What Personality Measures Could Predict Credit Repayment Behavior?

Dean Caire, CFA

Galina Andreeva, Wendy Johnson,
The University of Edinburgh

OUTLINE

Motivation

Previous research in Credit Risk Management

Pilot Study in SA Taxi

Exploratory Factor Analysis

Next Steps

MOTIVATION

Explore ways within the domain of ‘personality’ to quantitatively measure ‘willingness to repay’ when credit history not available

- Increase knowledge how/if personality plays a role in loan repayment behavior
- Share findings to improve financial inclusion

MOTIVATION

- Credit Scoring is based on observable information with historic associations with default

- Traditionally bankers consider ‘Character’ an important aspect in credit risk management –this is at least conceptually related to personality.

- Microfinance institutions consider ‘Character’, but very few attempt to measure it quantitatively.
  - How to ‘quantify’ and better use this information?

PREVIOUS RESEARCH

Literature on trait measures and credit outcomes:

↑ Conscientiousness:

↑ higher FICO Scores [Bernerth, 2012]

↓ lower probability of default [Klinger et al, 2013]

↓ lower credit scores [Rustichini, 2012] - ?

↑ Agreeableness:

↓ lower FICO scores [Bernerth, 2012]

↑ Integrity:

↓ lower probability of default [Klinger et al, 2013]

PREVIOUS RESEARCH

Literature on trait measures and credit outcomes:

↑ External Locus of Control:

↓ lower probability of default [Ding et al.*, 2009]

↓ lower probability of default[Perry, 2008]

↑ Risk Taking:

↑ higher probability of defaut [Ding et al.*, 2009]

↑ Cognative Ability:

↓ lower probability of default [Stockham & Hesseldenz, 1979]

THE UNIVERSITY OF EDINBURGH

CRC Credit Research Centre

PILOT STUDY IN SA TAXI

- Supported by a grant from the University of Edinburgh Business School Venture Fund
- Considerable financial resources, time and data contributed by SA Taxi
- Commercial goal: to better evaluate ‘thin file’ marginal bureau score declines

PILOT STUDY IN SA TAXI

SA Taxi
driving our nation forward

- All clients operate mini-bus 'route taxis'
- Removes one level of industry-specific "noise" that would normally be found with a small business loan portfolio

THE UNIVERSITY OF EDINBURGH

CRC Credit Research Centre

PILOT STUDY IN SA TAXI

CONSTRUCT	SOURCE	Number of Items	
		Positive	Negative
Conscientiousness	IPIP* from Measuring the 7 Factors from Saucier (1997)	6	6
Conscientiousness	IPIP from Big-Five Factor Markers	3	4
Integrity/Honesty/ Authenticity	IPIP Values in Action: Peterson & Seligman, 2004	4	4
Trust	IPIP from 30 NEO Facets	8	10
Social Desirability	10-item Short Form of Marlow-Crowne Scale	5	5
Honesty	BIOSS	3	3
Manipulation	BIOSS	6	0
Problem Solving	BIOSS	5	2
Self-Reported Intelligence	Trapnell's Smart scale (Trapnell, 1994)	4	0
Emotional Stability	BIOSS	4	6
Values	BIOSS	7	3
TOTAL : 98 Items		**55**	**43**

*International Personality Item Pool
www.***ipip***.ori.org/

Credit Research Centre

PILOT STUDY IN SA TAXI

Four point Likert-scale responses to all 98 personality measure items:

Please answer honestly, and remember that we are interested in the type of person you are now, not the type of person that you might be in the future.

Please use the scale below for questions 1 - 98

Completely agree	**Mostly agree**	**Mostly disagree**	**Completely disagree**

1. I try to follow the rules.
2. I believe laws should be strictly enforced.
3. I pay attention to small details.
4. I like order.

THE UNIVERSITY OF EDINBURGH

CRC Credit Research Centre

DIFFERENT LEVELS OF "NOISE"

introduced in data collection process

DATA SET: 299 Existing Clients with known credit outcomes

	THICK FILE	THIN FILE
GOODS	124	39
BADS	83	33
TOTAL	207	72

Low Response Rate: marketing research company contacted 2,835 clients to attract 300 participants

