



Institute  
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## An Update from Advanced Pricing Techniques GIRO Working Party

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Dani Katz, Optim Analytics

8 – 11 October, Edinburgh



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### Agenda

- Introduction
- Use of GLM in a competitive market
- Telematics and pricing
- Summary and Q&A

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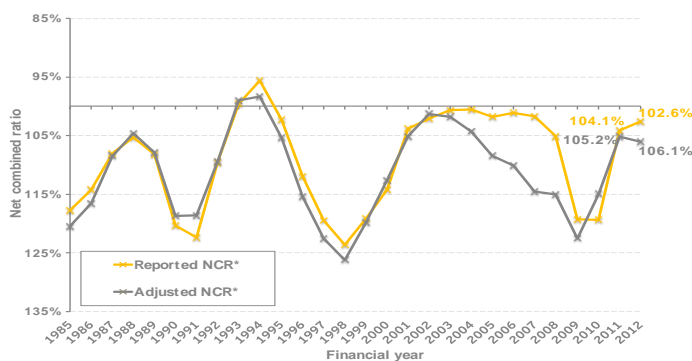
## Introduction

- Advanced Pricing Techniques (APT) GIRO working party was created in 2012
- 22 members working in three work streams with a focus on motor insurance market
  - Use of GLM
  - Telematics pricing
  - Conversion/Elasticity modelling

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## The UK motor insurance market has made overall profits only twice in the past thirty years



Source: S&amp;P and working party's interpretation

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With the dominance of price comparison websites, there is almost perfect competition in the market

	Annual Premium	Monthly Premium	Excess	Legal Cover	Courtesy Car	Breakdown Cover
<b>esure</b>	£200.09	1 x £35.04 10 x £18.29 £217.94	Vol: £250 Comp: £150 Excess: £400	£30.00 extra	✓	From £26.75
<b>M&amp;S Bank</b>	£259.73	1 x £38.96 11 x £22.27 £281.93	Vol: £250 Comp: £250 Excess: £600	From £24.99	✓	From £25.99
<b>POST OFFICE</b>	£294.23	1 x £38.94 11 x £24.28 £326.02	Vol: £250 Comp: £350 Excess: £600	✓	✓	£25.99 extra
<b>HALIFAX</b>	£322.72	1 x £48.49 11 x £27.88 £355.17	Vol: £250 Comp: £350 Excess: £600	£25.99 extra	✓	From £35.99
<b>autonet</b>	£323.46	1 x £72.75 10 x £31.41 £387.55	Vol: £250 Comp: £350 Excess: £600	£29.99 extra	✓	✗
<b>ASDA money</b>	£376.59	1 x £162.82 11 x £31.36 £447.78	Vol: £250 Comp: £275 Excess: £325	✓	✓	Check with provider
<b>AA</b>	£377.43	1 x £37.74 11 x £35.41 £427.25	Vol: £250 Comp: £150 Excess: £370	£25.99 extra	✓	✗
<b>ZURICH</b>	£469.68	1 x £61.92 11 x £62.63 £530.85	Vol: £250 Comp: £150 Excess: £400	£28.99 extra	✓	£36.99 extra
<b>hulleyinsurance.co.uk</b> Part of the Swire Group	£505.64	1 x £48.25 11 x £48.25 £579.00	Vol: £250 Comp: £275 Excess: £325	From £30.00	✓	From £40.41
<b>DA GENERAL ACCOUNT</b>	£757.70	1 x £124.31 10 x £71.29 £839.21	Vol: £250 Comp: £50 Excess: £300	Optional £27.00	✓	Optional From £33.18
<b>Drive</b>	£1378.12	1 x £206.72 9 x £149.64 £1553.48	Vol: £250 Comp: £350 Excess: £600	£15.00 extra	✓	From £60.00
<b>QUINNdirect</b>	£1702.49	1 x £363.25 10 x £145.28 £1816.05	Vol: £250 Comp: £250 Excess: £250	£22.00 extra	✗	✓

