

# Driving Data: telematics to improve insurance rates

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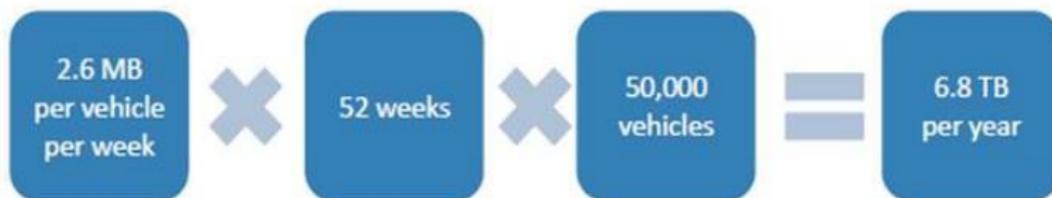
- 1 Introduction
- 2 Transition to telematics motor insurance
- 3 Data and results
- 4 Scenarios and conclusions
- 5 Going forward to optimal pricing

# 1 Introduction



## Sample Trip Summary Data – One Day

State Date	Start Time	Motorway Yards	Urban Yards	Other Yards	Motorway Seconds	Urban Seconds	Other Seconds	Total Speeding Yards	Total Speeding Seconds
3/3/2012	12:12:00	-	31	-	-	13,713	-	-	-
3/3/2012	14:17:11	-	3,355	-	-	7,934	-	-	-
3/3/2012	14:34:03	39,566	39,010	69,042	1,328	1,922	2,864	1,379	38
3/3/2012	15:47:59	-	11,346	907	-	858	60	-	-
3/3/2012	17:21:11	31,426	43,634	57,937	1,020	2,141	6,916	-	-
3/3/2012	19:36:07	-	4,501	5,401	-	2,912	330	-	-
3/3/2012	21:57:27	-	14,255	1,394	-	22,466	60	-	-
3/3/2012	22:24:43	-	-	-	-	386	-	-	-



Source: Jim Janavich ideas.returnonintelligence.com

Metromile

APP

CLAIMS

LOGIN

1.888.242.5204

📍 ENTER ZIP CODE

CHECK YOUR RATE

## Pay a low base rate

Your car is covered and fully insured even when it's parked.

Low rates start at \$29.

## Then just pennies per mile

With pay-per-mile, your bill is based on how far you drive.



example

$$\text{\$29} + (450 \times 6\text{¢}) = \text{\$56}$$

monthly rate

miles

cost

**\$56**

CHECK YOUR RATE

By Miles.[WHY?](#) [HOW?](#) [FAQ](#) [MAGAZINE](#)

SIGN IN &gt;

GET A QUOTE &gt;

# Pay-by-mile car insurance for savvy drivers.

A simple, straightforward policy that  
better fits the way you live.

● [WHY?](#)



## Get a quick quote

Answer a few simple questions to see a price in  
less than a minute.

GET A QUICK QUOTE &gt;



MENÚ EQ

verti



COCHE

CUENTAKMS

HOGAR

MOTO

6 RUEDAS

MASCOTA

CALCULAR PRECIO

TE LLAMAMOS

HOME &gt; SEGURO DE COCHE POR KILOMETROS

**CONTRATA TU SEGURO DE COCHE POR KILOMETROS  
Y NO PAGUES DE MÁS**



¿Chateamos?

# Main questions

- Should **pay-per-mile** replace traditional motor insurance? **No**
- Will **advanced driver assistance systems** impact the automobile insurance industry? **Yes**
- What **detailed telematics data** should be collected? **Only valuable**

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- **Usage-Based-Insurance (UBI)**. Telemetry provides the insurer with detailed information on the use of the vehicle and the **premium is calculated based on usage**.
  - **Pay-As-You-Drive (PAYD)** automobile insurance is a policy agreement linked to **vehicle driven distance**.
  - **Pay-How-You-Drive (PHYD)** considers **driving patterns**.
- **Distance and driving skills** of the drivers measure **speed, type of road and part of the day when the car is most frequently used,...** These new factors explain the risk of accident (Litman, 2005; Langford et al., 2008; Jun et al., 2007 and 2011; Ayuso, Guillen and Alcaniz, 2010; Verbelen et al., 2017; Henckaerts et al., 2017).

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- 2 There is **evidence of the relationship between speed, type of road, urban and nighttime driving** and the **risk of accident** (Rice et al., 2003; Laurie, 2011; Ellison et al, 2015; Verbelen et al. 2017).
- 3 **Telematics information can replace some traditional rating factors** and provide a pricing model with the same predictive performance (Verbelen et al. 2017; Ayuso et al., 2016b).

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## Strong evidence exists

- Information on mileage and driving habits improves the prediction of the number of claims compared to traditional rating factors and coverage exclusively by time (usually one year).
- If the use of advanced driver assistance systems (ADAS) mitigates risk, because they transform driving patterns, then the transition towards semi-autonomous vehicles is expected to contribute to a lower frequency of motor accidents

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## What we do:

- We explore the effect of **distance driven** (mileage, exposure to risk) and **other telematics data** on premium calculation.

