Skimming from the bottom: Empirical evidence of adverse selection when poaching customers

Online Appendix

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This online appendix contains supplementary material to (taken our for submission). First section contains supplementary descriptive analysis, and alternative specifications of the reduced for equations. Second section contains supplementary structural analysis including: asymmetric pricing, estimation with larger data set, and alternative specifications of the structural equations.

A Supplementary descriptive analysis

Panel A of Figure 1 depicts the empirical distribution of risk in the population as predicted by Poisson model. We use this distribution to show the gap between switchers and non-switchers in the context of the overall variation in risk. We find that the average non-switcher is at the 46th percentile of the distribution of risk in the population, while the average non-switcher is at the 67th percentile.

Similarly, according to Panel B of Figure 1, the average non-switcher with an excellent driving history places at the 32nd percentile of the population riskiness distribution, while the average switcher with similar history places at the 53rd percentile.

(A) All drivers (B) Drivers with excellent history

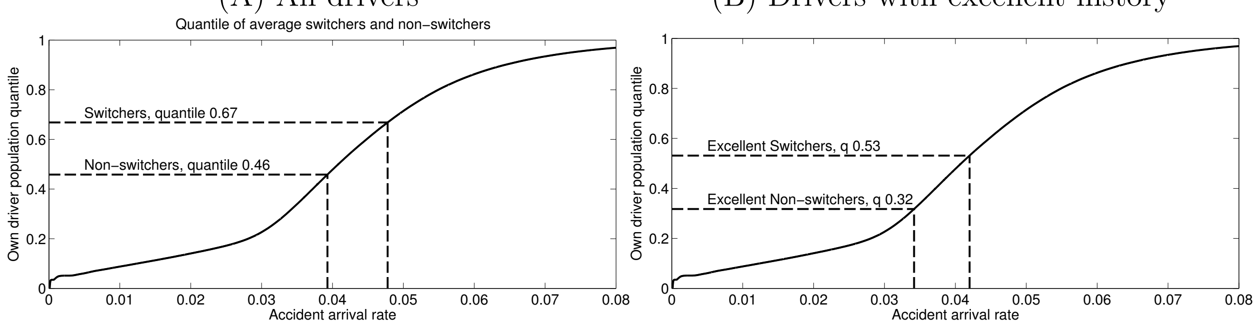

Figure 1: Distribution of risk arrival rates as predicted by the Poisson model and comparison of the riskiness between the average switcher and the average non-switcher.

B Supplementary structural analysis

In this appendix we present the robustness check of our results. We conducted three sets of checks: (a) we re-estimated the model using the full data set, (b) we relaxed the Assumption (ii) in Section 5.2, and (c) we re-estimated the alternative specifications of the model allowing for moral hazard, correlation between switching cost and riskiness and heterogeneous risk aversion. We show that none of the above alterations affect our results in a meaningful way.

B.1 Full data

Our main analysis is conducted on the subsample of the data composed of people driving a homogeneous, modal car in the data. The reasons are explained in Section 5.2. An alternative approach is to use the extended sample of the data and make parametric assumptions on the distribution of the riskiness conditional on car observables. Such assumptions are necessary, because the data contains a long tail of heterogeneous cars. As explained earlier, the parametric approach with full data trades off internal validity for some the external validity, i.e. the ability to generalize our results to the full population of drivers within the company.

We choose 15 most popular makes of cars in the data, which composes more than 95% of the data set. To maximize flexibility we use car make fixed effects for risk central tendency, risk aversion and outside option. We do not allow the switching cost to vary across car makes. Heterogeneity in switching cost across car makes is theoretically separately identified from the heterogeneity in outside option, however, it proves hard to identify in practice given the variation in our data. Specifically, the specification with both outside option and search cost variation across car makes generates statistically homogeneous estimates of switching cost. We also allow for linear impact of car value, weight, and horse power on the risk central tendency, risk aversion and outside option.

