MAX-PLANCK-INSTITUT FÜR SOZIALRECHT UND SOZIALPOLITIK
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How do unisex rating regulations affect gender differences in insurance premiums?

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16-2014

MEA DISCUSSION PAPERS

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September 19, 2014

Abstract

As of December 21, 2012, the use of gender as an insurance rating category was prohibited. Any remaining pricing disparities between men and women will now be traced back to the reasonable pricing of characteristics that happen to differ between the groups or to the pricing of characteristics that differ between sexes in a way that proxies for gender. Using data from an automobile insurer, we analyze how the standard industry approach to simply omit gender from the pricing formula, which allows for proxy effects, differs from the benchmark for what prices would look like if direct gender effects are removed and other variables do not adjust as proxies. We find that the standard industry approach will likely be influenced by proxy effects for young and old drivers. Our method can simply be applied to almost any setting where a regulator is considering a uniform-pricing reform.

Keywords: Automobile insurance, risk classification, unisex premium

JEL classification codes: G22, K20, C20

1 Introduction

Unisex premiums have been mandatory in the European insurance market since December 21, 2012. According to the Court of Justice of the European Union, the use of gender information in pricing is discriminatory. However, it is not at all clear how this regulatory intervention affects prices; when unisex tariffs are introduced, the extent to which it changes disparities in observed prices between the groups will depend on the direct gender pricing differentials prior to the change, the distribution of other variables used in rating that differ across the two genders, and the extent to which the new rating models will adjust the weight on other variables that are distributed differently across gender once gender is removed from the models. For example, young male drivers are classified as riskier than young female drivers and thus pay a higher premium for automobile insurance. Additionally, other pricing variables such as engine power are distributed differently between men and women. Once gender is excluded from the pricing model, such variables might then proxy for the omitted variable. The magnitude of these three effects determine the unisex tariff. The purpose of this study is to decompose the extent to which pricing differences can be traced back to these channels.

If a government imposes a uniform pricing regulation, any remaining pricing disparities between groups are likely to be a contentious issue, with one side arguing that they reflect the reasonable pricing of characteristics that happen to differ between the groups and the other side arguing that they reflect pricing of characteristics that differ between the groups in a way that proxies for the group-level characteristic (e.g., gender in this case). In this paper we present a method to back this debate quantitatively.

We estimate how gender impacts premium calculation in the automobile insurance market by using hedonic pricing regressions (Puelz and Kemmsies, 1993). For this, we use policy level data from a German insurer for the year 2011. First, we replicate the full pricing model in order to identify the price difference between men and women. Following a two step method developed by Pope and Sydnor (2011), we provide a way of establishing the benchmark for what prices would look like if direct gender effects were removed and other variables did not adjust as proxies. We also estimate a model in which the gender variable is simply removed, which is likely to be implemented as a standard approach in the insurance industry. In this model, other variables can proxy for the omitted gender variable. By comparing this standard approach to the Pope/Sydnor benchmark, we determine where on the spectrum between direct gender-based pricing to the benchmark the industry is likely to appear. We find that the industry is likely to be very close to the Pope/Sydnor benchmark, and hence is going to be close to fully eliminating the gender effect in prices for the majority of insureds. However, we find significant deviations for young and old drivers. The deviation is most pronounced for young female drivers.

Our paper provides two main contributions: first, we show that if the Pope/Sydnor method is not applied, remaining price differences between male and female drivers are caused partially by proxy effects for young and old drivers. This effect is particularly strong for young female drivers. We find that the proxy effect can easily be strengthened by adjusting the pricing formula. The proxy effect is negligible for all other age classes. Thus our paper reveals that the debate about proxy effects is valid and critical for specific age groups. Second, using data on existing insurance prices to estimate the effect of reforms instead of using loss data to re-estimate actuarial models is the other major contribution of this paper. This approach can be used at very low cost in almost any setting where a regulator is considering a uniform-pricing reform. There are frequent discussions in all insurance markets about the benefits and disparities of risk classification on dimensions such as age and income. It is much easier and requires a much smaller sample to estimate equations based on observed prices than to collect loss data and re-do the entire actuarial process.

The paper proceeds as follows. Section 2 provides an overview of the literature on unisex pricing regulation. Section 3 presents the method for the implementation of non-discriminatory premiums according to Pope and Sydnor (2011). Section 4 describes the dataset and section 5 outlines the empirical model and presents results. A discussion of the results takes place in section 6 and section 7 concludes.

2 Literature Review

This literature review starts out with studies focusing on the efficiency and social fairness of risk classification. The second part of the literature review presents existing studies on the impact of implementing unisex tariffs on the insurance market in general.

Risk classification, or more generally insurance, is confronted with a conflict between efficiency and equity or social fairness. Risk classification refers to the use of observable variables or behavior such as gender, age, and smoking, to price or to structure insurance policies (e.g., ABI (2008), Crocker and Snow (2013)). Insurance companies attempt to reduce informational asymmetries by collecting information and classifying applicants.

However, the use of premium differentiation is at the center of vivid public discussions. On the one hand, each insuree is supposed to pay premiums according to his or her risk; on the other hand it is perceived as unjust if the pricing of insurance premiums is based on characteristics such as gender or race, which are uncontrollable by the individual (e.g., Harrington and Doerpinghaus (1993)). Thiery and Van Schoubroeck (2006) argue that while insurers prefer a so called group approach, legislators favor an individualistic apporach. In contrast to the group approach, the individualistic approach posits that individuals should not be treated as members of a group. Thus, according to Thiery and Van Schoubroeck (2006) and the individualistic approach "an individual cannot be treated differently because of his or her membership in a such a group [...]". An example of this is the late court decision of the European Court of Justice to forbid gender as a variable for risk classification in insurance contracts (EC (2011)). Yet such legal restrictions may lead to a situation in which lower-risk individuals pay higher premiums than those corresponding to their true risk and cross-subsidize high-risk insurees, who pay lower premiums than justified by the actuarial equivalence principle (e.g., Oxera (2011c)). As a consequence, low-risk individuals might leave the risk-pool and, when the proportion of high-risk individuals is sufficiently high, premiums will rise considerably, leading to regulatory adverse selection (Polborn, Hoy, and Sadanand, 2006). Neudeck and Podczeck (1996) analyze the health insurance market in this respect and discuss various forms of regulation and their effect on the reduction of adverse selection.

However, critical views on adverse selection effects of failed premium differentiation also exist. Hemenway (1990) discusses the general assumptions of adverse selection and argues that favorable selection, the contrary of adverse selection is equally likely to occur. In practice, this makes it hard to anticipate what happens in the real world. Siegelman (2004) follows a similar argumentation and points out that adverse selection might be an exaggerated threat. Also Thomas (2007) argues that adverse selection should be regarded distinctively and should not be taken for granted.[1]

Having presented the view of regulators and insurers, the opinion of customers is also of interest: Schmeiser, Stoermer, and Wagner (2014) conduct a survey in which they test the acceptance of different risk classification factors in general and gender in greater detail. They find that survey respondents in UK, Germany, France, Italy, and Switzerland generally accept premium differentiation. However, gender and also age are the least accepted factors, especially when respondents were confronted with prevalent premium gaps.