## Our contribution:

- Propose a method to update premiums regularly with telematics data.
- Show that the price per mile depends on driving habits and price should not be proportional to distance driven. A zero claim is relatively more frequent for intensive users. Propose a predictive modeling approach for this purpose.
- Estimate the impact on prices and safety in a plausible scenario of assisted driving that would control speed limit violations.
- Derive some open-questions about risk measures to summarize **telematics big data** and **optimal pricing** when customers may lapse.

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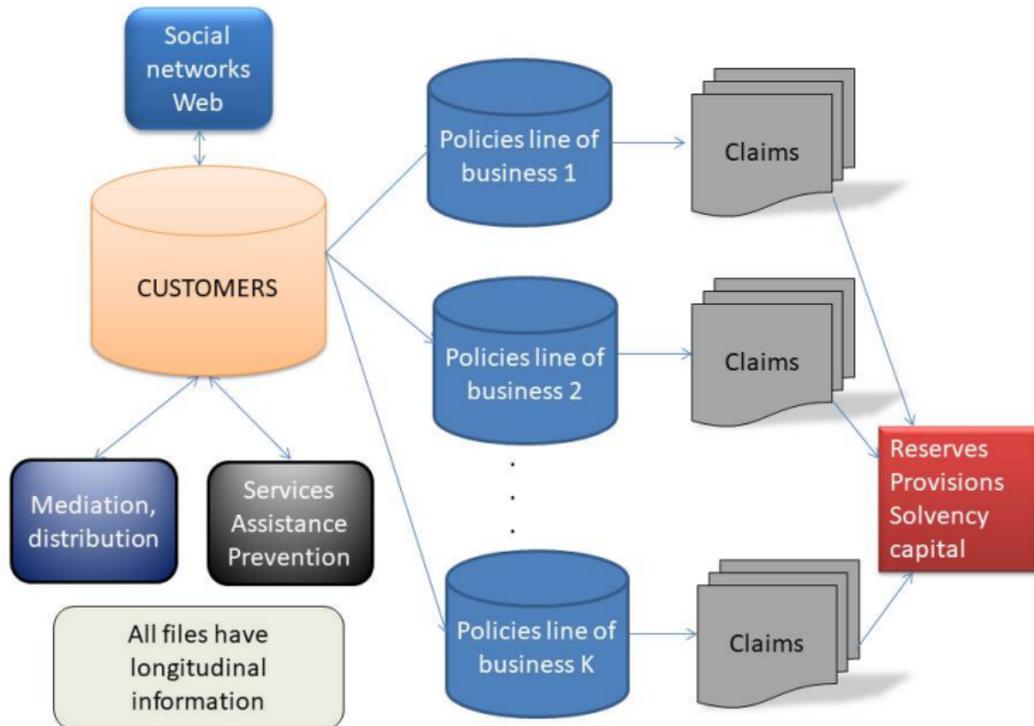
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## Why is insurance analytics a good example of big data in applied economics?



Source: Guillen, 2016

## 2 Transition to telematics

The **classical ratemaking** model is based on: a prediction of the number of claims (usually for one year) times the average claim cost plus some extra loadings.

- Subscript  $i$  denotes the  $i$ th policy holder in a portfolio of  $n$  insureds.
- Given  $x_i = (x_{i1}, \dots, x_{ik})$  (vector of  $k$  covariates), the number of claims  $Y_i$  (dependent variable) follows a Poisson distribution with parameter  $\lambda_i$ , which is a function of the linear combination of parameters and regressors,  $\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik}$ .

$$E(Y_i | x_i) = \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik}) \quad (1)$$

The unknown parameters to be estimated are  $(\beta_0, \dots, \beta_k)$ .

- Classical covariates are age, time since driver's license was issued, driving zone, type of car,...
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Transportation

<https://doi.org/10.1007/s11116-018-9890-7>

## Improving automobile insurance ratemaking using telematics: incorporating mileage and driver behaviour data

Mercedes Ayuso<sup>1</sup>  · Montserrat Guillen<sup>1</sup> · Jens Perch Nielsen<sup>2</sup>

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**Abstract** We show how data collected from a GPS device can be incorporated in motor insurance ratemaking. The calculation of premium rates based upon driver behaviour represents an opportunity for the insurance sector. Our approach is based on count data regression models for frequency, where exposure is driven by the distance travelled and additional parameters that capture characteristics of automobile usage and which may affect claiming behaviour. We propose implementing a classical frequency model that is updated with telematics information. We illustrate the method using real data from usage-based insurance policies. Results show that not only the distance travelled by the driver, but also driver habits, significantly influence the expected number of accidents and, hence, the cost of insurance coverage. This paper provides a methodology including a transition pricing transferring knowledge and experience that the company already had before the telematics data arrived to the new world including telematics information.

**Keywords** Tariff · Premium calculation · Pay-as-you-drive insurance · Count data models

In **Transportation** (2018) we proposed a method for assessing the influence on the expected frequency of usage-based variables which can be viewed as a **correction of the classical ratemaking model**.