In Table B3 we report make fixed effects and linear parameters on car characteristics. We note large variability in risk distribution across car makes, with BMW drivers being the safest, and Ford drivers being the most risky. This difference can be explained by technological differences across cars, such as, breaking distance and traction control, as well as, by the selection of different drivers to cars. For example, BMW tends to attract older population due its high price. We also observe that large variation in risk aversion across car makes, with BMW drivers being the closest to risk neutral and Fiat drivers being the most risk averse. This directly reflects the fact that BMW drivers purchases less comprehensive coverage than, for example, Fiat drivers, relatively to its price and actuarial value. We observe similar value in outside option across car makes. This is perhaps not surprising since most consumers are likely to face similar substitutes to driving.

Bottom three rows of Table B3 contain slope coefficients for car characteristics. These coefficients multiply demeaned value of a car characteristic, such that the fixed effects reflect the differences across car makes for an average value of the characteristic in the data. We find expected signs of these coefficients. Car value increases risk aversion and decreases outside option.

Car weight and horse power and largely unimportant. Notably horse power decreases outside option which reflects that richer people have higher disutility of not driving.

The remaining coefficients are quite similar to the main specification, suggesting that our main results are generalizable beyond that model car make and model. In particular, risk variability and switching costs are nearly identical across both data sets. The model estimated on the full data generates 6% switcher-stayer and 30% quitter-stayer riskiness gaps, which is statistically different from our main estimates (8%, and 31%, respectively), but generates economically similar conclusions.

B.2 Asymmetric pricing

In this section of the appendix we present the robustness check of our results to relaxing the Assumption (ii) in Section 5.2. This assumption states that the companies play a symmetric pricing equilibrium. To investigate if this assumption influences our findings we re-estimated our model under several asymmetric pricing schemes.

We consider a duopoly industry structure in which Firm A is the observed firm, and Firm B the unobserved competitor. We implement the pricing adjustments by shifting the mass of B's discretionary discount distribution in an analogous way as in Section 5.4. The size of the shift is computed by setting the discount distribution of Firm A at the distribution estimated using the baseline model, and choosing the discount distribution of Firm B to yield x percentage lower expected discount. Both discount distributions are re-estimated, while keeping the size of the shift constant. We consider 6 values of x, that is, $x \in \{\pm 30\%, \pm 20\%, \pm 10\%\}$. Since the insurance market in Portugal is competitive, such range is likely to contain the possible asymmetries in our sample. Subsequently, we fully re-estimate the model for the 6 cases.

The results of this exercise are presented in Table B2. We find that changing the price charged by the competitor has a moderate effect on the point estimates of the primitives. The estimates of the parameters gathering the distribution of risk are remarkably robust. In particular, the vast majority of the risk estimates fall within the 95% confidence intervals of the baseline estimates. The same is true for the parameters gathering risk aversion. We see more variability in the estimates of search cost and disutility of not driving. This is somewhat not surprising, since the incentives to switch depend on the competitor's price distribution. Specifically, higher competitor's price generates less incentives to switch, thus, we need lower search cost (and disutility of not driving) to rationalize the churn rate in the data. The lowest estimate of the search cost is 12.2 utils, which is equivalent to €96, and the highest estimate amounts to 18 utils, which is equivalent to €143.

The main objective of the structural estimation is to show that a simple search model with competition can generate the stayer–switcher riskiness gap observed in the raw data. For this reason, it is important to assess the impact of the variability in the search cost estimates on the ability of the model to explain the stayer–switcher gap. The last two rows of the Table B2 present the predicted stayer–switcher and stayer–quitter riskiness gaps for all pricing configurations. For every considered case, we find a sizable riskiness gap. Stayer–switcher gap varies between 6% and 11%, that being within 95% confidence interval of reduced form estimator presented in Section 4. The stayer–quitter gap varies between 29% and 36%. All in all, riskiness gaps obtain without assuming symmetric equilibrium.

B.3 Alternative specifications

We estimate three alternative specifications capturing extra economic dimensions possibly present in our setting. First row of the Table B5 contains estimates accounting for possible correlation between search costs and riskiness. Our main specification assumes that these two random coefficients are independent, see discussion in Footnotes 18 and 19 of the main manuscript. We reestimate the version of the model accounting for this correlation by modeling the conditional distribution of search cost as extreme value with mean $E[F|\lambda_i] = F_0 + \rho\lambda_i$ and estimated dispersion parameter σ_ϵ. This allows to keep convenient logit formulation. To implement simulated GMM estimated of this model we draw λ_i for each individual and use conditional distribution of switching cost for that individual where appropriate. We estimate statistically significant correlation of search cost and riskiness. In particular, we show that only the most risky individuals have statistically significant search costs. We find that the model with correlation generates 40% larger riskiness gap. Thus, little more than than 60% of the adverse selection is related to the contract structure, while the remaining adverse selection is a result of the correlation in the primitives. Results from our main specification should be regarded as conservative.

