	4.82**	0.188
Age ∈ [40,59], I = L	4.25**	0.18	4.25**	0.178	4**	0.169
Age ∈ [40,59], I = H	3.92**	0.171	3.91**	0.17	3.59**	0.162
Age ≥ 60, I = L	2.88**	0.228	2.95**	0.225	2.57**	0.213
Age ≥ 60, I = H	2.44**	0.228	2.55**	0.227	2.71**	0.205
Fuel cost						
Age < 40, I = L	-6.04**	0.242	-5.99**	0.243	-5.85**	0.226
Age < 40, I = H	-4.86**	0.217	-4.82**	0.216	-4.76**	0.204
Age ∈ [40,59], I = L	-5.07**	0.2	-4.99**	0.199	-4.94**	0.188
Age ∈ [40,59], I = H	-4.15**	0.186	-4.1**	0.184	-4.23**	0.183
Age ≥ 60, I = L	-4.15**	0.184	-4.18**	0.183	-3.83**	0.17
Age ≥ 60, I = H	-3.51**	0.18	-3.54**	0.178	-3.46**	0.167
Weight						
Age < 40, I = L	4.13**	0.243	4.08**	0.243	4**	0.231
Age < 40, I = H	4.03**	0.242	3.99**	0.242	3.9**	0.231
Age ∈ [40,59], I = L	4.18**	0.23	4.12**	0.23	4.03**	0.22
Age ∈ [40,59], I = H	3.87**	0.231	3.82**	0.232	3.86**	0.217
Age ≥ 60, I = L	3.49**	0.249	3.53**	0.248	3.19**	0.237
Age ≥ 60, I = H	3.52**	0.252	3.58**	0.249	3.49**	0.239
Three doors						
Age < 40, I = L	-0.08	0.178	-0.09	0.176	-0.05	0.173
Age < 40, I = H	-0.25	0.167	-0.25	0.166	-0.21	0.163
Age ∈ [40,59], I = L	-0.22	0.172	-0.22	0.17	-0.19	0.167
Age ∈ [40,59], I = H	-0.35*	0.169	-0.35*	0.167	-0.31†	0.168
Age ≥ 60, I = L	-0.6**	0.187	-0.61**	0.186	-0.56**	0.178
Age ≥ 60, I = H	-0.65**	0.184	-0.66**	0.184	-0.64**	0.175
Station wagon						
Age < 40, I = L	-0.6**	0.127	-0.59**	0.126	-0.6**	0.123
Age < 40, I = H	-0.42**	0.121	-0.41**	0.12	-0.43**	0.117
Age ∈ [40,59], I = L	-0.45**	0.121	-0.44**	0.12	-0.46**	0.117
Age ∈ [40,59], I = H	-0.47**	0.121	-0.45**	0.12	-0.51**	0.119
Age ≥ 60, I = L	-0.7**	0.126	-0.7**	0.126	-0.65**	0.119
Age ≥ 60, I = H	-0.67**	0.125	-0.68**	0.125	-0.65**	0.119

Reading notes: Standard-errors are robust to heteroscedasticity and computed using the standard formula for GMM. Significance levels: †: 10%, *: 5%, **: 1%.

Table 10: Estimation of parameters: nested logit model with uniform pricing and price discrimination, with our correction and Gandhi et al. correction.

The estimated parameters are generally similar to the ones for the random coefficient models presented in the paper. Note that for two groups (the old purchasers with low and high income), we obtain negative intra-segment correlations whereas this parameter should belong to $[0, 1]$. Thus, we constrain these two parameters to be equal to zero in the estimation, which amounts to consider the logit specification for these two groups of consumers.

We then present the same results as those given in Tables 6 and 8 of the main paper and Figures 1 and 2 and Table 6 of this supplement, but for the nested logit specification. Table 11 first shows that the average price elasticities are very similar to those obtained with the random coefficients model. Under price discrimination, they range from -6.4 to -3.7, almost identical to the range [-6.4, -3.9] that we obtain with the random coefficient model. Here again, older people are much less price sensitive than the other groups. Perhaps surprisingly, on the other hand, high-income individuals below 60 appear to be more price sensitive than the low-income ones, both under price discrimination and uniform pricing. The pivot group is nevertheless still the older, high-income group of consumers.