A two-step procedure:

- Step 1: Let  $\hat{Y}_i$  be the frequency estimate obtained as a function of the classical explanatory covariates  $x_i = (x_{i1}, \dots, x_{ik})$ .
- Step 2: Let  $z_i = (z_{i1}, \dots, z_{il})$  be the information collected periodically from a telematics unit. Then, the prediction from usage-based insurance information is a correction such that:

$$E(Y_i^{UBI} | z_i, \hat{Y}_i) = \hat{Y}_i \exp(\eta_0 + \eta_1 z_{i1} + \dots + \eta_k z_{ik}), \quad (2)$$

where the parameter estimates  $(\eta_0, \dots, \eta_l)$  can now be obtained using  $\hat{Y}_i$  as an offset.

### Note

This approach is less efficient than a full information model, but it works well in practice. Telematics data are collected on a continuous basis and this correction can be implemented regularly (i.e. on a weekly basis)

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## Risk Analysis

### The use of telematics devices to improve automobile insurance rates

DOI:10.1111/risa.13172

**Publication status**

Article accepted on 9 July, 2018

#### Guillen, M. et al (2018)

Most automobile insurance databases contain a large number of policyholders with zero claims. This high frequency of zeros may reflect the fact that some insureds make little use of their vehicle, or that they do not wish to make a claim for small accidents in order to avoid an increase in their premium, but it might also be because of good driving. We analyse information on exposure to risk and driving habits using telematics data from a Pay-as-you-Drive sample of insureds. We include distance travelled per year as part of an offset in a zero-inflated Poisson model to predict the excess of zeros. We show the existence of a learning effect for large values of distance travelled, so that longer driving should result in higher premium, but there should be a discount for drivers that accumulate longer distances over time due to the increased proportion of zero claims. We confirm that speed limit violations and driving in urban areas increase the expected number of accident claims. We discuss how telematics information can be used to design better insurance and to improve traffic safety.

In **Risk Analysis** (2018) we propose to include the distance travelled per year as an offset in a Zero Inflated Poisson model to predict the number of claims in *Pay as You Drive* insurance.

- *The Poisson model with exposure*: Let us call  $T_i$  the exposure factor for policy holder  $i$ , in our case  $T_i = \ln(D_i)$ , where  $D_i$  indicates distance travelled, then:

$$E(Y_i|x_i, T_i) = D_i \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik}) = D_i \lambda_i \quad (3)$$

**Excess of zeros** exists because:

- Some insureds do not use their car and so they do not have claims
- Some insured acquire exceptionally good driving skills and they do not have claims (*learning curve*).

- *The Zero-inflated Poisson (ZIP) model* : Now the probability of not suffering an accident is

$$P(Y_i = 0) = p_i + (1 - p_i)P(Y^* = 0) \quad (4)$$

where  $p_i$  is the probability of excess of zeros.  $Y_i^*$  follows a Poisson distribution with parameter  $\exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik})$ , and  $p_i$  may depend on some covariates.

## A ZIP Poisson model with exposure

We assume that  $p_i$  is the probability of an excess of zeros, and it is specified as a logistic regression model such that

$$p_i = \frac{\exp(\alpha_0 + \alpha_1 \ln(D_i))}{1 + \exp(\alpha_0 + \alpha_1 \ln(D_i))}. \quad (5)$$

The Poisson model for  $Y^*$  is specified as follows, with an exposure

$E(Y_i^* | x_i, T_i) = D_i \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik}) = D_i \lambda_i = \exp(\ln(D_i)) \lambda_i = \exp(T_i) \lambda_i$ , where  $T_i = \ln(D_i)$ . The expectation of the Poisson part is:

$$(1 - p_i) E(Y_i^* | x_i, T_i) = \frac{1}{1 + \exp(\alpha_0 + \alpha_1 \ln(D_i))} D_i \lambda_i = D_i^* \lambda_i \quad (6)$$

where  $D_i^* = \frac{D_i}{1 + \exp(\alpha_0 + \alpha_1 \ln(D_i))}$  is a **transformation of the original measure of exposure (distance driven)**  $D_i$ .

## A ZIP Poisson model with exposure

So, when we include zero-inflation there is a transformation of the exposure in the Poisson part of the model.

- When  $D_i$  is big then  $D_i^* = \frac{D_i}{1+\exp(\alpha_0+\alpha_1 \ln(D_i))}$  tends to zero if  $\alpha_1 > 1$ .
- When  $\alpha_1 = 1$  then  $D_i^*$  tends to constant  $\frac{1}{\exp(\alpha_0)}$  when  $D_i$  increases.
- Assuming that  $D_i \geq 1$ , when  $\alpha_1 > 1$  this is a concave transformation that scales exposure into the interval  $\left[0, \frac{1}{1+\exp(\alpha_0)}\right]$ . So, the larger the exposure the smaller the value whereas the smaller the exposure the larger the value.
- Assuming that  $D_i \geq 1$ , when  $\alpha_1 \leq 1$  then the transformation is a change of scale to the interval  $\left[\frac{1}{1+\exp(\alpha_0)}, +\infty\right)$ .