Second row of the Table B5 contains the estimates of the model that allows for heterogeneous risk aversion. We calibrate the dispersion of the risk aversion in the population using the numbers from Jeziorski et al. (2017), who estimate the size of unobserved risk heterogeneity in the subsample of our data. One caveat that complicates the calibration is that Jeziorski et al. (2017) use quadratic utility function, while we use exponential. For this reason, we cannot simply take the variance of their risk aversion parameter and apply it our risk aversion parameter γ. Instead, we compute the dispersion of the certainty equivalent of the comprehensive contract implied by their estimates, and calibrate the variance of γ to generate the same dispersion. This adjustment should generate similar dispersion of preferences for extra insurance in both models, since consumer buy comprehensive contract if their certainty equivalent is larger than the premium. We find that introducing dispersion in risk aversion decreases the estimate of σ_ϵ, which determines the dispersion of search cost in the population. This is perhaps not surprising, since heterogeneity in risk aversion is competing with heterogeneity in search cost to explain the variation in switching behavior in the data that is orthogonal to risk. At the same time, the estimate of variability in risk σ_λ is economically close to the one estimated using out baseline specification. More importantly, the risk gap generated by the new estimates is also economically similar. This suggests, that the source non-risk unobserved heterogeneity is less important as long as the relevant strength of risk and non-risk related heterogeneities match the switching patters in the data.

Third row of the Table B5 contains the estimates of the model that account for moral hazard. As demonstrated by Jeziorski et al. (2017), omitting moral hazard from estimation can potentially lead in the downward bias in the estimates of risk dispersion. In order to account for this bias it is important to understand the intuition behind it. In our model, risk dispersion is identified from the variation in realized risk across risk classes. The drivers in higher risk classes face stronger marginal incentives to drive well, because the penalty structure is convex. Thus, these, mostly risky drivers, may put more effort to reduce risk than, less risky drivers in lower risk classes. This will endogenously lower the riskiness gap across risk classes, making the population look more homogeneous than it actually is.

One way to account the bias to use adjusted ex-post riskiness conditional on the risk class, that accounts for endogenous risk adjustments. This should provide the first-order correction for the moral hazard bias.[1] We calibrate the risk adjustments using the results obtained by Jeziorski et al. (2017) reported in Table B1. Accident arrival rate is adjusted by a multiplicative factor as the individual moves across risk-classes. For example, an individual with risk λ_i in class 1, would have risk equal to $0.86\lambda_i$ in class 10. This is because he faces steeper incentives on the margin to drive well in class 10, as compared to class 1. Perhaps not surprisingly, we find larger dispersion

[1] Full estimation involving moral hazard would require exploring panel structure of the data and would add several assumptions about risk production. Since the main focus of the paper is not moral hazard across risk classes, but adverse selection during churn, we opted for the middle ground – making less assumptions and obtain first-order correction of the bias. Importantly, counterfactuals may require further corrections for moral hazard, because the risk adjustment schedule may depend on the primitives of the model. We leave this correction for further research.

of unobserved riskiness in the population which results in more extensive riskiness gap. Thus, the results in the main version of the paper should be treated as conservative.

RK	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Adj.	1	0.98	0.97	0.97	0.96	0.93	0.92	0.91	0.88	0.86	0.84	0.79	0.71	0.61	0.49	0.57	0.70	0.87

Table B1: Multiplicative risk adjustment factors for moral hazard across risk classes.