Group of	Price elasticity		Average mark-up		Average surplus	
consumers	Disc.	Unif.	Disc.	Unif.	Disc.	Unif.
Age $<$ 40, I $=$ L	-5.54	-6.23	22.1	22.3	585	585
Age $<$ 40, I $=$ H	-6.39	-7.24	19.9	21.5	663	662
Age $\in$ [40,59], I $=$ L	-5.52	-5.94	23	21.6	631	631
Age $\in$ [40,59], I $=$ H	-5.8	-6.32	22.5	21.6	998	996
Age $\leq$ 60, I $=$ L	-3.83	-3.87	30.9	23.6	836	848
Age $\leq$ 60, I $=$ H	-3.77	-3.68	31.7	22.9	1245	1275
Average	-5.1	-5.49	25.2	22.3	873	879

Table 11: Comparison of average price elasticities for the nested logit models with uniform pricing and unobserved price discrimination.

We also observe that the model without price discrimination overestimates price elasticities for all groups except the pivot and always overestimates the marginal costs as Figure 3 shows. The average difference in marginal costs is 11.6%, with important heterogeneity. In particular, the difference exceeds 20% for 12.9% of the products.

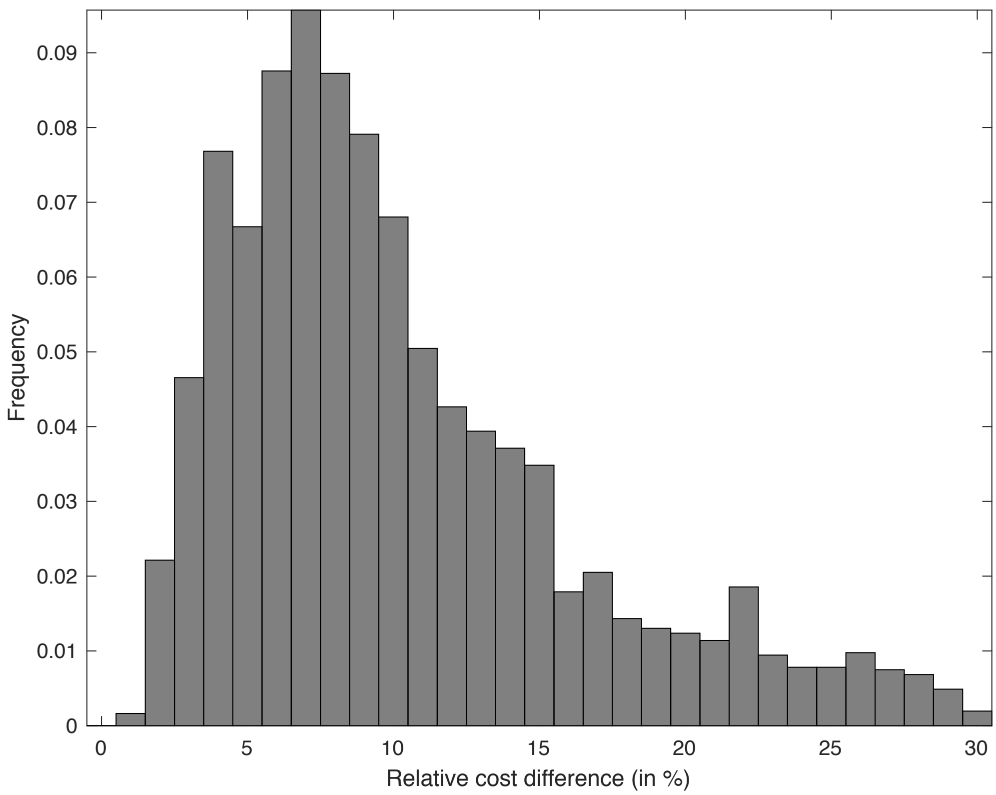

Figure 3: Distribution of the relative difference between estimated costs $\left(\frac{\hat{c}^{unif}-\hat{c}^{disc}}{\hat{c}^{disc}}\right)$.

Turning to the discounts, we obtain again that the youngest purchasers obtain the highest discounts, though such discounts are on average higher for the high income young purchasers. Interestingly, the oldest individuals with low income get a very small discount in average (2.6%) compared to an average of 10.3% with the random coefficient model. The average discount is nevertheless very close to the one obtained with the random coefficient model.