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## A ZIP Poisson model with exposure

If we look at the logistic regression part, we can also derive the following expression:

$$p_i = \frac{\exp(\alpha_0 + \alpha_1 \ln(D_i))}{1 + \exp(\alpha_0 + \alpha_1 \ln(D_i))} = \frac{\exp(\alpha_0 + \alpha_1 \ln(D_i))}{1 + \exp(\alpha_0 + \alpha_1 \ln(D_i))} \frac{D_i}{D_i} =$$

$$\exp(\alpha_0 + \alpha_1 \ln(D_i)) \frac{D_i}{1 + \exp(\alpha_0 + \alpha_1 \ln(D_i))} \frac{1}{D_i} = \exp(\alpha_0 + \alpha_1 \ln(D_i)) \frac{D_i^*}{D_i} \quad (7)$$

So, the probability of zero excess ( $p_i$ ) can be understood as a rescaling of the relative transformed exposure.

Interestingly, when  $\alpha_1 < 0$  then note that  $p_i$  tends to zero when  $D_i$  increases, whereas when  $\alpha_1 > 0$  then  $p_i$  tends to one when  $D_i$  increases.

In the empirical part we find  $\alpha_1 > 0$ , which means that there is a learning effect and the excess of zeros is more important than the Poisson part when distance driven increases.

# 3 Data and results

**YCAR**  
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EL SEGURO DE COCHE QUE  
PIENSA EN LOS JÓVENES  
Y EN SU BOLSILLO



MAPFRE,  
la aseguradora global de confianza

# Zero-inflation for the Number of Claims

Empirical application based on 25,014 insureds with car insurance coverage throughout 2011, that is, individuals exposed to the risk for a **full year**.

**Table I.** Frequency of claims per driver (n=25,014)  
in the Spanish insurance dataset (all claims, at fault, and not at fault)

Number of claims	Absolute frequency per driver		
	All claims	Claims at fault	Claims not at fault
0	20,608	22,837	22,432
1	3,310	1,750	2,111
2	889	385	424
3	165	37	40
4	34	4	6
5	7	1	1
6	1	0	0

One insured driver had 6 claims, 2 were at fault and 4 where not at fault.

**Table II.** Descriptive statistics for the risk exposure indicator  
(total kilometres travelled per year in 000s)

	All Sample n = 25,014	Drivers with no claims n = 20,608 (82.4%)	Drivers with claims n = 4,406 (17.6%)
Mean	7.16	6.99	7.96
1st Quartile	4.14	4.00	4.87
Median	6.46	6.28	7.22
3rd Quartile	9.40	9.22	10.30
Standard Deviation	4.19	4.14	4.35

**Table 2** Descriptive statistics by claims (quantitative variables)

	All sample N= 25,014		Drivers with no claims N= 20,608 (82.4%)		Drivers with claims N= 4406 (17.6%)	
	Mean	SD	Mean	SD	Mean	SD
Age	27.57	3.09	27.65	3.09	27.18	3.10
Age driving licence	7.17	3.05	7.27	3.07	6.73	2.94
Vehicle age	8.75	4.17	8.76	4.19	8.69	4.11
Power	97.22	27.77	96.98	27.83	98.36	27.46
Km per year (000s)	7.16	4.19	6.99	4.14	7.96	4.35
Km per year at night (%)	6.91	6.35	6.85	6.32	7.16	6.49
Km per year over speed limit (%)	6.33	6.83	6.28	6.87	6.60	6.59
Urban km per year (%)	25.87	14.36	25.51	14.31	27.56	14.47

**Table 3** Descriptive statistics by claims (categorical variables)

	All sample N= 25,014		Drivers with no claims N= 20,608 (82.4%)		Drivers with claims N= 4406 (17.6%)	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
<i>Gender</i>						
Men	12,235	48.91	10,018	48.61	2217	50.32
Women	12,779	51.09	10,590	51.39	2189	49.68
<i>Parking</i>						
Yes	19,356	77.38	15,912	77.21	3444	78.17
No	5658	22.62	4696	22.79	962	21.83