Another stream of literature mainly focused on the potential impact of the ban of gender on insurance markets. For example, Sass and Seifried (2014) assess the impact of unisex rulings in a monopolistic as well as a competitive insurance market and show that overall social welfare is reduced. It was widely discussed what changes would become necessary after the implementation. Riedel and Münch (2005) and Riedel (2006), for example, discuss the role of secondary (experience-based) premium differentiation after primary premium differentiation is restricted in health insurance. The authors show that in private health insurance the consequences of the ban of gender can be softened significantly through distinct secondary premium differentiation. Ornelas, Guillén, and Alcañiz (2013) point out difficulties in calculating longevity risks based on unisex mortality tables. Based on their analysis it is important to use separate mortality tables even when premiums are not differentiated in the end. Oxera (2011b) and Oxera (2011c) find that unisex premiums in automobile insurance are larger than the weighted average gender-based premiums in Belgium and the Netherlands. The author argues that the price mark-up could be due to direct costs associated with the ban of gender, such as re-pricing or changes in the IT system, or uncertainty for the insurer with regard to the pool composition after the change in law. Oxera (2011c) and ABI (2010) also refer to the All-Industry Research Advisory Council (AIRAC (1987)) and Wallace (1984) who provide evidence for increasing motor insurance premiums after the implementation of unisex tariffs in Montana and Michigan. A similar reasoning has been made by the Society of Acturaries

[1] A comprehensive analysis of asymmetric information in the German car insurance market can be found in Spindler, Winter, and Hagmayer (2014).

in Ireland (SAI (2004) and SAI (2011)). Additionally, Oxera (2011c) shows that before the implementation of unisex tariffs women in general pay lower term life insurance premiums than men, women get less pension annuity payments each month than men (however, women get this amount for a longer period of time than men due to the longer life expectancy), and young women pay less in automobile insurance than young men. Our study supports Oxera's findings with regard to the motor insurance.

Our study differs from the previous literature as we are mainly focusing on different approaches on how unisex pricing can be implemented. The European Commission published general guidelines (EC (2011)) which highlight that it is not allowed to use gender in insurance pricing. However, according to Schmeiser, Stoermer, and Wagner (2014) and paragraph 17 of the Guidelines on the Application of the Council Directive (EC, 2011) "the use of risk factors which might be correlated with gender [...], as long as they are true risk factors in their own right" is still permitted. Nevertheless, these guidelines provide only verbal reasoning and do not specify any quantitative methods. Therefore, different approaches are possible, apparently even approaches where proxies for the gender information are included. With the help of the example that men drive faster cars than females, Oxera (2011a) and ABI (2010) show that if other risk factors are correlated with gender, true gender-neutral tariffs cannot be established since proxy effects will exist. The authors argue that this could be resolved by banning correlated variables but also admit that such restrictions are very costly. Another way would be to implement transfer payments between risk pools. In our paper, we present a new method proposed by Pope and Sydnor (2011) which allows for correlated variables to be in the model without serving as proxies. This would address the major concerns raised in Oxera (2011a) and ABI (2010). ABI (2010) shows that young female drivers and old men will pay more after the change in law, whereas young men and old women will benefit. In this specific analyis, the author uses a dataset from a large motor insurer and allows for proxy effects. However, it is not clear whether the estimated premiums deviate significantly from benchmark gender-neutral premiums without proxy effects. In our analysis, we shed light on different pricing methods, discuss the differences and back the discussion with regard to proxy effects quantitatively using a policyholder data set as well as conducting simulations. Another contribution of this study is the ease with which our approach can be replicated. Since we use premium data instead of loss data, there is no need to replicate the whole actuarial process.

3 Implementing Non-Discriminatory Policies

In order to realize a ban of classification variables (gender in our case), there are different possibilities for implementing guidelines. Pope and Sydnor (2011) propose several approaches and compare them in the context of regression analysis. The "common approach" is to exclude the banned variable from the variables used for risk classification. This implies that the other variables which are correlated with the banned variable might take over some of this effect. For example, in automobile insurance, gender might be correlated with engine power. In the case of a ban on gender as a pricing variable, engine power will serve as a proxy for gender. Pope and Sydnor (2011) propose a method for eliminating such proxying effects. Their idea is to use all variables, i.e., even the banned variables, for risk classification and estimate a "full model" in a first step. In order to make predictions they take, in a second step, the estimated coefficients of the allowed variables and average over the banned variable. This method ensures that on the one hand, the forbidden variable is not influencing predicted values and on the other hand, variables that are correlated with the omitted variable maintain their "own" predictive power and do not serve as proxies. There are three comments worth making:

- The approach of Pope and Sydnor (2011) has a lower predictive power than the common approach. Intuitively, there is "more information" in the common model, since due to the omitted variable bias there is still some of the gender effect in the model. Pope and Sydnor (2011) provide both theoretical and empirical support for this ranking. Inasmuch as only the direct use of a certain variable has been forbidden, insurance companies would choose the common method as the standard industry approach, as it gives a better risk classification than the Pope/Sydnor method.

- The proposed procedure is not directly applicable to insurance. Under the assumption of actuarially fair premium calculation and that the composition of the risk pool does not change, simple averaging is not sufficient and must be replaced by a weighted average according to the distribution in the data set. For example, in our application the premium of male and female must be weighted according to their proportion in the data set, otherwise the restriction that the premium income is equal to the payments for claims is potentially not fulfilled.

- In order to calculate the gender-adjusted premium according to Pope and Sydnor (2011), the variable "gender" must be collected. This might be counterproductive as on the one hand, discrimination should be prevented, yet on the other hand this information must be known by the insurance company.

In this paper, we present estimates of premiums calculated according to the common and the Pope/Sydnor method. The common method allows us to identify how close to the full model premiums the insurance companies can get. This research does not depend on and does not investigate how premiums actually look in the aftermath of unisex tariffs. Instead, we wish to compare the common method premiums to the Pope/Sydnor premiums in order to identify the extent to which proxy effects might determine the potential standard industry approach.

4 The Data Set

In Germany, as in many other countries, automobile insurance has three pillars:

1. A *third party liability* insurance which is mandatory for all cars and covers damage inflicted on other drivers and their cars in the case of an accident.

2. A *first party, fire, theft*, also called *comprehensive coverage*, which is non-mandatory and covers own damages and losses caused by theft, natural disasters (storm, hail, lightning strike, flood), collision with furred game animals, and so on.

3. A *fully comprehensive* or *collision coverage*, which covers accidental damage to the driver's own car, even if caused by the insured, and damages caused by the vandalism of strangers. It is non-mandatory.

For both types of comprehensive insurance, a deductible can be chosen. In German car insurance, there is also a uniform experience rating system (*"Schadenfreiheitsrabatt"*) which, however, applies only to the compulsory liability insurance and to collision coverage but not to the comprehensive coverage. The number of years without an accident is counted separately for the two types (liability and collision) and in accordance with these numbers, every insured is divided into a class (*"Schadensfreiheitsklasse"*), which is associated with a bonus coefficient b_t. For any year t, the premium is defined as the product of a base amount and this coefficient. The base amount can be set freely by the insurance companies according to their risk classification, conditional on the characteristics of the insured (such as age, sex, profession, and location), but it cannot be related to past experience.