	Average discount (in % of posted price)		Average gross discount (in euros)	
Group of consumers	Sales-weighted	Basket-weighted	Sales-weighted	Basket-weighted
Age $<$ 40, I = L	13.96	13.62	2,447	2,473
Age $<$ 40, I = H	14.71	14.9	2691	2,706
Age $\in$ [40,59], I = L	10.76	11.04	1,994	2,005
Age $\in$ [40,59], I = H	11.37	11.61	2,111	2,111
Age $\geq$ 60, I = L	2.59	2.5	458	453
Age $\geq$ 60, I = H	0	0	0	0
Average	8.74	8.79	1,590	1,596

Reading notes: the "basket-weighted" discounts are obtained by using the same artificial basket of cars for all groups.

Table 12: Average discount by group of consumers for the nested logit model.

Finally, we display in Figure 4 the distribution of average discounts over car models. Both the average (7.2%) and the standard deviation (3.7%) are lower than the figures obtained with the random coefficient model (9.6% and 4.7%, respectively). For 10% of the cars the discount exceeds 17.6% (versus 13.9% unfder the random coefficient model). Finally, the regression of the discounts on cars' characteristics shows, as before, that large fuel costs and heavy vehicles are associated with lower discounts, while horsepower is associated to greater discounts. On the other hand, the list price has a negative rather than positive effect on discounts in this specification, no longer in lines with the results of Kaul et al. (2016).

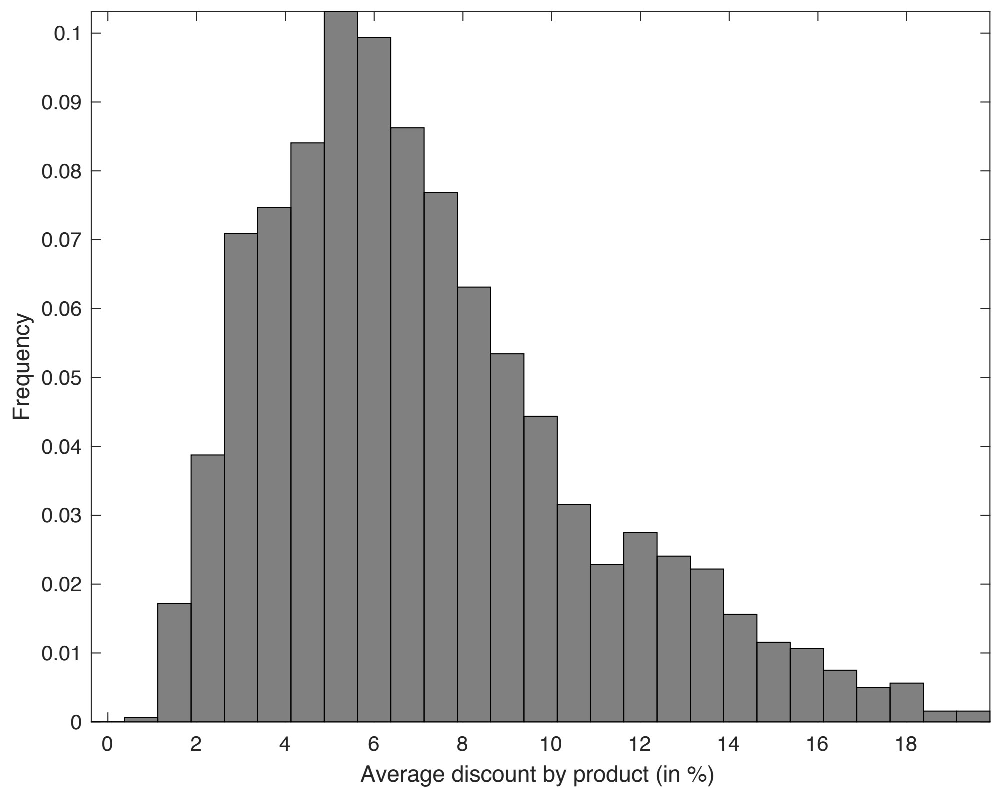

Figure 4: Distribution of estimated discounts for the nested logit model.