## Poisson model results. All types of claims.

	All variables		Non-telematics		Telematics		Telematics with offsets	
	Coefficient	(p-value)	Coefficient	(p-value)	Coefficient	(p-value)	Coefficient	(p-value)
<b>Intercept</b>	-1.503	0.122	0.135	0.888	-3.427	<.0001	-1.807	<.0001
<b>Age</b>	-0.132	0.064	-0.101	0.153				
<b>Age<sup>2</sup></b>	0.002	0.066	0.002	0.208				
<b>Male</b>	-0.040	0.155	0.084	0.003				
<b>Age Driving License</b>	-0.061	<.0001	-0.061	<.0001				
<b>Vehicle Age</b>	0.010	0.003	0.002	0.549				
<b>Power</b>	0.003	<.0001	0.003	<.0001				
<b>Parking</b>	0.031	0.347	0.037	0.252				
<b>Log of Km per year (thousands)</b>	0.644	<.0001			0.645	<.0001	0.620	<.0001
<b>Km per year at night (%)</b>	-0.004	0.295			-0.001	0.761	-0.007	0.067
<b>Km per year at night (%)<sup>2</sup></b>	0.0002	0.140			0.0001	0.413	0.0002	0.041
<b>Km per year over speed Limit (%)</b>	0.026	<.0001			0.026	<.0001	0.022	<.0001
<b>Km per year over speed Limit (%)<sup>2</sup></b>	-0.001	<.0001			-0.001	<.0001	-0.001	<.0001
<b>Urban km per year (%)</b>	0.023	<.0001			0.024	<.0001	0.022	<.0001
<b>AIC</b>	29,464.858		30,315.914		29,640.186		29,483.041	
<b>BIC</b>	29,578.638		30,380.931		29,697.076		29,539.931	

## Poisson model results. All types of claims.

**Table 6.** Poisson model results with offset km per year. All claim types (n=25,014)

	All variables		Non-telematics		Telematics		Telematics with offsets (Log of prediction of Non-telematics model - Column 2)	
	Coefficient	(p-value)	Coefficient	(p-value)	Coefficient	(p-value)	Coefficient	(p-value)
Intercept	-2.193	0.024	-0.472	0.625	-4.219	<.0001	-0.731	<.0001
Age	-0.145	0.043	-0.200	0.005				
Age <sup>2</sup>	0.003	0.040	0.004	0.005				
Male	-0.086	0.002	-0.049	0.076				
Age Driving License	-0.061	<.0001	-0.076	<.0001				
Vehicle Age	0.015	<.0001	0.022	<.0001				
Power	0.003	<.0001	0.001	0.063				
Parking	0.034	0.292	0.034	0.299				
Log of km per year (000s)	1.000	--	1.000	--	1.000	--	1.000	--
Km per year at night (%)	-0.008	0.051			-0.005	0.161	-0.009	0.017
Km per year at night (%) <sup>2</sup>	0.0002	0.062			0.0001	0.193	0.0002	0.033
Km per year over speed Limit (%)	0.015	0.004			0.014	0.006	0.019	<.001
Km per year over speed Limit (%) <sup>2</sup>	-0.001	0.001			-0.001	0.003	-0.001	<.001
Urban km per year (%)	0.029	<.0001			0.031	<.0001	0.028	<.0001
AIC	29,631.281		30,624.100		29,809.179		29,658.447	
BIC	29,736.934		30,689.117		29,857.942		29,707.210	
LogL	-13,742.650		-14,244.060		-13,838.600		-13,763.230	
Chi-2	1,357.220	<.0001	354.400	<.0001	1,165.320	<.0001	1,316.060	<.0001

## Concordant predictions of all models (in percentages).

		All variables	Non-telematics	Telematics	Telematics with offsets
Poisson model results. All types of claims	All	62.28	55.91	61.34	62.10
Poisson model results with offsets (Log of Km per year in thousands). All types of claims		62.15	58.60	61.18	62.05
Poisson model results. Claims where the policyholder is guilty		62.70	57.72	61.13	62.65
Poisson model results with offsets (Log of Km per year in thousands). Claims where the policyholder is guilty		62.38	58.96	60.89	62.43

Prediction with telematics and offset

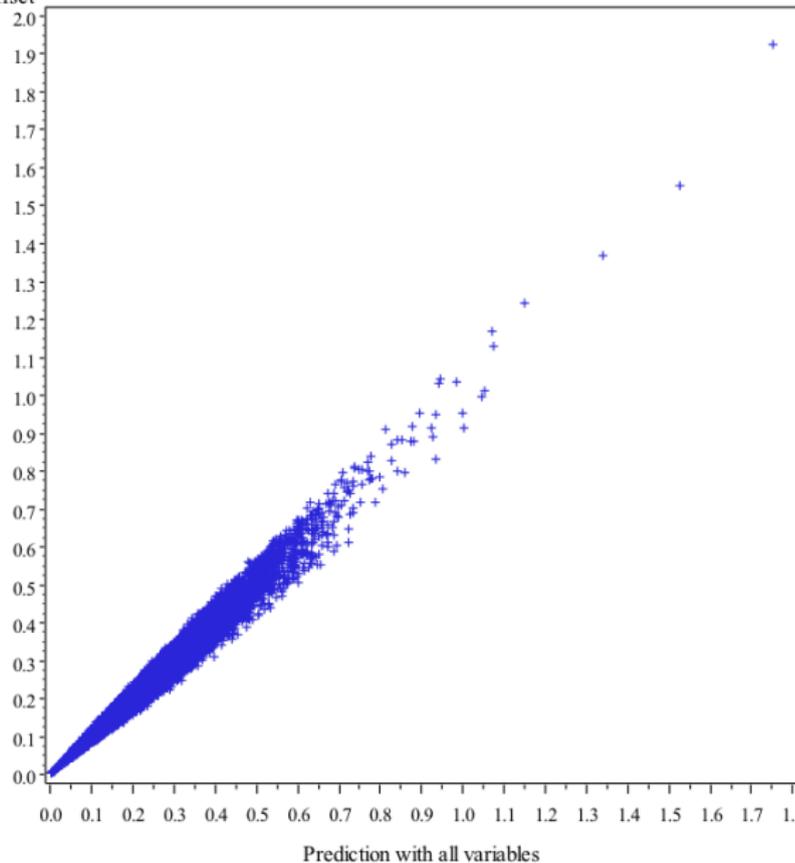


Table IV. Zero-inflated Poisson model with offsets (Log of km per year in 000s). All types of claims.