Table 1: Summary statistics

	male					female				
VARIABLES	N	mean	sd	min	max	N	mean	sd	min	max
Annual Premium in Euros	23,952	470.417	202.358	11.48	1,891.85	12,787	457.432	147.858	11.48	1,588.17
Age of the Car	24,343	6.148	6.290	0	50	13,117	5.279	5.414	0	50
Period of Ownership	24,298	4.010	4.105	0	41	13,115	4.024	3.942	0	39
Kilometers Traveled per Year	24,571	10.976	7.063	0	175	13,140	10.402	5.795	0	195
Engine Power in KW	24,571	83.700	40.156	0	426	13,140	68.216	28.334	0	311
Proprietary - Own used Home	24,571	0.337	0.473	0	1	13,140	0.296	0.456	0	1
Proprietary - Own used multiple dwelling	24,571	0.049	0.216	0	1	13,140	0.039	0.193	0	1
Proprietary - Own used flat	24,571	0.094	0.292	0	1	13,140	0.086	0.280	0	1
Proprietary - No Information	24,571	0.028	0.165	0	1	13,140	0.026	0.159	0	1
Garage - No Garage	24,571	0.378	0.485	0	1	13,140	0.419	0.493	0	1
Garage - Single or Double	24,571	0.476	0.499	0	1	13,140	0.437	0.496	0	1
Garage - Multiple	24,571	0.071	0.257	0	1	13,140	0.072	0.258	0	1
Garage - Carport	24,571	0.059	0.235	0	1	13,140	0.066	0.248	0	1
Garage - No Information	24,571	0.016	0.127	0	1	13,140	0.006	0.078	0	1
Age from 17 to 20	24,571	0.003	0.051	0	1	13,140	0.004	0.062	0	1
Age from 21 to 25	24,571	0.024	0.154	0	1	13,140	0.073	0.261	0	1
Age from 26 to 30	24,571	0.074	0.262	0	1	13,140	0.089	0.285	0	1
Age from 31 to 35	24,571	0.128	0.334	0	1	13,140	0.112	0.316	0	1
Age from 36 to 40	24,571	0.113	0.317	0	1	13,140	0.104	0.305	0	1
Age from 41 to 45	24,571	0.129	0.335	0	1	13,140	0.122	0.327	0	1
Age from 46 to 50	24,571	0.124	0.330	0	1	13,140	0.118	0.322	0	1
Age from 51 to 5	24,571	0.107	0.309	0	1	13,140	0.103	0.305	0	1
Age from 56 to 60	24,571	0.087	0.283	0	1	13,140	0.093	0.290	0	1
Age from 61 to 65	24,571	0.073	0.261	0	1	13,140	0.069	0.254	0	1
Age from 66 to 70	24,571	0.055	0.228	0	1	13,140	0.047	0.213	0	1
Age from 71 to 75	24,571	0.047	0.213	0	1	13,140	0.041	0.197	0	1
Age from 76 to 80	24,571	0.024	0.152	0	1	13,140	0.018	0.131	0	1
Age from 81 to 85	24,571	0.009	0.096	0	1	13,140	0.005	0.074	0	1
Age from 86 to 90	24,571	0.002	0.040	0	1	13,140	0.001	0.035	0	1

For our analysis, we use the database of the insurance contracts of one German insurance company for the year 2011. Our database is representative for the whole market as descriptive statistics indicate. Furthermore, during the period of analysis there was close to full competition in the German car insurance market which leads to a comparable market situation for all insurers. In 2011, the compulsory liability insurance covered 57.12 million cars, the total number of registered cars in Germany. In total, premium income was €20.9 billion and expenditures for claims were €20.4 billion. (GDV (2012))

In this paper, we only analyze the liability insurance line.[2] Furthermore we restrict our analysis to a subsample of individual contract owners. By considering contracts which are held by only one person, we make sure that the policyholder's characteristics and especially their gender are actually the characteristics of the driver; i.e. we exclude contracts where more than one person is allowed to drive the car.

Table 2: Mean variables by gender

	engine power in kw				kilometers per year in 1000				age of the car in years				period ownership in years			
age	male	female	p-value	corr	male	female	p-value	corr	male	female	p-value	corr	male	female	p-value	corr
17-20	56.48	54.71	0.745	-0.0286	8.06	9.82	0.062	0.1730	11.86	7.86	0.003	-0.2651	0.67	0.80	0.449	0.0713
21-25	78.04	58.62	0.000	-0.3059	10.68	11.11	0.159	0.0191	8.96	6.78	0.000	-0.1918	1.34	1.89	0.000	0.1579
26-30	84.53	65.40	0.000	-0.2667	11.49	11.36	0.563	-0.0140	7.53	6.19	0.000	-0.1159	2.24	2.61	0.000	0.0715
31-35	86.20	67.28	0.000	-0.2405	11.88	11.09	0.000	-0.0559	6.97	5.93	0.000	-0.0851	2.97	3.21	0.011	0.0363
36-40	84.34	68.62	0.000	-0.2098	11.44	10.74	0.000	-0.0559	6.75	5.81	0.000	-0.0775	3.54	3.65	0.344	0.0157
41-45	83.01	68.94	0.000	-0.1895	10.89	10.65	0.275	-0.0226	6.53	5.32	0.000	-0.0962	3.83	3.94	0.292	0.0159
46-50	81.43	68.23	0.000	-0.1745	10.88	10.45	0.023	-0.0367	6.44	5.40	0.000	-0.0798	4.08	4.03	0.675	-0.0062
51-55	81.71	70.75	0.000	-0.1458	11.09	10.83	0.219	-0.0289	6.29	5.13	0.000	-0.0894	4.11	4.07	0.762	-0.0044
56-60	82.77	70.02	0.000	-0.1719	11.23	10.48	0.001	-0.0622	5.65	4.69	0.000	-0.0795	4.37	4.61	0.116	0.0265
61-65	85.53	73.40	0.000	-0.1583	11.22	9.63	0.000	-0.1126	5.01	3.96	0.000	-0.0915	4.66	5.10	0.015	0.0470
66-70	86.74	71.26	0.000	-0.1884	10.12	8.74	0.000	-0.1116	4.15	3.58	0.018	-0.0514	5.47	6.07	0.009	0.0593
71-75	86.02	71.60	0.000	-0.1970	9.38	7.57	0.000	-0.1729	3.53	3.45	0.779	-0.0077	6.44	6.73	0.297	0.0257
76-80	86.00	63.97	0.000	-0.2536	8.38	6.71	0.000	-0.2011	3.20	3.78	0.190	0.0481	7.07	7.77	0.117	0.0564
81-85	78.76	64.31	0.001	-0.1762	7.58	7.03	0.208	-0.0616	3.75	4.20	0.577	0.0307	8.66	8.45	0.809	-0.0143
86-90	82.70	74.75	0.361	-0.1181	7.45	6.25	0.186	-0.1587	3.65	5.44	0.452	0.1340	7.28	9.00	0.380	0.1326

Note: p-values indicate whether differences are significantly different, based on a two tailed t-test.
Corr indicates the correlation between the respective variable and the gender dummy.

Table 1 shows summary statistics broken up by gender. There are about 25,000 male observations and 13,000 female observations in our data set. It can be seen that the distribution of several key pricing variables differs between men and women. Male drivers seem to own older cars, drive longer distances, possess cars with higher engine power, are more likely to own a home, and are more likely to own a single or double garage. Table 2 shows the correlations of some key variables with gender for different age classes. We find that men drive faster cars than women for all age ranges except for the very young (17-20) and very old (86-90) drivers. However, due to specific characteristics of these two groups and a limited number of observations, these age classes should be treated with caution. In general, men seem to drive

[2] In an earlier draft of this paper we also made the analysis for comprehensive and collision coverage. The results were qualitatively the same.

more kilometers per year than women - however, the difference is not statistically significant for all age groups. Men drive older cars than female drivers. The difference in age of car is not significant for old drivers. Male drivers own their car for a shorter time than women - however, the difference is only significant for young and old drivers. The Figures 4, 5, and 6, which can be found in appendix A, show kernel density plots of the different key variables by gender and for different age categories (young, middle age range, and old drivers). The graphs show that distributions significantly differ between male and female drivers for young people. The differences reduce or even vanish for middle age ranges. For instance, there seems to be no differences between male and female drivers with regard to period of ownership. The distributions of engine power and age of the car are obviously getting closer, too. For old drivers, the distributions seem to deviate stronger again compared to the middle age range (except for the variable age of cars). Our preliminary analysis shows that significant differences between male and female drivers exist. The distribution of several key pricing variables seems to be different between male and female, particularly for young and old drivers. Depending on how unisex tariffs are implemented there is a very high potential for proxy effects after the gender ban for certain age groups.