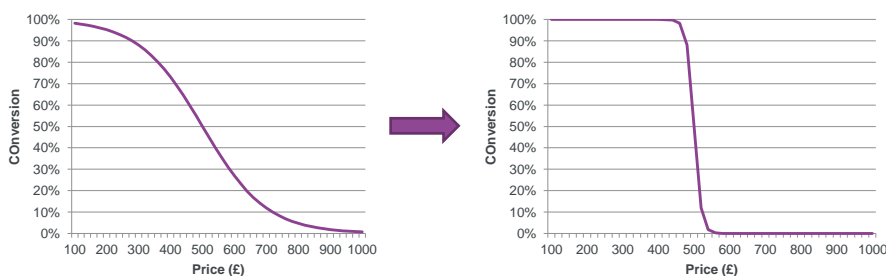
Quotes for a 40 year old married female with a clean licence held for 15 years for a 59 plate diesel Golf GTD 2.0L 3 door hatchback. Car is kept at home and parked on a driveway for social use only, approx 7000 miles

Source: Confused.com

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## Conversion elasticity modelling

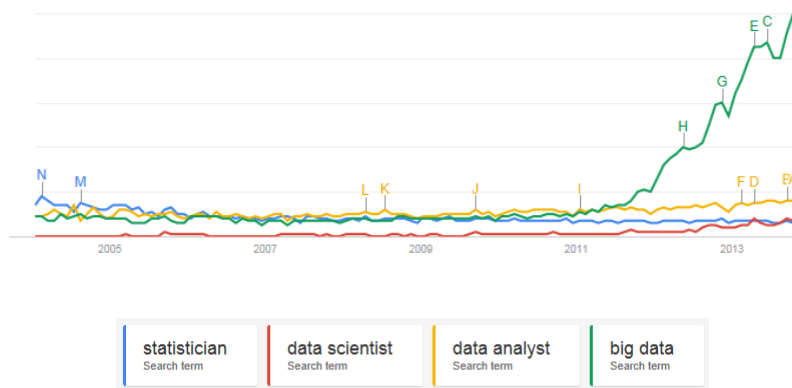


- Rating factor
- Purchase behavior
- Market condition
- Brand value
- Market condition
- Brand value

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## Big data – the rise of the data analyst?

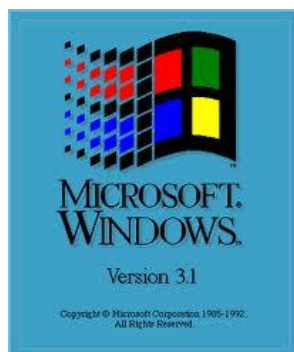


Source: google.com

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Despite the significant evolution of the market, pricing techniques haven't changed much



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There are a wide range of quoted premium on the market, while similar pricing techniques are used throughout market.

	Annual Premium	Monthly Premium	Excess	Legal Cover	Courtesy Car	Breakdown Cover
	£200.09	1 x £35.04 10 x £18.29 £217.94	Vol: £250 Comp: £150 Excess: £400	£30.00 extra	✓	From £36.75
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	£294.23	1 x £58.94 11 x £24.28 £326.02	Vol: £250 Comp: £250 Excess: £600	✓	✓	£25.99 extra
	£322.72	1 x £48.49 11 x £27.88 £355.17	Vol: £250 Comp: £250 Excess: £600	£25.99 extra	✓	From £39.99
	£323.46	1 x £73.75 10 x £31.41 £387.85	Vol: £250 Comp: £250 Excess: £600	£29.95 extra	✓	✗
	£376.59	1 x £102.82 11 x £31.36 £447.78	Vol: £250 Comp: £275 Excess: £525	✓	✓	Check with provider
	£377.43	1 x £37.74 11 x £35.41 £427.25	Excess: £370	£25.99 extra	✓	✗
	£469.68	1 x £61.92 11 x £42.63 £530.85	Vol: £250 Comp: £150 Excess: £400	£28.99 extra	✓	£26.99 extra
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Quotes for a 40 year old married female with a clean licence held for 15 years for a 59 plate diesel Golf GTD 2.0L 3 door hatchback. Car is kept at home and parked on a driveway for social use only, approx 7000 miles