Variable	Parameter	Std-err
Intercept	18.06**	2.07
Posted price	-1.36**	0.18
Horsepower	2.3**	0.35
Fuel cost	-2.34**	0.32
Weight	-3.25**	0.45
Three doors	0.71**	0.13
Station wagon	0.22**	0.08
Executive	-3.65**	0.44
Small Family	-3.24**	0.41
Large Family	-4.25**	0.5
Small MPV	-2.68**	0.34
Large MPV	-1.85**	0.3
Sports	-3.22**	0.41
Allroad	-2.16**	0.32
R^2	0.76	

Reading notes: The regression includes segment dummies. Standard-errors are robust to heteroscedasticity and account for the first-step errors in the estimated discounts. Significance levels: †: 10%, *: 5%, **: 1%.

Table 13: Regression of average product discount on cars characteristics.

2.3.2 Differences in marginal costs across groups

Our segmentation in groups of consumers aggregates homogeneous municipalities (e.g., rich versus poor) so one could worry that the assumption of identical marginal costs across consumer groups is not satisfied. The cost of selling for car dealers potentially depends on local production factors (e.g., labor or real estate cost). To check how such heterogeneous local cost affect the robustness of our estimates, we collected data on estate costs for a sample of 1,395 municipalities through notary data in 2017.[1] We then compute the average estate prices for each demographic group as $\bar{\rho}^d = \sum_m q^d_m \rho_m / \sum_m q^d_m$ with q^d_m the number of car sales in the municipality m from purchasers of group d and ρ_m is the average estate price in municipality m). According to the National Automobile Dealer Association in the U.S. the estate cost represents on average \$961 per car in 2009, which corresponds to €689 using the average exchange rate for 2009.[2] We use this figure to compute the average additional cost of estate by demographic group taking the pivot group as the reference. Average estate prices and incremental costs are displayed in the first two columns of Table 14. We then simulate the new market shares and prices in market equilibrium with heterogeneous marginal costs and estimate a model that neglects the cost heterogeneity. Results, presented in Table 14, show that the effect of neglecting such cost heterogeneity is very small. While the average discounts differ by 1.4 points, average mark-ups and price elasticities are almost identical.

[1] Municipalities were drawn without replacement from the database of all French municipalities, with probability proportional to their size.

[2] See nada.org/dealershipfinancialprofile/.

Group	Estate price	Additional cost	Discount (%)		Mark-up (%)		Price elasticity	
			True	Est.	True	Est.	True	Est.
Age $<$ 40, I = L	2,871	-337	15.3	13.4	17.6	17.2	-6.28	-6.42
Age $<$ 40, I = H	4,622	35	11.8	12	17.8	17.8	-6.19	-6.18
Age $\in$ [40,59], I = L	2,315	-455	14	11.5	19.2	18.7	-5.86	-6.01
Age $\in$ [40,59], I = H	3,843	-131	10.3	9.6	20.4	20.2	-5.5	-5.54
Age $\geq$ 60, I = L	2,529	-410	12.9	10.5	21.1	20.5	-5.42	-5.55
Age $\geq$ 60, I = H	4,459	0	0	0	28.2	28.3	-3.94	-3.94
Average	3,247	-257	11.1	9.7	20.6	20.3	-5.54	-5.62

Reading notes: Estate prices are in euros per square meter for houses. "True" corresponds to the values calibrated with heterogeneous costs. "Est." corresponds to the values estimated when neglecting the cost heterogeneity.

Table 14: Effect of neglecting cost differences across consumer groups.

2.3.3 Discrimination with respect to gender

We check the robustness of our results to further price discrimination within groups of consumers. For instance, sellers price discriminate according to an unobserved characteristic such as the gender of the buyer. We use our estimated parameters of demand and marginal costs and modify the primitives by introducing some discrete unobserved heterogeneity within groups. Specifically, we consider that each group of consumers is equally composed of men and women, and that men have higher price sensitivities than women. We use our estimates for the price sensitivities of women and then calibrate the men price sensitivities so that the average transaction price for men is €250 lower. The value of the average price difference is inspired by Langer (2016), who finds a difference of $250 using transaction prices, data. All other preferences parameters are assumed identical for men and women. We then solve for the new market equilibrium using this new set of parameters.