5 Empirical Model and Results

5.1 Claim Analysis and Motivation of Pricing Approach

An obvious approach for this study would be to regress loss data on characteristics. We conducted a regression with the individual number of accidents per year as the dependent variable. We assume that the number of accidents in which an individual is involved during a period is Poisson distributed $\mathcal{P}(\lambda_i)$ with individual parameter λ_i which also equals the expected value. In doing so, we make the assumptions that the accidents of an individual are independent over time, the length of a time period influences the probability that an individual has a certain number of accidents in that period, and the probability that an individual has more than one accident during a period is sufficiently small (Dionne and Vanasse, 1992). We model the parameter λ_i in the following way:

$$\lambda_i = \beta_0 + \beta_{GEN} * GEN_i + \sum_{j=1}^{k} \beta_j * AGE_{ij} * GEN_i + \rho' * X_i + \epsilon_i \tag{5.1}$$

The unit of observation is individual policy level. The dependent variable (λ_i) in equation 5.1 is the number of liability claims in 2011 per insured. The independent variables of interest are the gender variable (GEN) and the interactions of age and gender ($AGE * GEN$). X is a vector of the control variables that affect accident probability (choice of deductible, type of car, regional class, kilometers traveled, age class of driver, type of garage, engine power, period of ownership, proprietary, age of car, bonus malus coefficient) and ρ is a corresponding parameter vector. We defined age classes in steps of five years, except for the youngest age class, which we defined to be between 17 and 20 years. k denotes the number of age classes (less the reference group). This class serves as the reference group in the regressions. Equation 5.1 also includes a stochastic error term (ϵ_i). For our estimation we use the same variables the insurance company uses for risk classification and pricing.

The Poisson regression results (see appendix 5) reveal that we are not able to recover the insurers pricing model with the observed claim data available. Only very few variables seem to have a significant impact on losses. A natural explanation for this would be that we do not have enough of the loss data to reliably estimate pricing equations.

In contrast to this approach, it is much easier and requires a much smaller sample to estimate equations based on observed prices than to collect loss data and re-do the entire actuarial process. This approach can be used at very low cost in almost any setting where a regulator is considering a uniform-pricing reform. Under the assumption that the original prices are based on a sound statistical model that comes close to capturing the true data-generating process for claims, our analysis can be conducted using just the observed prices and rating variables. We support the use of this method by conducting a simple simulation exercise.[3] In this simulation, we generate three variables x1, x2, and x3 with x2 and x3 being correlated. Claims "y" are explained by a linear combination of these three variables and an

[3]We are very grateful to an anonymous reviewer for suggesting the simulation approach.

Table 3: Simulation

VARIABLES	(1) y	(2) y_hat	(3) y_hat	(4) y
x1	3.038***	3.038	3.093***	3.093***
	(0.0360)	(0)	(0.0263)	(0.0445)
x2	4.043***	4.043	5.242***	5.242***
	(0.0595)	(0)	(0.0375)	(0.0635)
x3	2.359***	2.359		
	(0.0590)	(0)		
Constant	1.007***	1.007	1.564***	1.564***
	(0.0359)	(0)	(0.0241)	(0.0409)
Observations	3,000	3,000	3,000	3,000
R-squared	0.867	1.000	0.919	0.797

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

error term. Presumably, the insurer regresses the claims on the three variables. Instead, we regress the predicted prices on the risk characteristics. In this simulation, we exclude one of the correlated variables (x3) and investigate how the coefficients differ between the true underlying process and our regression with just observed prices. The results are presented in Table 3. We find that while the coefficients exactly match, standard errors are tighter in our estimation. This means that significances should be treated with caution. However, since we are not interested in whether coefficients are significant, this "cost" of the method is negligible in this paper. However, it should generally be kept in mind when applying this method.

After motivating our pricing approach, we now look in detail into pricing in the automobile insurance industry.

5.2 Pricing in the Automobile Insurance Industry

We first analyze how the characteristic "gender" enters into the pricing formula and assess the implicit price of the individual specific characteristics and contract characteristics. We apply a hedonic price / premium function approach. A hedonic price function describes the equilibrium relationship between the characteristics of a product and its price. It is used to predict the prices of new goods, to adjust for quality change in price indexes, and to measure consumer and producer valuations of differentiated products.[4] The hedonic pricing approach was applied to insurance by Puelz and Kemmsies (1993). To estimate the implicit prices of gender and other underwriting attributes, we apply the following hedonic function:

$$P_i = \beta_0 + \beta_{GEN} * GEN_i + \sum_{j=1}^{k} \beta_j * AGE_{ij} * GEN_i + \rho' * X_i + \epsilon_i \tag{5.2}$$

The unit of observation is the individual policy level. The dependent variable (P_i) in equation 5.2 is the annual premium for the year 2011. All other variables are as defined in equation (5.1). The independent variables of interest are the gender variable (GEN_i) and the interactions of age groups and gender ($AGE_{ij} * GEN_i$). X_i is a vector of the variables that also affect pricing (type of car, regional class, kilometers traveled, age class of driver, type of garage, engine power, period of ownership, proprietary, age of car, bonus malus coefficient). Equation 5.2 also includes a stochastic error term (ϵ_i).

The results of the hedonic premium regression are presented in columns (1) through (4) of Table 4. In addition to the baseline model (columns (1) and (2)), we also estimate a log-linear model (columns (3) and (4)), where the dependent variable is $ln(P_i)$. We ran both regressions with and without interaction terms between age classes and the four variables engine power, kilometers driven, age of car, and period of ownership. Including interactions seems natural, and a very low cost way of increasing proxy effects once gender is omitted. All four regression show similar results. The inclusion of the interaction effects takes away the significance of the single age classes. We use column (1) for the interpretation of age and gender effects.

[4] For a survey article on hedonic price functions, refer to Nesheim (2006).

