Application scoring in utilities:

What do the people we can't reject tell us about the power of reject inference?

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History of credit scoring at British Gas

Started life in 1812 as Gas Light and Coke Company

Became British Gas as current structure in 1997

Started credit scoring residential customers in 1998

In house application scores for residential customers implemented Jan 2012

Credit scoring is not at the heart of what British Gas does

Particular problems due to being an energy supplier

We cannot reject any customers

We have not disconnected a customer for several years

From a debt point of view the final aim is to get a prepayment meter fitted

We are under external pressure to simplify pricing

Force fitting a prepayment meter is a lengthy and expensive process

Debt customers continue to accrue debt at a rate of around £2 per day

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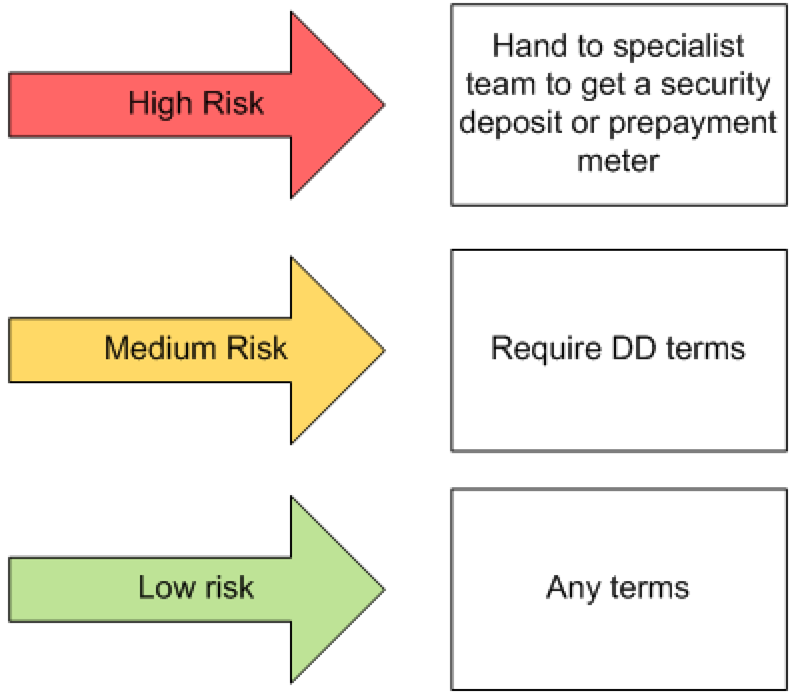
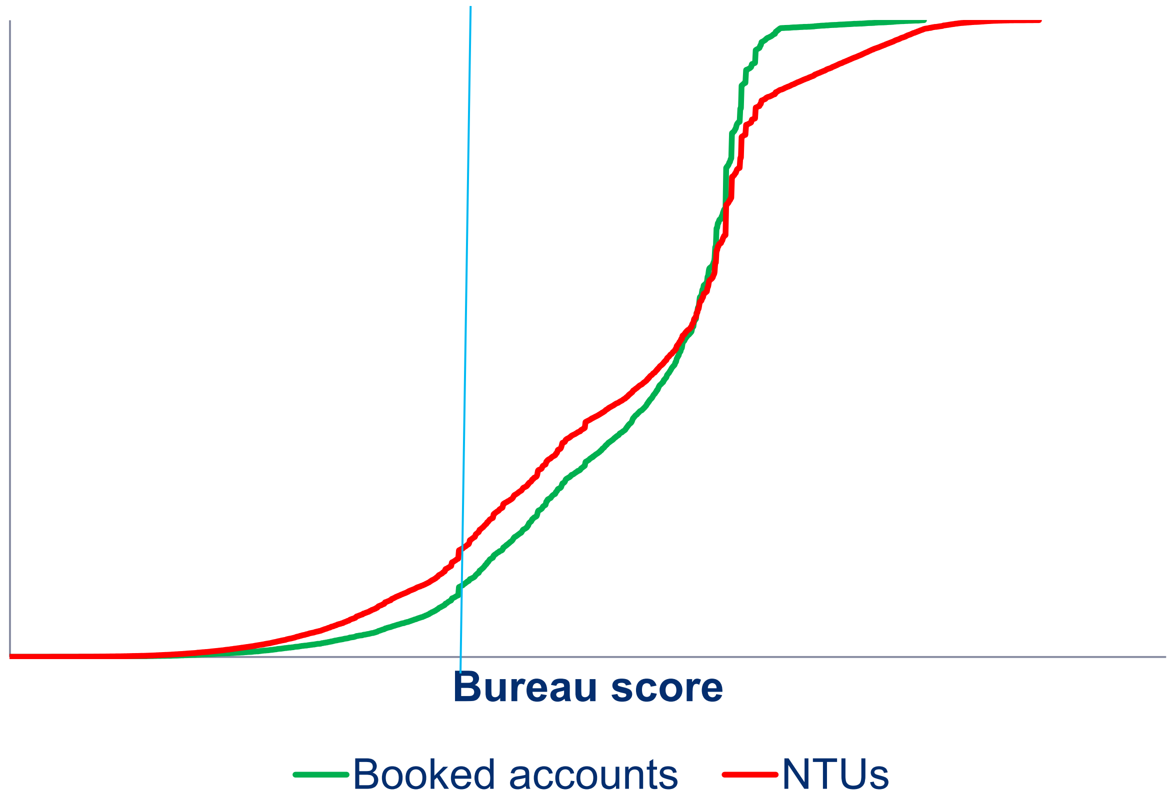
Application scoring strategies