We then analyze how neglecting the gender in this setting affects the main results (see Table 15). The differences in mark-ups and price elasticities are quite small, in particular the total average mark-up and price elasticity differ by 0.1 to 0.2 points. As expected, the average discount is underestimated, but not by much since price discrimination with respect to gender is very small compared to price discrimination with respect to the six groups we consider. Additionally, the mean absolute relative error in the estimated marginal costs is very small (0.24%) and the price sensitivity parameters we obtain are a convex combination of the men's and women's parameters.

Group	Average discount (%)		Average mark-up (%)		Average price elasticity	
	True	Estimated	True	Estimated	True	Estimated
Age < 40, I = H	13.6	12.2	19.6	18	-6.86	-6.22
Age ∈ [40,59], I = L	12.7	11.5	20.2	18.7	-6.53	-6.02
Age ∈ [40,59], I = H	8.9	9.7	18.1	20.3	-5.02	-5.55
Age ≥ 60, I = L	11.6	10.5	22	20.5	-6.02	-5.55
Age ≥ 60, I = H	0.9	0	26.1	28.5	-3.77	-3.93
Average	10.4	9.8	20.5	20.4	-5.8	-5.63

Reading notes: "True" stands for the model with the calibrated parameters for the gender. "Estimated" stands for the estimated parameters in the model that neglects price discrimination on gender.

Table 15: Effect of neglecting the gender on discounts, mark-ups and price elasticities.

2.3.4 Trade-in and financing

The existence of multiple components occurring at the same time as the car purchase can be source of further unobserved price heterogeneity within consumer groups. Some individuals may use their old car as trade-in, while some others may prefer to keep it or sell it themselves. This leads to an opportunity for the sellers to use the trade-in value to further price discriminate within groups. Furthermore, to the extent that both operations enter additively in the sellers' profit function, the introduction of the trade-in is equivalent, from the seller's point of view, to a constant marginal cost difference between the transactions with trade-in and those without. This in turns violates Assumption 1 of identical costs, but this time the cost difference is within each group of consumers.

To investigate the robustness of our results to neglecting the trade-in of an old car, we generate the equilibrium prices and market shares of a model based on our parameter estimates, but with a fraction of buyers selling their used cars in each of the 6 consumers groups. We use the fraction of transactions that involved a trade-in observed on BdF within each age class.[3] We obtain that 80%, 76% and 83% of transactions involve the trade-in of an old car for respectively the young, middle age and old purchasers. We then set the resale value of the car to €3,000, which is approximately the median trade-in value observed in BdF. This resale value is added to the utility associated to the outside option which implies that the outside option has a greater value for the subgroup of traders than for the subgroup of non-traders. Finally, we set the margin of the seller on the traded car to be €500.

Using this DGP, we estimate our model again, neglecting the trade-in. Table 16 shows that the estimated price parameters are almost identical to the true parameters. The coefficients of the intercept are overestimated. This could be expected, as It is more profitable to sell to consumers with a trade-in car. This translates, when neglecting the trade-in, into larger mean utilities of holding a car. On the other hand, the average mark-ups and price elasticities are

[3] Since we do not have this information by income class, we use the same fraction for each income subcategory.

very close to their true values (see Table 17).

	Estimated		"True"	
Group	Parameter	Std. error	Parameter	Std. error
Price parameters				
Age $<$ 40, I = L	-4.84**	0.117	-4.83**	0.12
Age $<$ 40, I = H	-4.52**	0.116	-4.52**	0.119
Age $\in$ [40,59], I = L	-4.32**	0.115	-4.32**	0.118
Age $\in$ [40,59], I = H	-3.96**	0.114	-3.96**	0.116
Age $\geq$ 60, I = L	-4.22**	0.131	-4.21**	0.133
Age $\geq$ 60, I = H	-3.06**	0.13	-3.05**	0.134
σ^p	0.99**	0.083	0.98**	0.086
Intercept				
Age $<$ 40, I = L	-6.03**	0.207	-6.24**	0.208
Age $<$ 40, I = H	-6.72**	0.206	-6.92**	0.207
Age $\in$ [40,59], I = L	-6.67**	0.206	-6.85**	0.208
Age $\in$ [40,59], I = H	-6.73**	0.205	-6.9**	0.207
Age $\geq$ 60, I = L	-6.29**	0.225	-6.48**	0.226
Age $\geq$ 60, I = H	-6.17**	0.274	-6.31**	0.282

Reading notes: "Estimated" stands for the estimated parameters in the model that neglects the trade-in of an old car. "True" stands for the model with a fraction of individuals with trade-ins.