Source: Confused.com

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## Background to Generalised Linear Models

### What are Generalised Linear Models?

A Generalised Linear Model (GLM) is a statistical model intended to relate an observed or dependent variable ( $Y$ ) to a linear combination of predictors ( $\eta$ ).

The formulation is typically in terms of three components:

#### 1. Random component

Each observation of  $Y$  is independent and is from one of the exponential family of distributions.

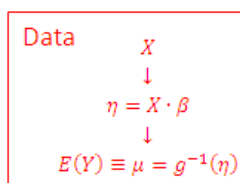
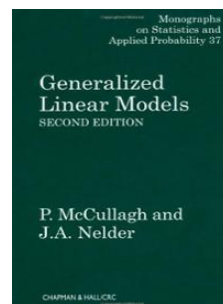
#### 2. Systematic component

A linear combination of the predictors gives the linear

predictor,  $\eta = X \beta$ :

#### 3. Link function

The relationship between the random and systematic components is specified via a link function,  $g$ , such that  $E(Y) = g^{-1}(\eta)$



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## Topic 1: Credibility and GLM

- A interview question: Your chief underwriter has read in the news that postcode XYZ have more claims and asked you to add it as a new level in the postcode grouping. What should you do?

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### Postcode lottery: We moved 175 yards – and our car insurance doubled!

By LAUREN THOMPSON  
UPDATED: 00:34, 11 January 2012

Share Tweet +1 Share 21 View comments

A family saw their car insurance more than double after moving less than 175 yards down the road.  
Source: Thisismoney.com



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## Either Zero or Full Credibility is given to rating factors



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## Apply credibility blending in GLM

- Credibility theory can be used to blend results
  - Following on from our previous example, suppose an insurer begins writing policies on a new postcode XYZ
  - They will have no data from existing policies on which to base their price, and only sparse data for the first few months once they start writing these policies
  - One solution would be to use a credibility weight which is updated as we get more data from policies of Ferrari Enzo drivers
  - How do you calculate the credibility factor Z?
- A credibility factor can be used to blend predicted averages produced by different models (with different rating factors)
  - There is no standard way of calculating the credibility factor – it can be calculated based on
    - Volume
    - Standard deviation / Variance
    - p-value.

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## Generalised linear mixed models (GLMMs) provide a potential solution

- GLMMs are an extension to GLM, in which the linear predictor contains random effects to allow for connection between data in addition to the usual fixed effects.
- It provides a convenient way of applying credibility blending within GLM.

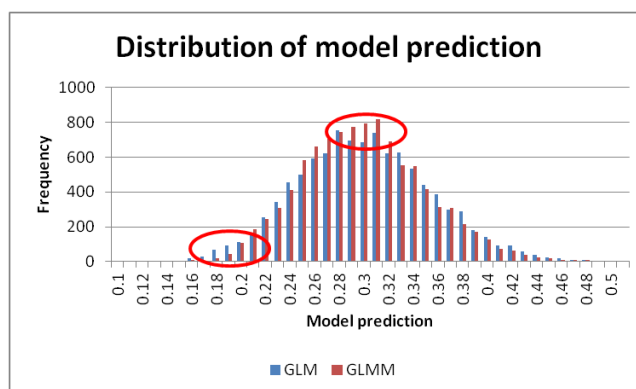
$$y_i = \mathbf{X}_i\beta + \mathbf{Z}_i\mathbf{b}_i + \epsilon_i$$

Random  
effect

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## GLMM produces fewer extreme predictions - example