	All variables		(Only significant)		Non-telematics		Telematics	
	Coefficient	(p-value)	Coefficient	(p-value)	Coefficient	(p-value)	Coefficient	(p-value)
<b>Poisson part</b>								
Intercept	-2.148	0.045	-3.396	<.001	-0.829	0.440	-3.461	<.001
Age	-0.094	0.232			-0.123	0.121		
Age <sup>2</sup>	0.002	0.221			0.002	0.131		
Male	-0.068	0.029	-0.074	0.017	-0.011	0.719		
Age Driving Licence	-0.059	<.001	-0.056	<.001	-0.067	<.001		
Vehicle Age	0.014	<.001	0.014	<.001	0.017	<.001		
Power	0.003	<.001	0.003	<.001	0.001	0.017		
Parking	0.029	0.420			0.032	0.381		
Log of km per year (thousands) - offset	1.000	--	1.000	--	1.000	--	1.000	--
Km per year at night (%)	-0.004	0.312					-0.001	0.771
Km per year at night (%) <sup>2</sup>	0.0001	0.467					0.000	0.931
Km per year over speed limit (%)	0.019	0.001	0.019	0.001			0.018	0.001
Km per year over speed limit (%) <sup>2</sup>	-0.001	0.001	-0.001	0.001			-0.001	0.003
Urban km per year (%)	0.026	<.001	0.026	<.001			0.027	<.001
<b>Zero-inflation part</b>								
Intercept (Logit)	-0.847	<.001	-0.857	<.001	-1.639	<.001	-0.795	<.001
Log of km per year (thousands) (Logit)	0.404	<.001	0.410	<.001	0.824	<.001	0.406	<.001
AIC	28,877.112		28,870.556		29,427.423		29,005.172	
BIC	28,999.019		28,951.828		29,508.694		29,070.189	

## Concordant predictions of all models (in percentages).

	All variables	Non-telematics	Telematics	Telematics with offsets
<b>Zero Poisson model results with offsets (Log of Km per year in thousands). All types of claims</b>	62.36	59.10	61.39	62.20
<b>Poisson model results with offsets (Log ok Km per year in thousands). All types of claims</b>	62.15	58.60	61.18	62.05
<b>Zero Poisson model results with offsets (Log of Km per year in thousands). Claims where the policyholder is at fault</b>	62.71	59.85	61.17	62.77
<b>Poisson model results with offsets (Log ok Km per year in thousands). Claims where the policyholder is at fault</b>	62.38	58.96	60.89	62.43

# Changing driving habits

We study a sample of 9,614 young drivers with a pay-how-you-drive (PHYD) policy in force during the entire year 2010 in a Spanish insurer.

Variable	Definition	Mean	Std. Dev.
km	Distance traveled during the year measured in kilometers	13,063.71	7,715.80
speed	% of kilometers traveled at speeds above the limit	9.14	8.76
urban	% of kilometers traveled on urban roads	26.29	14.18
age	Age of the driver	24.78	2.82
claims	Number of "at fault" accident claims during the year	0.10	0.32

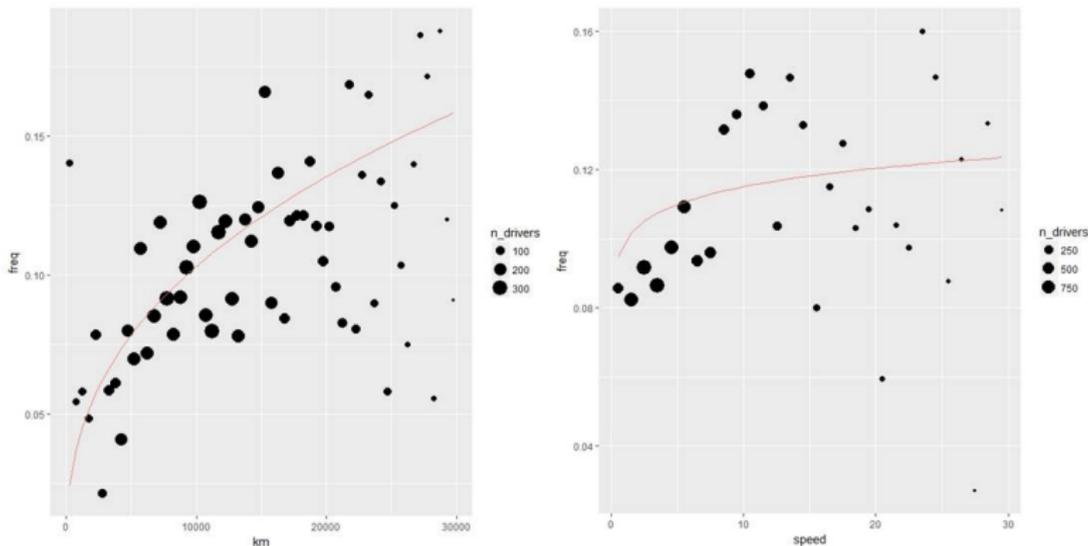
One of the basic modeling approaches is the classical Poisson model. Even under the presence of overdispersion, the Poisson model provides consistent parameter estimates of the linear predictor.