Application scores are not used to reject residential customers as this contravenes supply license conditions. Instead the aim is to get people onto more secure payment terms



On average those who come onto book have only slightly better characteristics than those who don't



Without the ability to say no, credit scoring doesn't seem to be making a big difference to the credit worthiness of the portfolio, although some of the low scorers are moved onto a prepayment meter to secure their energy costs

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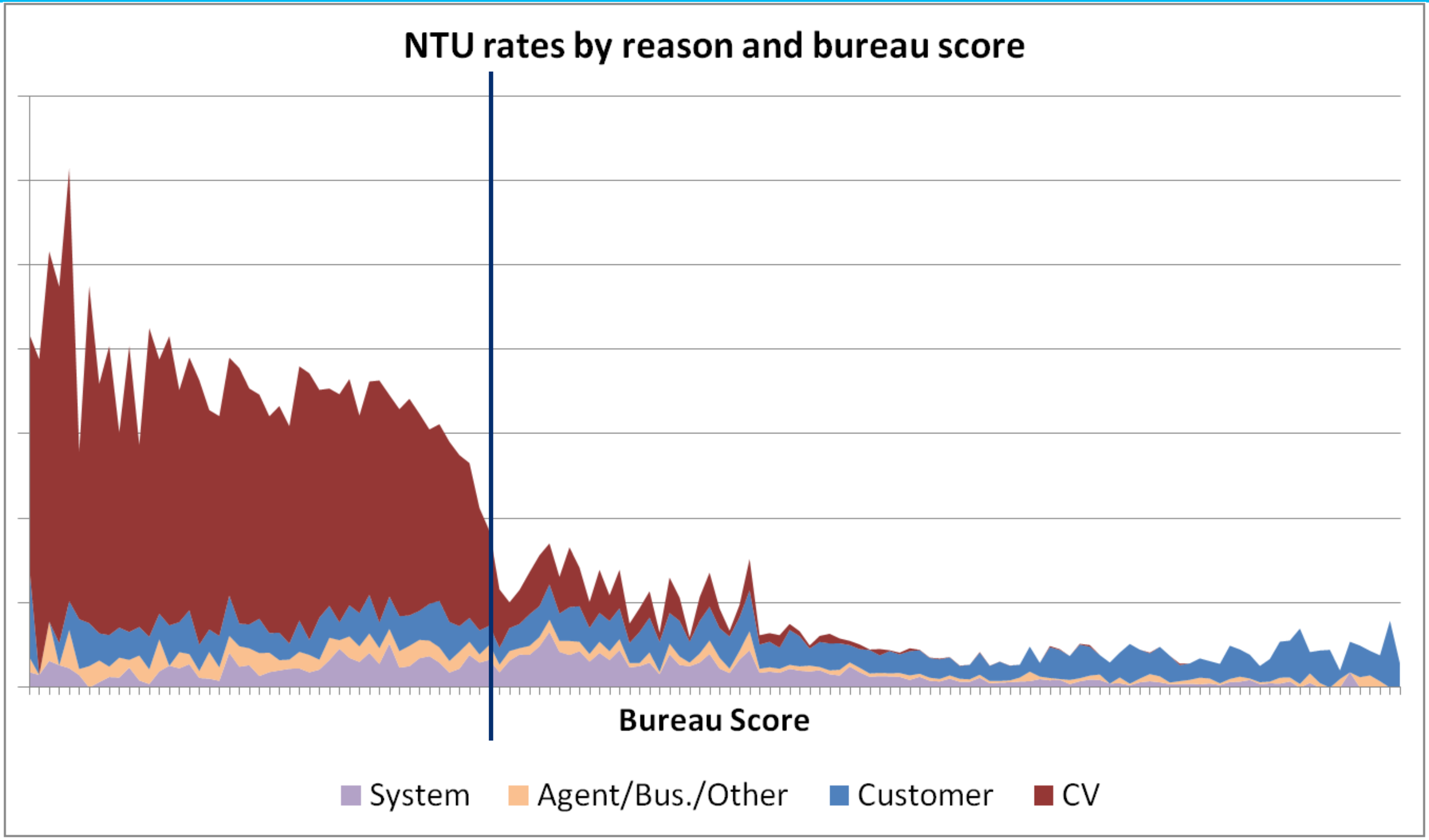
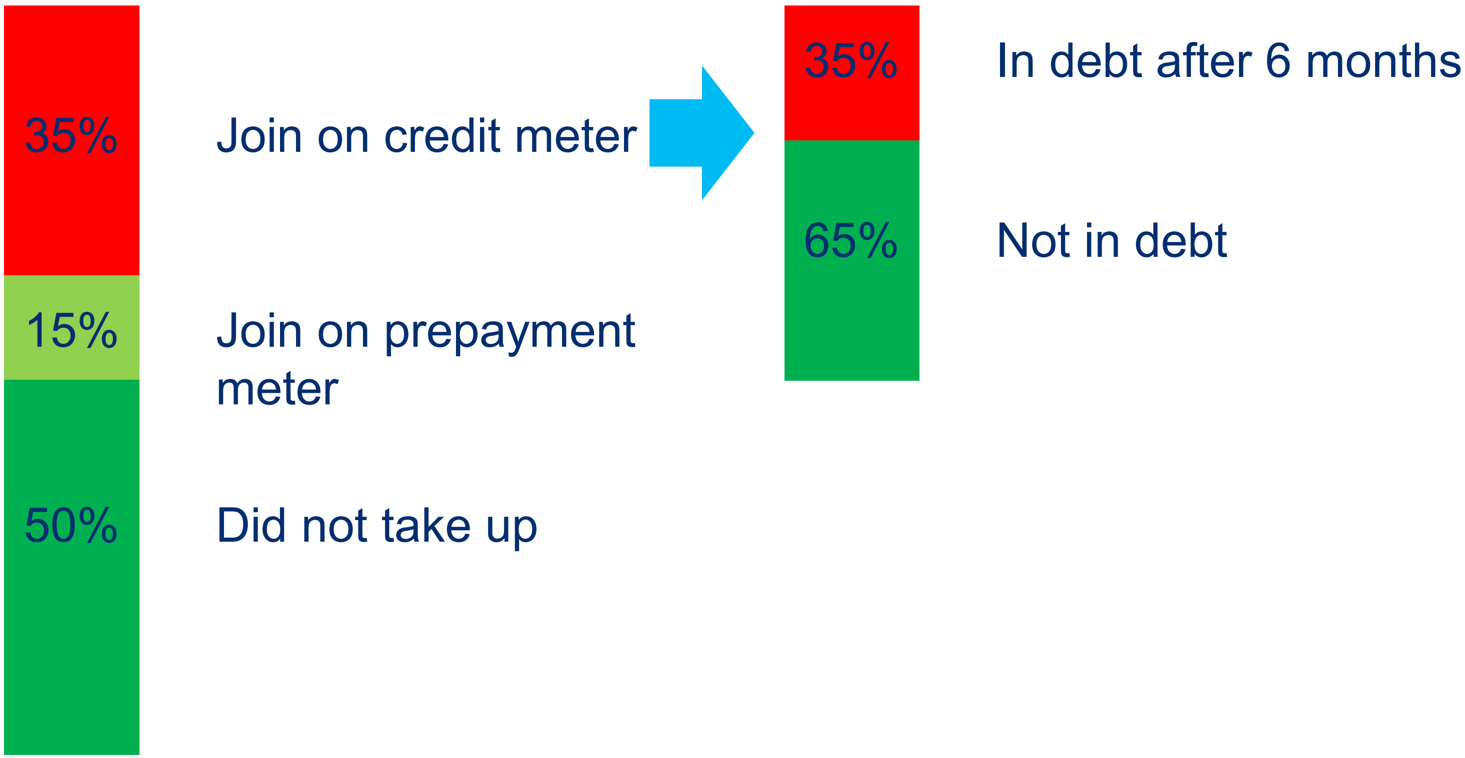
What does our not taken up population look like?



Credit scoring is making a more obvious difference here, dissuading poor scoring applicants from joining us. Take-up rates for other reasons are relatively flat

Cost to the business of not being able to reject customers

Following a credit vet, for a customer scoring below the cutoff:



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Question:

What affect is this having on our modelling power?