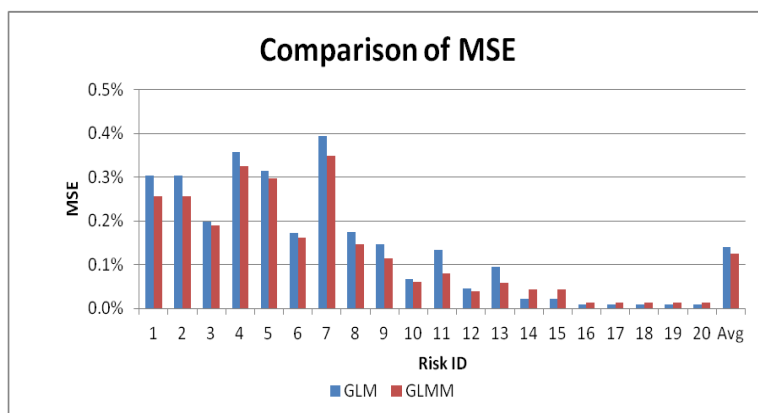


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## GLMM produces fewer extreme predictions – by risk



## Topic 2: dependence of unrelated risk profiles

- GLMs impose a linear structure on the data – the mean of the model output is calibrated to be equal to the mean of your sample data
- The GLM will do this for each factor used in the model (e.g. driver age Old/Young, car age New/Old)

		New car	Old car
Young driver	Number of claims	100	100
	Avg claim size (£)	8,000	5,000
Old driver	Number of claims	100	100
	Avg claim size (£)	3,000	1,000

- This builds a dependency on the claims experience of each segment into the results
- Additionally, the GLM builds a dependency on the number of observations in each segment into the results

## Example of a simple GLM

- We start by building a simple GLM on the dataset below, which consists of four policies each with two rating factors: 'Driver Age' and 'Car Age'.
- Each policy has had a single claim of differing severity. We use the GLM to get a prediction of average loss severity for each policy.

Driver Age	Car Age	Claim Amount (£k)		Driver Age	Car Age	Prediction (£k)
Old	Old	1	➔	Old	Old	1.4
Old	New	3		Old	New	2.6
Young	Old	5		Young	Old	4.6
Young	New	8		Young	New	8.4

- We will now consider two test cases to demonstrate the impact that a change in loss experience or exposure has on model predictions.

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## Test Case 1: double the claim severity for the "Old – Old" policy

- If the data is revised so that the severity of the "Old – Old" claim is doubled, we can see that the GLM produces different predictions for **all** policies.

Driver Age	Car Age	Claim Amount		Driver Age	Car Age	Prediction
Old	Old	1	➔	Old	Old	1.4
Old	New	3		Old	New	2.6
Young	Old	5		Young	Old	4.6
Young	New	8		Young	New	8.4

Driver Age	Car Age	Claim Amount		Driver Age	Car Age	Prediction
Old	Old	2 (+)	➔	Old	Old	1.9 (+)
Old	New	3		Old	New	3.1 (+)
Young	Old	5		Young	Old	5.1 (+)
Young	New	8		Young	New	7.9 (-)

- Here, the predicted claims severity for "Young – New" drivers decreases.


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## Test Case 2: double the number of claims in the “Old – Old” segment

- In this test case we duplicate the “Old – Old” claim – so average claims severity in this segment remains the same.


Driver Age	Car Age	Claim Amount
Old	Old	1
Old	New	3
Young	Old	5
Young	New	8



Driver Age	Car Age	Prediction
Old	Old	1.4
Old	New	2.6
Young	Old	4.6
Young	New	8.4

Driver Age	Car Age	Claim Amount
Old	Old	1
Old	Old	1
Old	New	3
Young	Old	5
Young	New	8



Driver Age	Car Age	Prediction
Old	Old	1.3 (-)
Old	New	2.5 (-)
Young	Old	4.5 (-)
Young	New	8.6 (+)

- Once again, the predictions for **all** subsets change. This time the prediction for the “Young – New” policy increases.