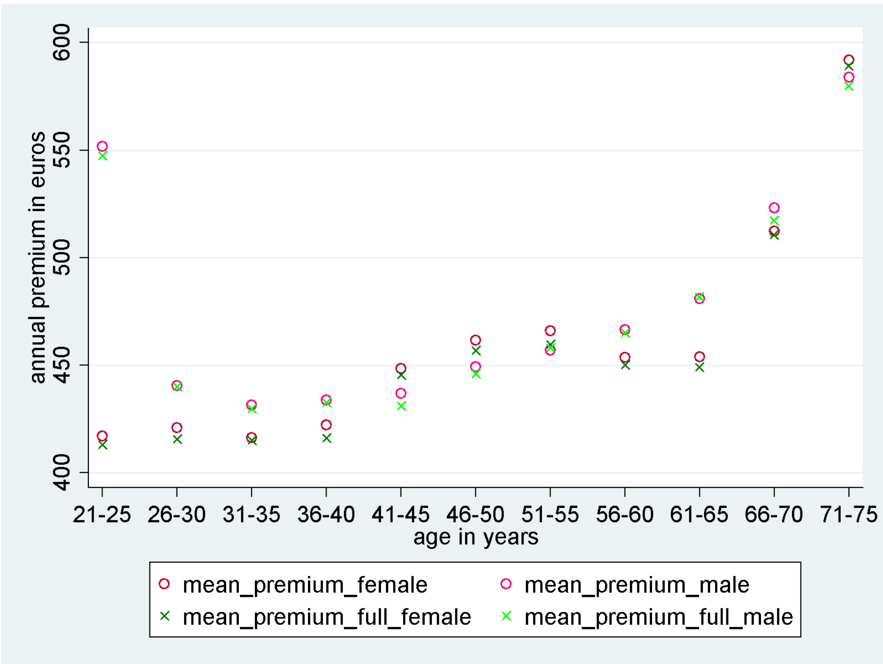
Table 4: Regression results for full and omitted model

	FULL MODEL				OMITTED MODEL			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	premium	premium	ln_premium	ln_premium	premium	premium	ln_premium	ln_premium
age2125	-110.442***	47.372	-0.212***	0.107	-149.664***	-13.050	-0.316***	-0.067
	(28.469)	(49.841)	(0.054)	(0.143)	(17.543)	(37.886)	(0.033)	(0.111)
age2630	-258.396***	-58.503	-0.512***	-0.190	-221.271***	-10.178	-0.461***	-0.131
	(28.052)	(48.455)	(0.053)	(0.140)	(17.332)	(36.653)	(0.032)	(0.110)
age3135	-281.130***	-52.288	-0.571***	-0.236*	-237.907***	4.061	-0.504***	-0.151
	(28.036)	(48.072)	(0.053)	(0.139)	(17.327)	(36.185)	(0.032)	(0.108)
age3640	-266.844***	-66.180	-0.546***	-0.264*	-224.996***	-10.076	-0.483***	-0.181*
	(28.064)	(48.194)	(0.053)	(0.138)	(17.347)	(36.253)	(0.032)	(0.108)
age4145	-243.186***	-30.171	-0.507***	-0.203	-199.968***	29.868	-0.436***	-0.102
	(28.070)	(48.634)	(0.053)	(0.140)	(17.363)	(36.859)	(0.032)	(0.110)
age4650	-224.112***	-45.630	-0.467***	-0.208	-181.969***	13.709	-0.397***	-0.109
	(28.090)	(48.256)	(0.053)	(0.139)	(17.372)	(36.339)	(0.032)	(0.109)
age5155	-228.117***	-44.552	-0.463***	-0.145	-186.359***	13.307	-0.399***	-0.063
	(28.087)	(48.280)	(0.053)	(0.138)	(17.374)	(36.442)	(0.032)	(0.108)
age5660	-241.327***	-48.422	-0.493***	-0.192	-197.035***	12.438	-0.420***	-0.095
	(28.096)	(48.337)	(0.053)	(0.139)	(17.386)	(36.466)	(0.032)	(0.109)
age6165	-233.573***	-44.664	-0.469***	-0.149	-191.868***	11.669	-0.407***	-0.072
	(28.098)	(48.448)	(0.053)	(0.139)	(17.397)	(36.642)	(0.032)	(0.109)
age6670	-183.527***	-10.739	-0.383***	-0.097	-137.075***	54.764	-0.301***	0.015
	(28.149)	(48.628)	(0.053)	(0.140)	(17.456)	(36.827)	(0.033)	(0.110)
age7175	-109.660***	32.110	-0.245***	-0.002	-57.200***	115.489***	-0.153***	0.141
	(28.215)	(49.024)	(0.053)	(0.142)	(17.540)	(37.219)	(0.033)	(0.111)
age7680	5.390	82.928	-0.066	0.151	55.003***	171.267***	0.023	0.295***
	(28.583)	(50.935)	(0.054)	(0.144)	(17.979)	(39.513)	(0.033)	(0.113)
age8185	117.759***	183.921***	0.116**	0.383***	168.772***	265.933***	0.196***	0.496***
	(29.769)	(57.498)	(0.054)	(0.142)	(19.428)	(47.478)	(0.034)	(0.113)
age8690	281.550***	286.374**	0.291***	0.578***	319.040***	349.846***	0.357***	0.666***
	(42.745)	(116.711)	(0.058)	(0.162)	(30.306)	(103.419)	(0.038)	(0.134)
female	-85.156***	-81.886***	-0.130**	-0.118*				
	(32.143)	(31.422)	(0.059)	(0.068)				
age2125_female	-43.539	-25.825	-0.139**	-0.119*				
	(32.712)	(31.982)	(0.061)	(0.070)				
age2630_female	76.330**	73.644**	0.098	0.092				
	(32.268)	(31.538)	(0.060)	(0.069)				
age3135_female	93.334***	83.226***	0.143**	0.123*				
	(32.228)	(31.505)	(0.060)	(0.069)				
age3640_female	89.320***	82.865***	0.131**	0.121*				
	(32.259)	(31.559)	(0.060)	(0.069)				
age4145_female	93.368***	88.575***	0.156***	0.148**				
	(32.260)	(31.530)	(0.060)	(0.069)				
age4650_female	90.270***	88.390***	0.152**	0.146**				
	(32.298)	(31.588)	(0.060)	(0.069)				
age5155_female	88.572***	85.580***	0.133**	0.119*				
	(32.299)	(31.580)	(0.060)	(0.069)				
age5660_female	95.082***	90.164***	0.158***	0.142**				
	(32.302)	(31.599)	(0.060)	(0.069)				
age6165_female	87.982***	82.802***	0.129**	0.111				
	(32.305)	(31.586)	(0.060)	(0.069)				
age6670_female	103.230***	99.548***	0.190***	0.172**				
	(32.405)	(31.693)	(0.060)	(0.070)				
age7175_female	122.009***	125.571***	0.220***	0.214***				
	(32.495)	(31.799)	(0.060)	(0.070)				
age7680_female	115.728***	135.601***	0.220***	0.221***				
	(33.562)	(32.919)	(0.061)	(0.071)				
age8185_female	127.405***	142.399***	0.202***	0.193***				
	(37.769)	(36.596)	(0.064)	(0.072)				
age8690_female	75.392	97.736*	0.140**	0.132*				
	(58.007)	(57.186)	(0.070)	(0.080)				
kilometers traveled per year	6.641***	14.904***	0.014***	0.028***	6.596***	13.770***	0.013***	0.027***
	(0.256)	(2.668)	(0.001)	(0.006)	(0.252)	(2.618)	(0.001)	(0.006)
engine power in kw	0.294***	2.102***	0.001***	0.003***	0.306***	2.309***	0.001***	0.004***
	(0.024)	(0.510)	(0.000)	(0.001)	(0.024)	(0.497)	(0.000)	(0.001)
age of the car in years	4.566***	6.241***	0.007***	0.013***	4.679***	7.763***	0.007***	0.015***
	(0.164)	(2.203)	(0.001)	(0.005)	(0.164)	(2.227)	(0.001)	(0.004)
period of ownership in years	-5.924***	-11.631	-0.015***	-0.019	-5.883***	-10.581	-0.015***	-0.016
	(0.173)	(16.497)	(0.000)	(0.042)	(0.174)	(16.683)	(0.000)	(0.042)
Interaction terms		X		X		X		X
Constant	173.271	5.240	3.779***	3.555***	135.864	-48.107	3.734***	3.483***
	(222.355)	(208.311)	(0.753)	(0.695)	(221.839)	(207.450)	(0.754)	(0.693)
Observations	36,362	36,362	36,362	36,362	36,362	36,362	36,362	36,362
Adjusted R-squared	0.7475	0.7540	0.8387	0.8410	0.7418	0.7499	0.8361	0.8391