Table 16: Effect of neglecting the trade-in part of the transaction on the price parameters and the coefficients of the intercept.

	Average mark-up (%)		Average price elasticity	
Group	"True"	Estimated	"True"	Estimated
Age $<$ 40, I = L	17.8	17.2	-6.26	-6.41
Age $<$ 40, I = H	18.4	17.8	-6.06	-6.2
Age $\in$ [40,59], I = L	19.2	18.7	-5.87	-6
Age $\in$ [40,59], I = H	20.8	20.2	-5.43	-5.54
Age $\geq$ 60, I = L	21.1	20.5	-5.41	-5.55
Age $\geq$ 60, I = H	28.8	28.1	-3.88	-3.97
Average	20.9	20.3	-5.5	-5.63

Reading notes: "True" stands for the model with the calibrated parameters for the model with trade-in. "Estimated" stands for the estimated parameters in the model that neglects the trade-in part the transaction. For the groups with trade-in cars, mark-ups include the margin on the trade-ins while price elasticities are calculated using the price gross of the trade-in resale value.

Table 17: Effect of neglecting the trade-in part of the transaction on average mark-ups and price elasticity.

2.3.5 Temporary promotions

To put in perspective the importance of third degree price discrimination compared to manufacturer discounts, we obtained data on monthly promotions for a sample of car models. This is the sample used by the consumer price index department of the French national institute of statistics (Insee). We have monthly data on temporary promotions for a sample of around 200 cars, 97 model names and 23 brands over the period 2004-2006. We match this dataset with monthly sales data from CCFA (2003-2006). We match the two datasets on the brand and model name, the fuel type and annual average price. When available in the promotion dataset, we also use the cylinder capacity, the horsepower and the body style. We match each car model $\times$ fuel type from the promotion data to its nearest neighbor in the CCFA dataset using the sum of the squared difference between the following standardized variables: horsepower, cylinder capacity and price. At the end, we obtain an unbalanced panel of 194 cars over 36 months (4,303 observations).

We find that the level of promotions is rather small compared to our estimated average discounts. The average sales weighted rebate is €666, which represents 3.2% of the average posted price. This is 3 times lower than our estimated average discount (2,023 euros). We also find that temporary rebates do not display important seasonality patterns. They tend to be the largest in March (€200 more than the average) and in July (€127 more than the average) and the lowest in May (€152 less than the average) and April (€123 less than the average). Finally, we investigate whether promotional activity is driven by low past sales. For that purpose, we regress the temporary promotion on the sales in the past three months using different fixed effects. In Specification (1) of Table 18, we control for the month and the year while in Specification (2) we use the date (month $\times$ year) as control. In Specification (3) we control for the month, the year and the model name. Finally in Specification (4) we add car model age dummies as controls. In the first two specifications only the sales three month before appear to be positively correlated with very low levels of statistical significance. However the sales at the past periods do not seem to drive the magnitude of promotions.

	(1)		(2)		(3)		(4)	
	Estimate	Std err	Estimate	Std err	Estimate	Std err	Estimate	Std err
Sales t-1	-0.008	0.121	-0.003	0.122	-0.165	0.103	-0.153	0.101
Sales t-2	0	0.141	-0.02	0.143	-0.043	0.117	-0.038	0.114
Sales t-3	0.216†	0.11	0.224*	0.111	0.015	0.093	0.047	0.091
Month, year FE	X							
Month $\times$ year FE			X					
Month, year, model FE					X			
Month, year, model, model age FE							X	

Reading notes: Significance levels: †: 10% *: 5% **: 1%. The model age fixed effects in Specification (4) include every age dummy from 1 to 6 and the reference are the models older than 6 year-old. All the specifications estimated using 3,548 observations.

Table 18: Regression of the rebate on past sales and some controls.

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