Do we build more predictive models by not having strict reject rules?

If we could influence take-up rates through price discrimination, how would that change the models?

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Modelling scenarios:

Three possible options for data available in the development sample

1: Weak reject rules – current situation, with weak results of credit scoring and flat take-up distribution by score above the cut-off

2. Rigorous reject rules – as if we were allowed to reject applications and had full compliance
   - Any customer below cut-off used in reject inference, along with the not taken up population

3. Price discrimination – take ups change based on risk
   - Take ups scaled based on risk score to simulate being able to offer risk based pricing

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Modelling process

To test this we build 3 hypothetical models based on the data that would have been available in the modelling scenarios. These are then all implemented in the same way, with the same volumes rejected.

1. Example models built off the same development sample from 2009 & 2010 as our current application score.
2. Model builds use SAS Enterprise Miner, with a ever 90days past due in 12 month bad definition
3. All applications for subsequent year scored according to the three resultant models with bad rates approximated by those of equivalent bureau score if the applications did not come onto book.
4. Comparison of models using bad rates, debt amounts, and revenue

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Variable comparisons

Number of variables of each type	Weak reject rules	Strict reject rules	Price discrimination
Bureau score	1	1	1
Geo-demographic data	2	2	1
Electoral roll identity confirmation	1	1	1
Indebtedness index			1
Value of CAIS	1	2	
Number of CAIS	2	2	
Worst status	1	2	
Balance change over time	1	1	1
Age of CAIS		1	
Total	**9**	**12**	**5**

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Gini Comparisons from build data

	Weak reject rules	Strict reject rules	Price discrimination
Gini	61.7	55.9	47.3

When you have more information about your reject population and those closest to them, the gini improves.

Despite more variables in the ‘Strict reject rules’ scorecard, its performance is not as good.

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Validation data

5 months of applications Feb 12-June 12.

For those who came onto book:

- Bad definition same as development sample
- Value of debt and provision given at Jan 13.

For those who didn't come onto book,

- Estimate bad rates, debt, and provision based on bureau score

Projected performance comparisons on all testing applications

	Weak reject rules	Strict reject rules	Price discrimination
Indexed bad rate in 'to secure' group	100	94	89
Indexed bad rate in 'any terms' group	100	103	108
Average additional debt per 'any terms' applicant after a year		£0.93	£1.96

Performance weakens with less data for the scorecard build

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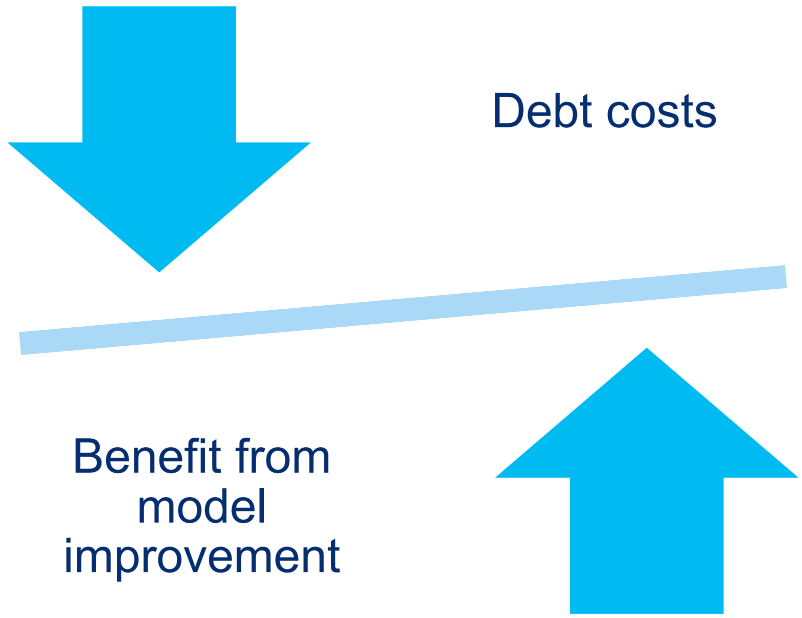
Conclusions

- There is an unavoidable cost to the business from being unable to reject customers

- A small proportion of this cost is recouped through building more predictive models

- It is a balancing act, and there is an optimal amount of poor performing customers to take onto book.



In an ideal world we would be able to both prevent debt from applications while leveraging the predictive power of their data.

Reject inference does not provide enough information to get around this problem.

In the utilities sector there may be more data available by analysing prepayment meter data to identify those who reduce their usage.

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