Parameter	Baseline	Adjustment of competitor's price					
		-30%	-20%	-10%	$+10\%$	$+20\%$	$+30\%$
Risk: central tendency – μ_λ	0.023^{***}	0.020^{***}	0.023^{***}	0.024^{***}	0.021^{***}	0.021^{***}	0.022^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Risk: central tendency, zipcode 2 fe	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004^{*}	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Risk: central tendency, zipcode 3 fe	0.017^{***}	0.015^{***}	0.018^{***}	0.017^{***}	0.017^{***}	0.016^{***}	0.012^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Risk: variability – σ_λ	0.034^{***}	0.034^{***}	0.032^{***}	0.032^{***}	0.033^{***}	0.034^{***}	0.035^{***}
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Risk: young multiplier – λ^{YOUNG}	1.845^{***}	2.051^{***}	1.904^{***}	1.834^{***}	1.889^{***}	1.911^{***}	1.751^{***}
	(0.498)	(0.568)	(0.516)	(0.517)	(0.504)	(0.502)	(0.470)
Risk: inexperienced multiplier – λ^{INEX}	2.112^{***}	1.951^{***}	2.142^{***}	2.152^{***}	2.108^{***}	2.057^{***}	1.904^{***}
	(0.699)	(0.703)	(0.732)	(0.724)	(0.730)	(0.687)	(0.618)
Risk aversion – γ	0.129^{***}	0.133^{**}	0.133^{***}	0.128^{***}	0.133^{***}	0.128^{***}	0.128^{***}
	(0.022)	(0.055)	(0.023)	(0.021)	(0.023)	(0.026)	(0.025)
Search cost (€)	13.0^{*}	18.1^{*}	14.8^{*}	14.0^{*}	12.2	12.6	12.7
	(7.1)	(10.4)	(8.1)	(7.6)	(8.7)	(8.9)	(8.4)
Disutility of not driving (€)	429.6^{***}	456.6^{***}	444.5^{***}	437.4^{***}	416.3^{***}	404.0^{***}	390.7^{***}
	(12.7)	(34.3)	(13.7)	(14.2)	(11.9)	(10.7)	(10.7)
2.5% discount prob.	0.686^{***}	0.720^{***}	0.709^{***}	0.698^{***}	0.665^{***}	0.647^{***}	0.615^{***}
	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.020)	(0.018)
7.5% discount prob.	0.102^{***}	0.089^{***}	0.095^{***}	0.091^{***}	0.094^{***}	0.095^{***}	0.093^{***}
	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
12.5% discount prob.	0.075^{***}	0.078^{***}	0.077^{***}	0.082^{***}	0.090^{***}	0.090^{***}	0.105^{***}
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
17.5% discount prob.	0.123^{***}	0.103^{***}	0.106^{***}	0.115^{***}	0.137^{***}	0.154^{***}	0.175^{***}
	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(0.011)	(0.010)
Variability of private shock (utils) – σ_ϵ	0.033^{***}	0.034^{**}	0.033^{***}	0.032^{***}	0.035^{***}	0.034^{***}	0.036^{***}
	(0.006)	(0.016)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)
Stayer–switcher risk gap	8%	11%	10%	9%	7%	6%	6%
Stayer–quitter risk gap	31%	36%	35%	34%	32%	32%	29%

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Robustness to asymmetric pricing.

Make	Risk central tendency, μ	Risk aversion coefficient, γ	Outside option, u_0
Renault	0.025***	0.185***	-402.113***
	(0.0009)	(0.0009)	(22.9219)
Opel	0.026***	0.193***	-443.163***
	(0.0014)	(0.0310)	(0.0231)
Volkswagen	0.025***	0.356***	-381.920***
	(0.0052)	(0.0349)	(0.0045)
Peugeot	0.035***	0.252***	-382.427***
	(0.0012)	(0.0249)	(0.0090)
Ford	0.040***	0.366***	-363.308***
	(0.0007)	(0.0325)	(0.0069)
Toyota	0.030***	0.168***	-520.246***
	(0.0016)	(0.0275)	(0.0369)
Mercedes	0.029***	0.136***	-451.448***
	(0.0016)	(0.0221)	(0.0184)
Citroen	0.032***	0.216***	-402.170***
	(0.0014)	(0.0071)	(0.0093)
Fiat	0.033***	0.477***	-347.316***
	(0.0025)	(0.0660)	(0.0053)
Mitsubishi	0.039***	0.372***	-392.126***
	(0.0020)	(0.0317)	(0.0120)
Seat	0.038***	0.369***	-386.990***
	(0.0007)	(0.0030)	(0.0046)
Nissan	0.038***	0.211***	-476.452***
	(0.0114)	(0.0120)	(0.0167)
Audi	0.029***	0.251***	-402.174***
	(0.0086)	(0.0145)	(0.0125)
BMW	0.015***	0.165***	-402.225***
	(0.0045)	(0.0286)	(0.0128)
Honda	0.035***	0.391***	-382.173***
	(0.0038)	(0.0869)	(0.0079)
Car value slope	0.007***	0.067***	-0.148***
	0.0001	0.0123	0.0047
Car weight slope	0.005	-0.051	0.035*
	0.0031	0.0549	0.0203
Horse power slope	-0.005	0.008	-0.246***
	0.0081	0.0409	0.0288