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## Possible solutions: revolution vs. evolution

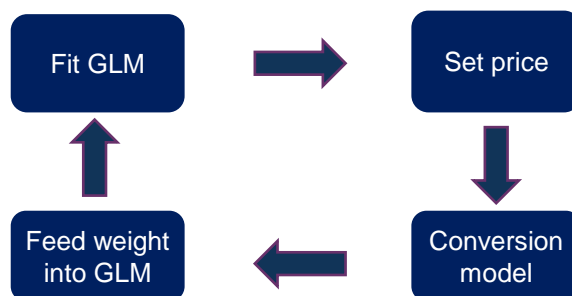
- Take account of the expected future business mix
- Obtain claims data from the market
- Setting the correct assumptions for future inflation, IBNR, expenses etc
- An iterative modelling approach to obtain the correct "weight"

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## An iterative modelling approach

- An iterative approach can be developed – a GLM is trained on the historical portfolio and a price is derived from this. The results are then run through a conversion model to get a predicted future mix of business. A second GLM can then be run based on this revised mix of business, and so on.



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## Telematics



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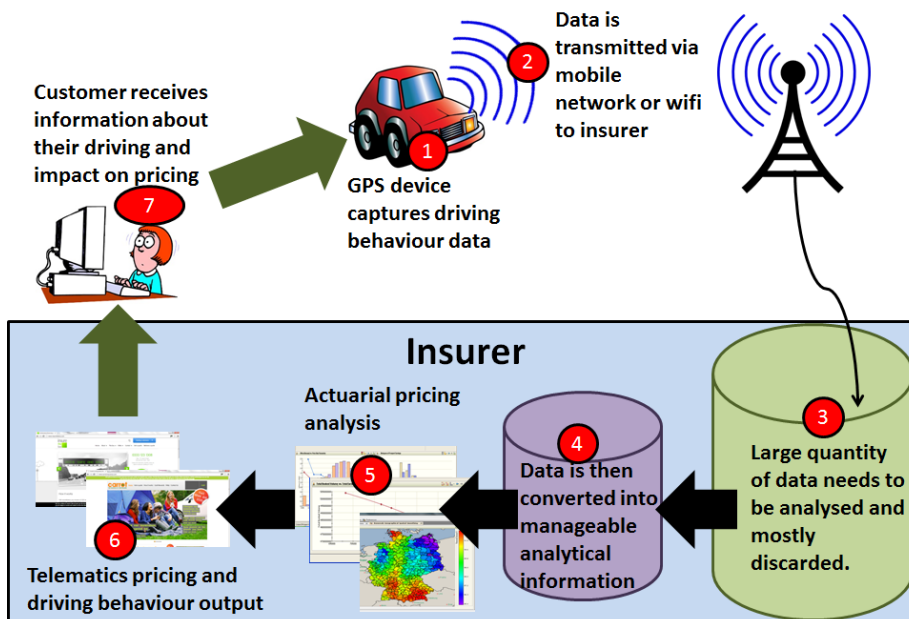
## The impact of telematics on pricing depends on the product structure

- While telematics products are becoming more common, the products offered are diverse.
- As a result, the pricing approach and use of telematics data depends on the underlying product characteristics.
- The cost of introducing telematics products will depend on how the data is used. The value gained is also dependent on the pricing approach.
- We have surveyed telematics providers to understand product characteristics, the data used and their possible impacts on the pricing approach.