Poisson model results:

Parameter	Estimate	Std. error
Intercept	-3.2465	1.1662
ln(km)	0.3931	0.0593
ln(speed)	0.0653	0.0345
ln(urban)	0.4794	0.0692
ln(age)	-1.3580	0.2827

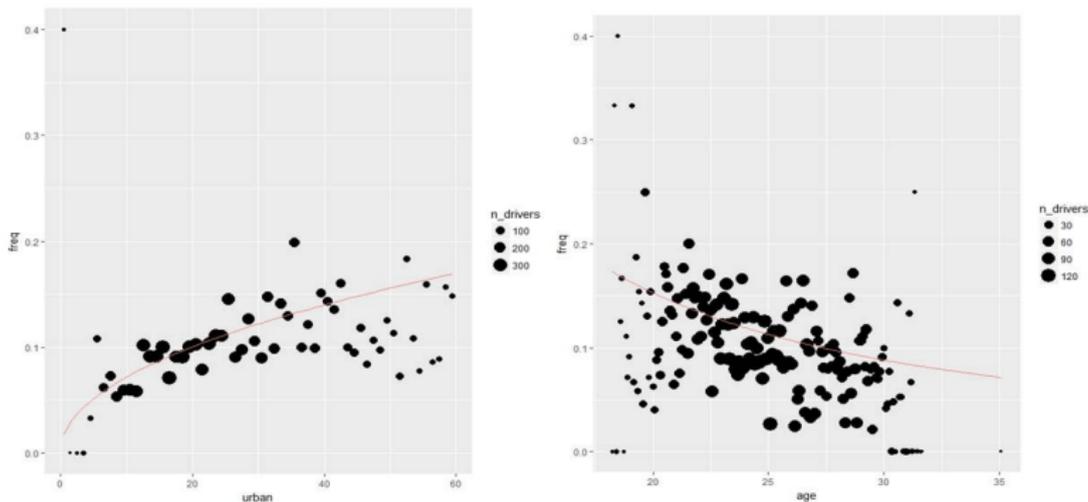
Guillen, Pérez-Marín (2018)

Figure: Expected number of claims vs. Distance (Km) and Excess Speed (%)



Guillen, Pérez-Marín (2018)

Figure: Expected number of claims vs. Urban (%) and Age (years)



Guillen, Pérez-Marín (2018)

- The expected number of claims at fault increases with the distance travelled, but the increase is not proportional.
- Driving above the speed limits and extensive urban driving also increase the expected number of claims.
- The expected number of claims decreases with age.

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# 4 Scenarios

Speed	Expected number of claims per 1,000 drivers
0%	63.04
1%	98.99
2%	103.57
5%	109.95
7%	112.39
9%	<b>114.25</b>
10%	115.04
12%	116.42
15%	118.13
17%	119.10
20%	120.37

All values in the matrix are in percentage. Source: Guillen, Pérez-Marín (2018)

At the average level of speed limit violation (9%) the expected number of claims at fault per 1,000 drivers is 114. Elimination of speed limit violations (0%) leads to 63 claims per 1,000 drivers

Therefore, the initial level would be reduced by approximately one half.

**Figure:** Relative change in expected number of claims per 1,000 drivers due to a change in the level of speed violation

	After										
Before	0%	1%	2%	5%	7%	9%	10%	12%	15%	17%	20%
0%	0	35.94	40.52	46.90	49.35	51.21	51.99	53.37	55.08	56.05	57.32
1%	-35.94	0	4.58	10.96	13.40	15.26	16.05	17.43	19.14	20.11	21.38
2%	-40.52	-4.58	0	6.38	8.82	10.68	11.47	12.85	14.56	15.53	16.80
5%	-46.90	-10.96	-6.38	0	2.44	4.30	5.09	6.47	8.18	9.14	10.42
7%	-49.35	-13.41	-8.82	-2.44	0	1.86	2.65	4.02	5.73	6.70	7.97
9%	-51.21	-15.26	-10.68	-4.30	-1.86	0	0.79	2.17	3.87	4.84	6.11
10%	-51.99	-16.05	-11.47	-5.09	-2.65	-0.79	0	1.38	3.09	4.05	5.33
12%	-53.37	-17.43	-12.85	-6.47	-4.02	-2.17	-1.38	0	1.71	2.68	3.95
15%	-55.08	-19.14	-14.56	-8.18	-5.73	-3.87	-3.09	-1.71	0	0.97	2.24
17%	-56.05	-20.11	-15.53	-9.14	-6.70	-4.84	-4.05	-2.68	-0.97	0	1.27
20%	-57.32	-21.38	-16.80	-10.42	-7.97	-6.11	-5.33	-3.95	-2.24	-1.27	0