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

Table 4 shows that relative to the reference group of 17 to 20-year-old policyholders, individuals up to age 75 pay a lower premium. The age class of 76 to 80-year-olds pays the same as 17 to 20-year-olds. Individuals above 80 face an even higher premium than 17 to 20-year-olds. The overall gender effect as denoted by the dummy variable "female" indicates a €85 premium reduction for women compared to men. A combined interpretation of the female dummy and interaction terms between female and age classes indicates that in younger years (17 to 25), women pay substantially less than their male equivalent. Over the middle age classes (26 to 65), men and women pay, ceteris paribus roughly the same. As an example, women between 41 and 45 pay €8.21 (93.368 - 85.156) more than men with the same characteristics in this age group. The premium difference increases for individuals over 65 where women pay more than men. For example, women between 71 and 75 pay €36.85 (122.009 - 85.156) more than men with the same characteristics. The adjusted R^2 for the baseline regression is 0.75. Including additional interaction terms and applying a log-linear

Figure 1: Full model premiums vs. actual premiums



form increases the adjusted R^2 to 0.84. We use the log-linear specification in the further analysis as it achieves the best model fit. Additionally, we ran correlations between actual premiums and predicted premiums and reached values of up to 0.838. Figure 1, which shows the mean values of actual and predicted premiums for different age groups, highlights the good fit of our model. What is surprising in this graph is the missing gender gap for older policyholders.

We now derive what unisex tariffs might look like by applying two different methods: the standard approach that is likely to be implemented by the insurance industry, and a method proposed by Pope and Sydnor (2011) which provides a way of establishing the benchmark for what prices would look like if direct gender effects were removed and other variables did not adjust as proxies.

5.3 Unisex Tariffs

5.3.1 The "common method" as the standard industry approach

In this section, we respond to the question whether the implementation of unisex tariffs leads to significant changes in what male and female drivers have to pay if simply the gender variable is dropped from the equation. This, however, would allow other factors to capture the original gender effects, so that parts of the gender effect might still be in the model even if gender is taken out as a risk factor itself. We apply the following hedonic function, which differs from equation 5.2 only in the fact that gender and the gender interaction terms are left out:

$$P_i = \beta_0 + \rho * X_i + \epsilon_i \tag{5.3}$$

In columns (5) to (8) of table 4 we see the pricing regression results when gender is disregarded as an independent variable. To have an indicator for the loss in predictive power due to omitting gender as a pricing variable, we analyze the decrease in the adjusted R^2. Relative to the comparable model specification, only a marginal decrease by less than 1% occurs. Recalling our summary statistics (see Table 1), this slight decrease could be explained by other variables that differ in their distribution between male and female drivers proxying for the omitted variable.

The correlation between actual premiums and predicted premiums when gender is disregarded as a pricing variable is 0.836, which is only marginally less than the correlation of 0.838 if gender is used as a risk factor. This could be seen as further evidence that part of the gender effect can be captured very easily by other variables. So, even after the implementation of unisex tariffs, insurance firms seem to be able to establish premium differences between male and female drivers. This effect can easily be strengthened: insurance firms could simply include interactions of variables they already use to increase the proxying effect. This can be seen in columns (6) and (8) of Table 4, where interaction between age and policyholders' characteristics are included.

Before we analyze the gender effect for the different age groups, we introduce unisex tariffs, where both direct gender effects are removed and other variables do not adjust as proxies.

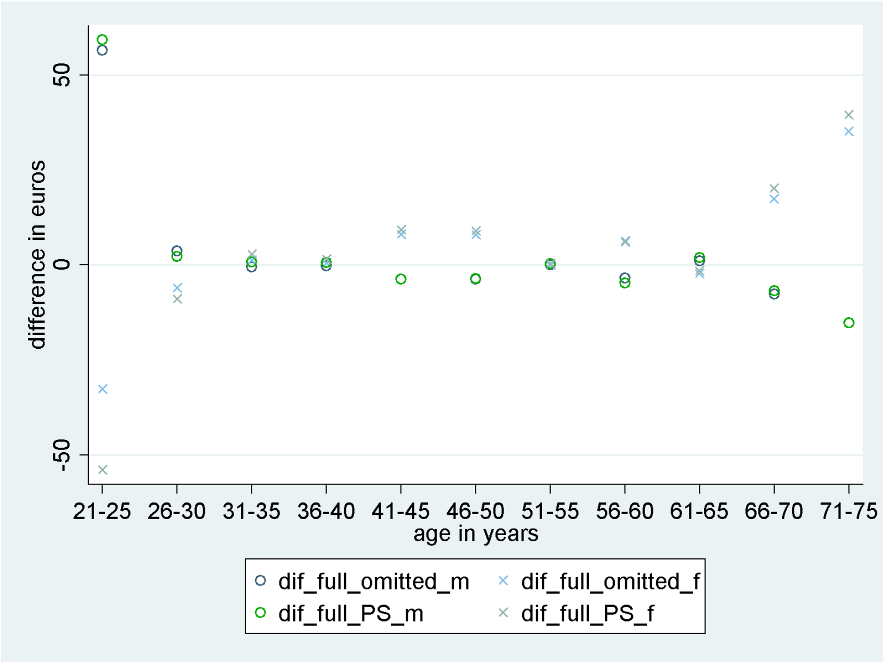
5.3.2 The Pope/Sydnor method - a two step procedure

For our calculation we applied the method proposed by Pope and Sydnor (2011). Our weighting is based on the actual proportion of male and female drivers in a specific age group. We make the tacit assumption that the decomposition of gender proportion does not change due to changed premiums. In these calculations we neglected the fact that the insurance company might add some mark-ups to the premiums because they do not know how the risk pool might change because of the implementation of unisex tariffs.

In order to visualize outcomes of the different unisex premium approaches relative to the premiums of the full model, Figure 2 shows the difference between average premiums of the full model and premiums of the common and Pope / Sydnor approach. Differences are plotted by age groups. Two things should be noted: 1) for the middle age groups, the omitted variable model and the Pope / Sydnor model are almost identical, which indicates that the proxying effect of other characteristics is relatively weak; 2) for very young and very old people, true gender-neutral tariffs make a difference and lead to a convergence between men and women; the largest deviation between the Pope / Sydnor premiums and the common method premiums can be found for young female drivers.

The interaction between both unisex approaches and characteristics which potentially act

Figure 2: Differences between premiums of the full, omitted and PS model



as proxies, are analyzed in more detail in the next subsection.