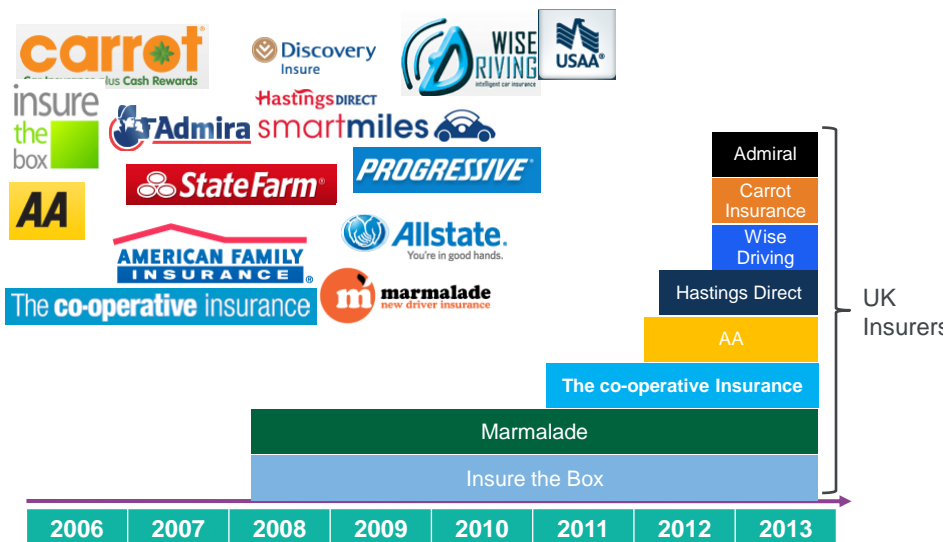
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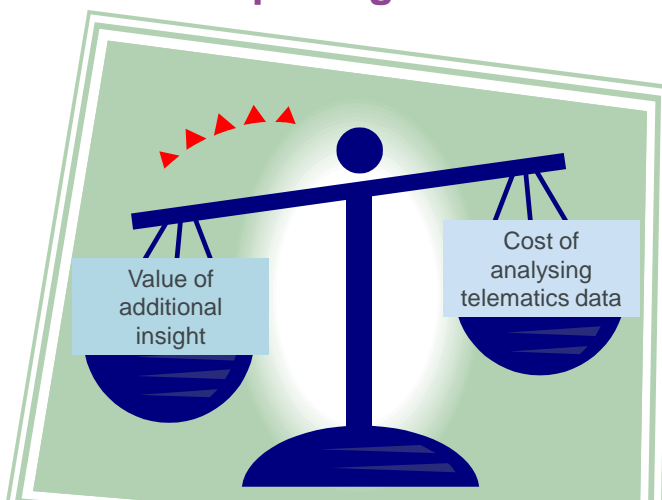
## How will Telematics Change the Pricing Process?



## Growth in telematics providers



## How important is the additional information for pricing motor insurance?



The value of the data depends on the product proposition

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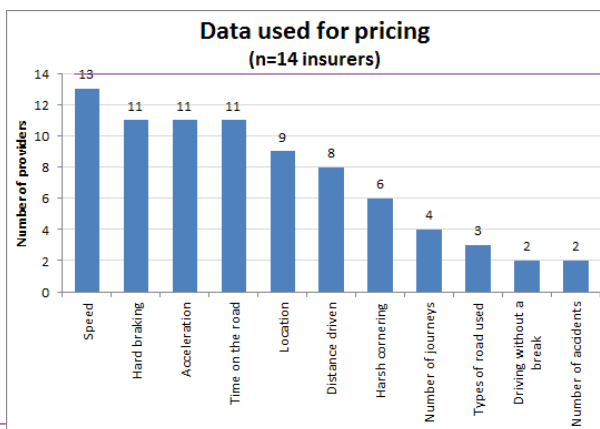
## The product and pricing methods vary significantly

- What impact does the data have on the pricing process?
- We conducted a survey of 14 providers of telematics insurance products, including some non-UK insurers.
- We reviewed policy documents to understand product features as well as the data used to price policies.
- The diversity of products and methods used to price policies was striking, and the analytical requirements depend on the product offering, the premium terms and the data used in the pricing process.