Guillen, Pérez-Marín (2018)

**Figure:** Percentage of variation in the price of insurance due to a change in the level of speed violation, with 20% premium loading

Before	After										
	0%	1%	2%	5%	7%	9%	10%	12%	15%	17%	20%
0%	0%	45.6%	51.4%	59.5%	62.6%	65.0%	66.0%	67.7%	69.9%	71.1%	72.7%
1%	-29.1%	0%	3.7%	8.9%	10.8%	12.3%	13.0%	14.1%	15.5%	16.2%	17.2%
2%	-31.3%	-3.5%	0%	4.9%	6.8%	8.2%	8.9%	9.9%	11.2%	12.0%	13.0%
5%	-34.1%	-8.0%	-4.6%	0%	1.8%	3.1%	3.7%	4.7%	5.9%	6.6%	7.6%
7%	-35.1%	-9.5%	-6.3%	-1.7%	0%	1.3%	1.9%	2.9%	4.1%	4.8%	5.7%
9%	-35.9%	-10.7%	-7.5%	-3.0%	-1.3%	0%	0.5%	1.5%	2.7%	3.4%	4.3%
10%	-36.1%	-11.2%	-8.0%	-3.5%	-1.8%	-0.5%	0%	1.0%	2.1%	2.8%	3.7%
12%	-36.7%	-12.0%	-8.8%	-4.4%	-2.8%	-1.5%	-0.9%	0%	1.2%	1.8%	2.7%
15%	-37.3%	-13.0%	-9.9%	-5.5%	-3.9%	-2.6%	-2.1%	-1.1%	0%	0.7%	1.5%
17%	-37.6%	-13.5%	-10.4%	-6.1%	-4.5%	-3.2%	-2.7%	-1.8%	-0.6%	0%	0.8%
20%	-38.1%	-14.2%	-11.2%	-6.9%	-5.3%	-4.1%	-3.5%	-2.6%	-1.5%	-0.8%	0%

Guillen, Pérez-Marín (2018)

## Recap:

- Proposed a method to **update premiums** regularly with telematics data.
- Showed that the **price per mile** depends on driving habits and is not proportional to distance driven. A zero claim is relatively more frequent for intensive users.
- Estimated the impact on prices and safety in a plausible scenario of **assisted driving** that would control speed limit violations.
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- Showed that the **price per mile** depends on driving habits and is not proportional to distance driven. A zero claim is relatively more frequent for intensive users.
- Estimated the impact on prices and safety in a plausible scenario of **assisted driving** that would control speed limit violations.
- Still want derive some **open-questions** about risk measures to summarize telematics big data and optimal pricing when customers may lapse.

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# 5 Going forward to optimal pricing



## Summary



- |   |                                       |  |
|---|---------------------------------------|--|
| • Linear models                                   | • Longitudinal and panel data models  | • Bayesian regression models                               |
| • Regression with categorical dependent variables | • Linear mixed models                 | • Generalized additive models and nonparametric regression |
| • Regression with count-dependent variables       | • Credibility and regression modeling | • Non-linear mixed models                                  |
| • Generalized linear models                       | • Fat-tailed regression models        | • Claims triangles/loss reserves                           |
| • Frequency and severity models                   | • Spatial modeling                    | • Survival models  |
|   | • Unsupervised learning               | • Transition modeling                                      |

... and then correct premium



## Pricing and Personalization



In dependent modelling **claims**, **lapse** and **usage** are all interconnected



## Pricing and Personalization



Innovations create the demand for new insurance products for which there is no historical information and so, no mathematical way of measuring the risk of an accident. Actually, insurers have always faced demand for new products.

## Challenge

The adaptation to digital innovations in the insurance companies themselves

- 1) Central role of data chief officer (CDO)
- 2) Promote CEOs cross-sectional vision of data analytics
- 3) Let data speak, Data-speak language is more than a number.  
**Analytics should express conclusions in sentences**, analysts should find the meaning to formulas, algorithms, figures and digits.

## What have we learned?

- 1) The statistics on **driving style** are much more informative than the traditional rating factors
- 2) The level of **personalization** and the role of insurance changes
- 3) **Insurance** is reinvented in order to protect people and prevent accidents.

## What comes ahead?

Insurance as a utility for protection, not only for compensation

Insurance pools

Autonomous/assisted driving. Joint ventures insurers-manufacturers

An extended version has been awarded the **Best Paper in the Non-Life Section of the International Congress of Actuaries (2018)** 

The full version can be found at: [www.ub.edu/riskcenter](http://www.ub.edu/riskcenter)

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# Driving Data: telematics to improve insurance rates

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