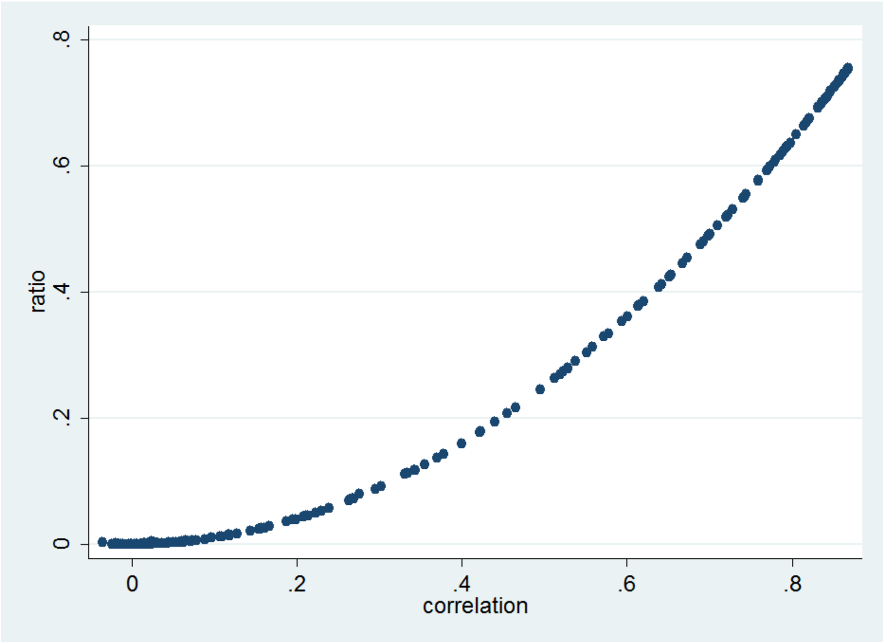
5.3.3 Simulation results

In order to provide results for a more general case, we expanded the simulation introduced in section 5.1 and varied the correlation between $x2$ and $x3$. The focus of this simulation is to show that the degree of correlation between $x2$ and $x3$ decides whether the omitted model approach produces results that are closer to the fully non-discriminatory Pope / Sydnor results or converge to the original discriminatory results. Starting with the same specification as above, we increased the correlation between $x2$ and the dummy variable $x3$ from 0 to 0.86 with 100 simulations. To visualize the results in a simple way, we calculated the following gender gap ratio:

$$GG_{Ratio} = \frac{(y_{OM}^{female} - y_{OM}^{male}) - (y_{PS}^{female} - y_{PS}^{male})}{(y_{Full}^{female} - y_{Full}^{male}) - (y_{PS}^{female} - y_{PS}^{male})} \tag{5.4}$$

This ratio indicates the size of the gender gap under the omitted model relative to the gender

Figure 3: Simulation



gap in the full model. From Figure 3 it can be seen that the ratio is zero if the correlation is zero and increases with an increasing correlation. In this example, a relatively high correlation of 0.6 leads to a GG_{Ratio} of approximately 0.3. One possible explanation why the premiums according to the common approach were very similar to the Pope / Sydnor approach might be the low correlation of gender with other characteristics. The highest correlation in our case was between engine power and gender in the age group of 21 to 25-year-olds (see table 2), which is a potential explanation for the large difference between the Pope / Sydnor premiums and the common method premiums when young female drivers are regarded.

6 Discussion and Policy Implications

In this paper, we first analyze the influence of gender as a pricing variable in premium calculations before the implementation of unisex tariffs. Our results reveal that gender is used as a risk factor in the automobile insurance industry and that the differences in prices due to gender differences can be quite high. For example, young men aged between 21 and 25 pay €129 more than comparable female drivers. The difference in prices due to gender seems to be high compared to the study of Puelz and Kemmsies (1993) analyzing the gender ban in the U.S. which took place in the 1980s, but closer to Dahlby (1992) analyzing the Canadian automobile insurance. Besides the premium difference between young men and women, our dataset also shows that this relation turns around for the old age groups. This means that the introduction of unisex tariffs might not only favor young male drivers but also old female drivers, which has already been presented by ABI (2010).

Although non-discriminatory tariffs have been mandatory since December 2012, no detailed methodology has been specified. Pope and Sydnor (2011) suggest two different models: the "common method" of simply omitting the gender variable and the Pope/Sydnor method, which is based on the full information predictive power of the other independent variables and the average of the banned variable. Pope and Sydnor (2011) show theoretically and empirically that the common method is the second best method in terms of predictive accuracy. Since this is the basis of risk classification, we assume that insurance firms will use the common method after the implementation of unisex tariffs. The common method has nearly the exact same overall predictive power as the full method using all the independent variables. We showed this by comparing the adjusted R^2. We then applied the Pope/Sydnor method to calculate premiums where direct gender effects are banned and other variables do not proxy for the omitted variable. The Pope/Sydnor tariffs show a very similar pattern as the omitted variable tariffs. However, siginificant differences can be identified for very young and very old drivers. The largest difference persists for young female drivers. This means that if the standard industry approach is implemented young female drivers will pay significantly less than they should according to true gender-neutral premiums. One explanation for the general pattern could be the overall relatively low correlation between gender and other pricing relevant characteristics. Simulations where this correlation was varied artificially confirmed this hypothesis. However, the simulation showed that a relatively high correlation can lead to a situation in which the common approach produces premiums in which gender differences are largely maintained.

A definite way to make sure that actual non-discriminatory premiums are implemented would be to make the Pope/Sydnor approach the industry standard. Ironically, the application of the Pope/Sydnor method requires gender information. So, the legislature would have to make sure that insurance firms still elicit gender information to guarantee unisex tariffs that really do not incorporate any gender effects. Alternatively, an easy way to gauge the extent to which the common approach deviates from the Pope/Sydnor approach would be to follow a procedure along the line of this paper. If it turns out that the differences can be neglected, there is no need to define a specific method.

7 Conclusion

In this article, we examine how unisex rating regulations affect gender differences in insurance premiums. We contribute to the debate whether remaining gender differences in premiums after the implementation of unisex tariffs can be traced back to reasonable pricing of characteristics that differ between sexes or to pricing of characteristics that differ between men and women in a way that proxies for the omitted gender variable. Using automobile insurance data, we compare two different approaches to calculate unisex tariffs. We estimate premiums according to a method proposed by Pope and Sydnor (2011) as a benchmark for what premiums would look like if direct gender effects are removed and other variables do not proxy for the omitted variable. The idea is to use all variables, i.e., even the banned variables, for risk classification and estimate a "full model" in a first step. In a second step, the estimated coefficients of the allowed variables and the average over the banned variable are used for predictions. This method ensures that on the one hand, the banned variable is not influencing predicted values and on the other hand, variables that are correlated with the omitted variable maintain their "own" predictive power and still do not serve as proxies. We compare the outcome of this method to a method which is likely to be the standard industry approach. This approach, where the gender variable is simply omitted, allows for proxying effects which potentially restore the premium differences. We found that both approaches generated very similar results for our dataset due to the fact that correlations are low and therefore the proxy effect is relatively weak. Significant deviations only exist for very young and very old drivers, and in particular for young female drivers. However, we showed in a simple simulation that results of both approaches can differ substantially if correlations are sufficiently large.

We also contribute to the literature by using data on existing insurance prices to estimate the effect of reforms instead of using loss data to re-estimate actuarial models. It is much easier and requires a much smaller sample to estimate equations based on observed prices than to collect loss data and re-do the entire actuarial process. Our approach can be used at very low cost in almost any setting where a regulator is considering a uniform-pricing reform, e.g. there are frequent discussions in all insurance markets about the benefits and disparities of risk classification on dimensions such as age and income.