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## Data used in pricing

- For all 14 insurers reviewed, there wasn't one driving data metric used by all of them.
- Most insurers use speed data for pricing, while very few analyse the type of road, the time without a break and the number of accidents measured in the data.



Source: Policy documents from telematics providers.

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## Telematics Data

How is the data used?


- To calculate insurance premiums based on actual driving information.
- To validate insurance claims, e.g. verifying the location and speed at the time of accident.
- To provide theft tracking services, or any other services that may require the use of a telematics device.
- To give insight into driving behaviors to support ongoing insurance product developments.

The main issue for insurers is managing the volume of data and analysing it. We need to understand the value of different data elements to ensure this process adds value.

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## How valuable is the data available to telematics insurers?

Risk factors		Standard pricing	Telematics pricing
Car information (model, year, etc.)		✓	✓
Driver information (age, sex, etc.)		✓	✓
Accident history		✓	✓
Price optimisation		✓	✓
Quality of road (curves, etc.)		✗	✓
Traffic density		✗	✓
Laws, regulations, and other external factors		✗	✓
Mileage		✗	✓
Speed		✗	✓
Weather conditions		✗	✓
Seasonal use of car		✗	✓
Day and/or night use of car		✗	✓

Much of the value may be generated by self selection!

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## Understanding the cost of telematics data

The cost of acquiring telematics data continues to fall, however it is still higher than that for traditional insurance.

Cost items	One off cost	On-going cost	Comments
Buying and installing the telematics device in the car	✓✓		Cost is high, but reducing
Creating a process to obtain data and setting up analytics databases	✓✓		High initially, reducing as techniques standardise and technology costs reduce.
Obtaining driving data from the telematics device		✓✓	Depends on quantity of data
Analysing the data		✓✓	High but spread across lots of customers
Storing the data		✓✓	Cost is reducing, but data quantity is still very large.

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## Comparison of telematics product offering

### Similarities

- ✓ All insurers highlighted potential savings
  1. Renewal discounts
  2. Cash back, cash rewards
  3. Discounts when you buy products from partner companies
- ✓ All encourage safer driving
  1. Earn cash rewards; calculate premium
  2. Reward miles if you drive well

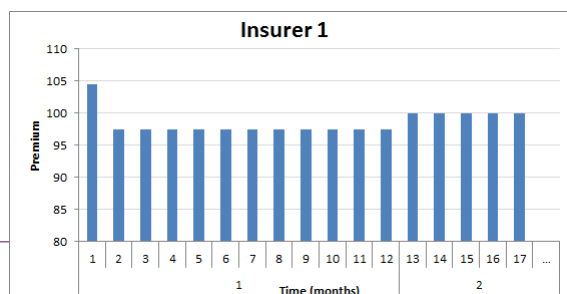
### Differences

- ✓ Differences in product structure
- ✓ There are differences in specific pricing features for similar plans e.g. the annual mileage limit
- ✓ Differences in the data used for pricing
- ✓ Differences in the timing and extent of premium changes
- ✓ Discount methods vary markedly, e.g.:
  1. Reward miles for good driving
  2. Cash back
  3. Partner discounts

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## Insurer 1

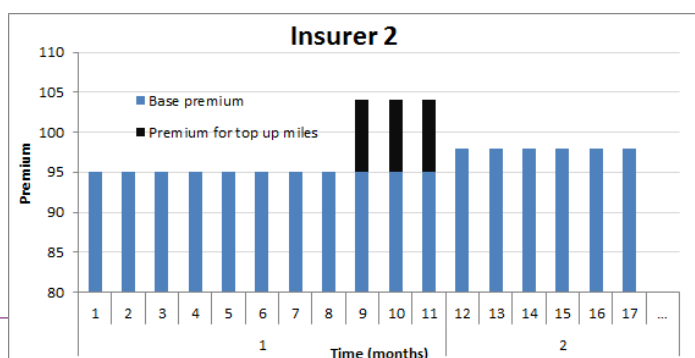
- Policyholder is offered a starting premium rate with no allowance for driving behaviour. The insurer attaches the telematics device for 30 days and gets a personalised premium rate (always a discount to the starting rate).
- The technology is not a GPS, therefore it doesn't record the type of roads used or location, but it does measure speed and time spent travelling.
- After 5 more months of driving, a renewal discount is calculated which is carried forward for future policy periods until policy expiration.
- The device is removed from the car, with no more tracking of behaviour unless the insurer elects to re-monitor the vehicle or revise its driving behaviour discount factors.