Table B3: Estimates with extended data set – fixed effects.

Parameter	Estimate
Risk: central tendency, zipcode 2 fixed effect	-0.002**
	(0.0006)
Risk: central tendency, zipcode 3 fixed effect	0.018***
	(0.0009)
Risk: variability – σ_λ	0.034***
	(0.0001)
Risk: young multiplier – λ^{YOUNG}	1.845***
	(0.1013)
Risk: inexperienced multiplier – λ^{INEX}	2.112***
	(0.1627)
Search cost (€) – average car value	13.0***
	(4.5095)
Search cost (€) – car value slope (€1,000s)	0.1***
	(0.0227)
2.5% discount prob.	0.686***
	(0.0046)
7.5% discount prob.	0.102***
	(0.0011)
12.5% discount prob.	0.075***
	(0.0010)
17.5% discount prob.	0.123***
	(0.0025)
Variability of private shock (utils) – σ_ϵ	0.060***
	(0.0036)

Table B4: Estimates with extended data set – other structural parameters.

		(1) Correlation between riskiness and search cost	(2) Heterogeneous risk aversion	(3) Moral hazard
Risk	Central tendency – μ_λ	0.023***	0.025***	0.034***
		(0.0026)	(0.0021)	(0.0009)
	Central tendency Zip 2 fixed effect	-0.004	-0.005*	-0.004***
		(0.0026)	(0.0028)	(0.0001)
	Central tendency Zip 3 fixed effect	0.016***	0.018***	0.018***
		(0.0034)	(0.0033)	(0.0001)
	Variability – σ_λ	0.032***	0.039***	0.061***
		(0.0035)	(0.0022)	(0.0009)
	Young Multiplier – λ^{YOUNG}	1.833**	1.650***	1.910***
		(0.7410)	(0.5823)	(0.4299)
	Inexperienced Multiplier – λ^{INEX}	1.953**	1.812**	2.221**
		(0.9413)	(0.7472)	(0.9524)
Risk aversion	Central tendency – γ	0.132**	0.015*	0.114
		(0.0517)	(0.0082)	(0.0714)
	Variability – σ_γ	-	0.092	-
			(calibrated)	
Search cost	Average riskiness	14.710	12.265***	13.547*
		(10.2265)	(1.8455)	(7.5579)
	Conditional on mean+1σ riskiness	33.466*	-	-
		(17.5580)		
	Conditional on mean-1σ riskiness	6.466	-	-
		(3.9934)		
Other parameters	Disutility of not driving (€)	423.947***	371.009***	409.124***
		(23.0303)	(4.3599)	(43.0057)
	2.5% discount prob.	0.673***	0.653***	0.682***
		(0.0206)	(0.0135)	(0.0121)
	7.5% discount prob.	0.092***	0.101***	0.099***
		(0.0040)	(0.0028)	(0.0028)
	12.5% discount prob.	0.090***	0.091***	0.079***
		(0.0052)	(0.0034)	(0.0029)
	17.5% discount prob.	0.130***	0.140***	0.127***
		(0.0104)	(0.0071)	(0.0060)
	Variability of private shock (utils) – σ_ϵ	0.034**	0.013***	0.032
		(0.0137)	(0.0012)	(0.0224)
Risk gap	Switcher	16.2%	9.2%	8.6%
	Quitter	31.9%	41.4%	37.8%

Table B5: Alternative specifications.

References

Jeziorski, P., E. Krasnokutskaya, and O. Ceccarini (2017): "Adverse Selection and Moral Hazard in a Dynamic Model of Auto Insurance," Tech. rep., UC Berkeley.