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A Appendix

Figure 4: Kernel density plots for ages 21 - 25

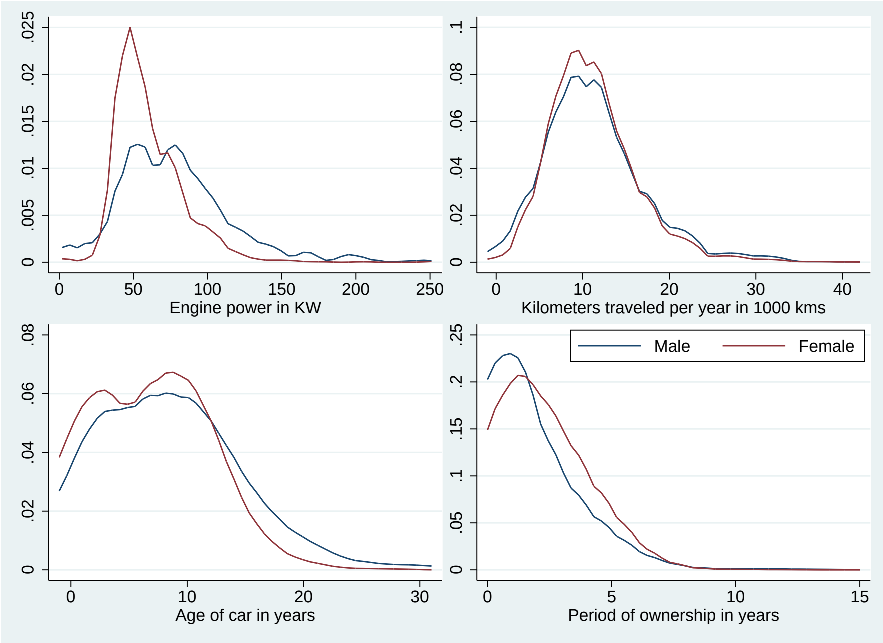

Figure 5: Kernel density plots for ages 26 - 65

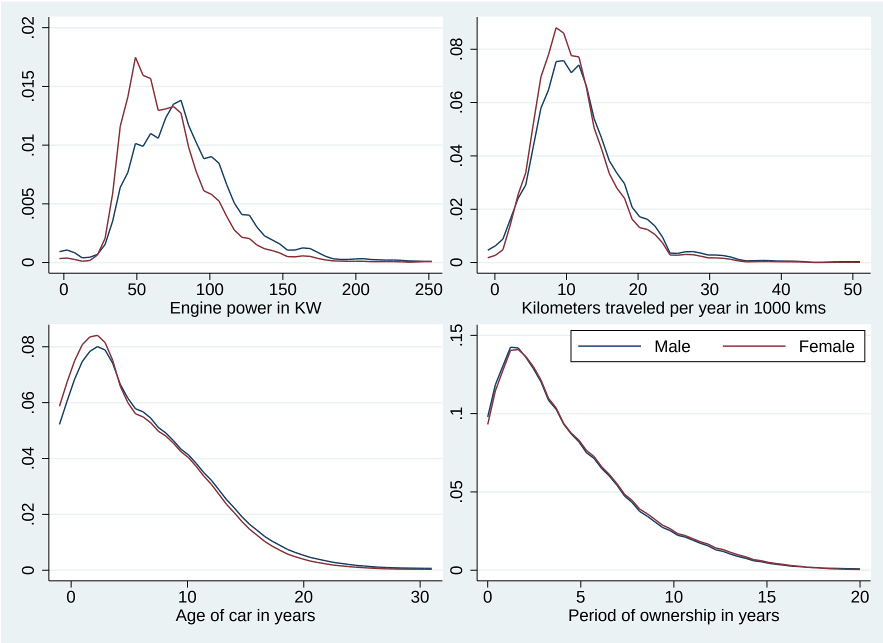

Figure 6: Kernel density plots for ages 66 - 75

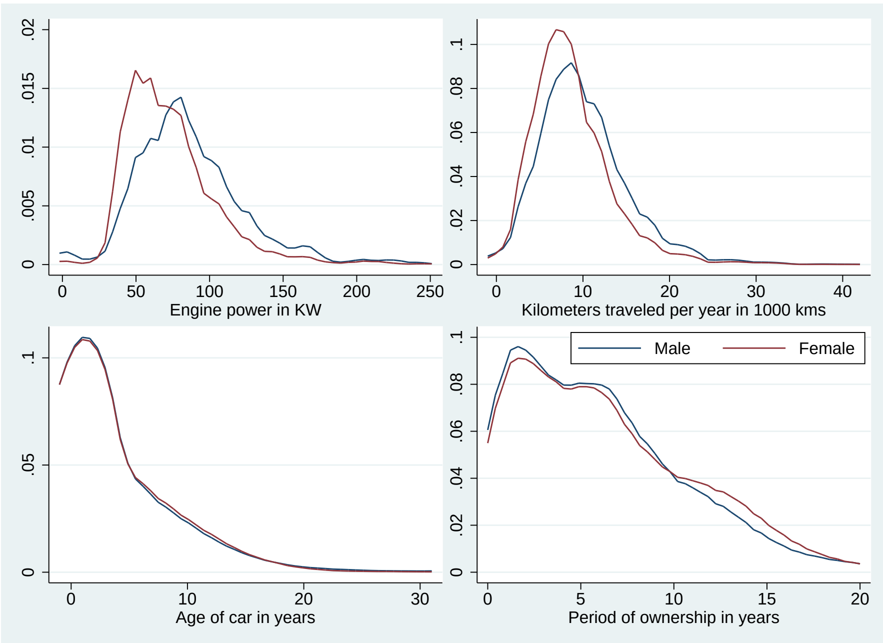

Table 5: Poisson regression - number of accidents as dependent variable

VARIABLES	(1) without interaction terms	(2) including interaction terms
age2125	-0.286	0.816
	(0.416)	(1.463)
age2630	-0.663	0.339
	(0.406)	(1.436)
age3135	-0.596	-0.034
	(0.402)	(1.421)
age3640	-0.598	0.493
	(0.404)	(1.425)
age4145	-0.535	0.229
	(0.404)	(1.418)
age4550	-0.462	0.737
	(0.405)	(1.419)
age5155	-0.452	0.038
	(0.406)	(1.422)
age5660	-0.369	0.245
	(0.408)	(1.422)
age6165	-0.464	-0.200
	(0.412)	(1.440)
age6670	-0.404	-0.213
	(0.419)	(1.449)
age7175	0.046	0.092
	(0.416)	(1.448)
age7680	0.389	1.188
	(0.426)	(1.475)
age8185	0.427	1.559
	(0.466)	(1.632)
age8690	1.000*	3.927*
	(0.552)	(2.122)
female	-1.245	-0.989
	(0.815)	(0.884)
age2125_female	0.857	0.557
	(0.836)	(0.907)
age2630_female	1.387*	1.038
	(0.828)	(0.897)
age3135_female	1.306	1.081
	(0.825)	(0.894)
age3640_female	1.179	0.891
	(0.828)	(0.897)
age4145_female	1.292	1.029
	(0.826)	(0.895)
age4650_female	1.336	1.016
	(0.826)	(0.894)
age5155_female	1.340	1.117
	(0.828)	(0.896)
age5660_female	1.351	1.138
	(0.829)	(0.898)
age6165_female	1.145	0.914
	(0.839)	(0.907)
age6670_female	1.589*	1.385
	(0.842)	(0.910)
age7175_female	1.208	1.003
	(0.844)	(0.912)
age7680_female	1.188	0.966
	(0.863)	(0.932)
age8185_female	1.022	0.747
	(0.960)	(1.022)
age8690_female	-16.604	-14.449
	(4,349.637)	(1,332.514)
kilometers traveled per year	0.013***	-0.052
	(0.003)	(0.088)
engine power in kw	-0.001	0.008
	(0.001)	(0.009)
age of the car in years	0.007	0.063
	(0.006)	(0.048)
period of ownership in years	-0.025***	0.020
	(0.008)	(0.427)
Constant	-24.777	-24.384
	(0.000)	(0.000)
Observations	37,328	37,328

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1