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## Insurer 2

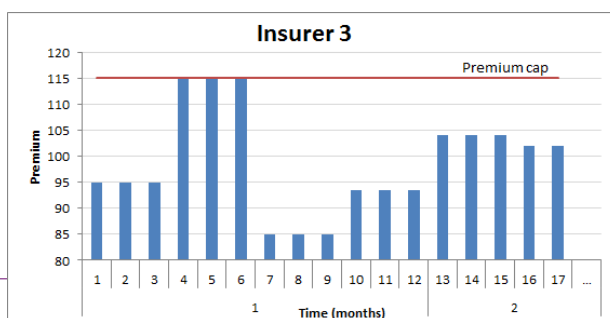
- Insurer offers insurance for maximum annual driving distance, charging a different premium base on a low free annual mileage allowable.
- The car is tracked using a telematics device to determine the distance travelled and driving habits. If a policyholder travels more than the allowable distance during the policy year, they will need to either top up the miles or earn bonus miles due to better driving behaviour.
- The allocation of bonus miles as well as the price of the top up miles is dependent on driving habits, giving an incentive to the policyholder to improve their driving. In addition, the company offers reward miles at renewal that can be used to buy consumer goods.



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## Insurer 3

- Product is designed to give a better deal to young drivers who drive safely.
- Install GPS device to record driving behaviour, primarily speed, acceleration and deceleration, cornering and time of day.
- The premium is then adjusted every 90 days based on past driving behaviour, with a maximum increase in one year.
- At renewal, the premium is recalculated and will include a No Claim Discount.



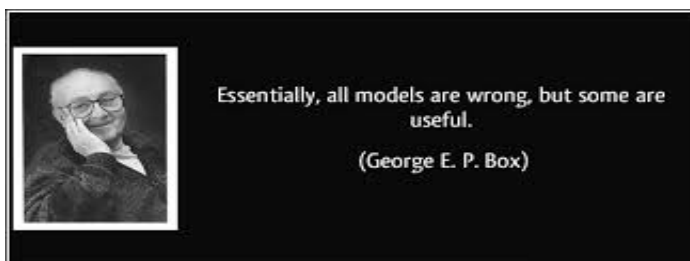
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## Pricing Considerations

- How do we use telematics data to optimise pricing?
  - Enhanced claims models using driving variables
  - Is price sensitivity impacted by driving patterns (e.g. high mileage => greater price tolerance?)
  - Changes in driving behaviour will impact claims risk, and therefore price
  - Does the frequency of testing driving behaviour matter, or is one test enough?
- To better enable traditional actuarial functions, telematics data should be organized, enriched, and consolidated. (with support of software such as SQL, Access)
- To ensure data is of sufficient quality to analyse, regular checks and professional judgments is required.
- Need to be mindful of data privacy and protection issues.
- Behavioural economics insight - information needs to be provided to the policyholder to explain pricing outcomes (i.e. it must be clear that good driving behaviour drives a better price). (This helps with the self selection effect)

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## Summary



- But what makes a useful model?
  - Output of model does have a significant impact on commercial decision
  - Limitations of the model is fully understood and communicated efficiently to key stakeholders



# Questions

# Comments

Expressions of individual views by members of the Institute and Faculty of Actuaries and its staff are encouraged.

The views expressed in this presentation are those of the presenter.