+ free lunch

Language modified and translated;
Tests offered in choice of 4-languages

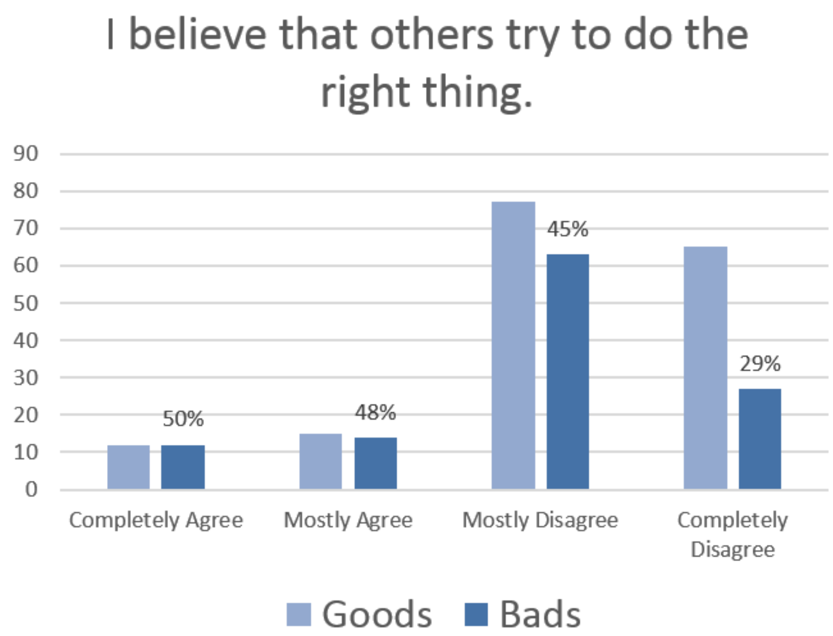
57%	English
30%	Zulu
10%	Sepedi
3%	Venda

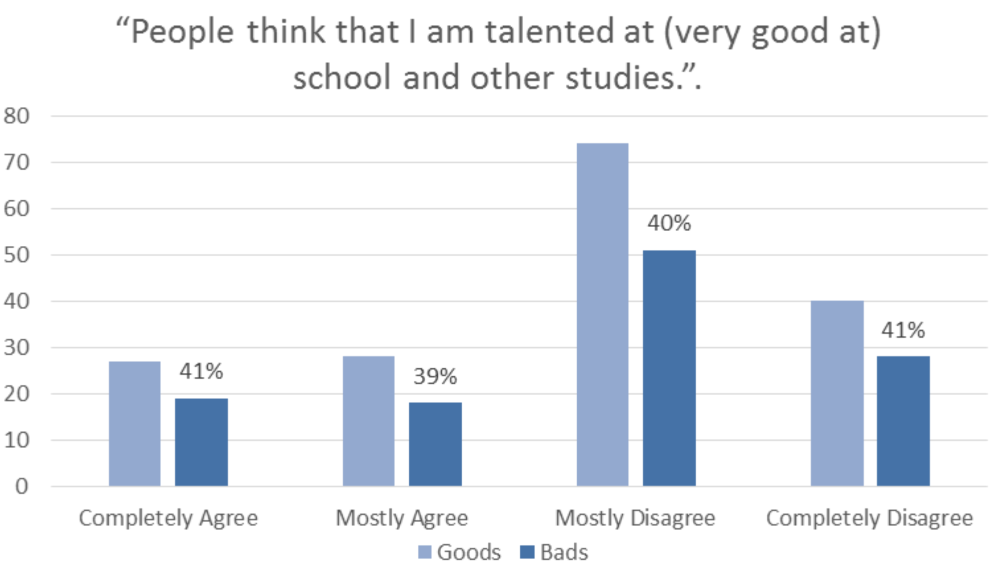
Choice of paper or Ipad test

THE UNIVERSITY OF EDINBURGH

CRC Credit Research Centre

DATA PATTERNS





Many items highly skewed, some with non association or non-monotonic relationship with 'Bad'* loans

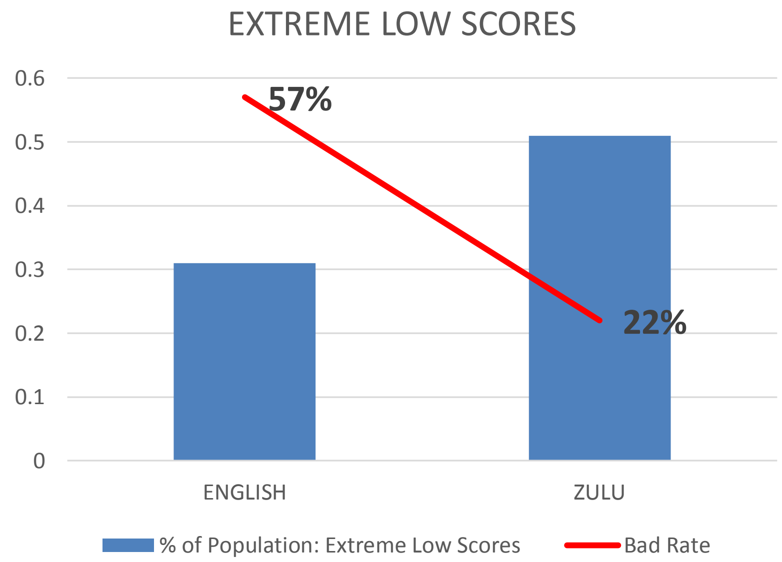
- 2 missed payments in the client's first 15 Months
- Bad rate for data set 41%.

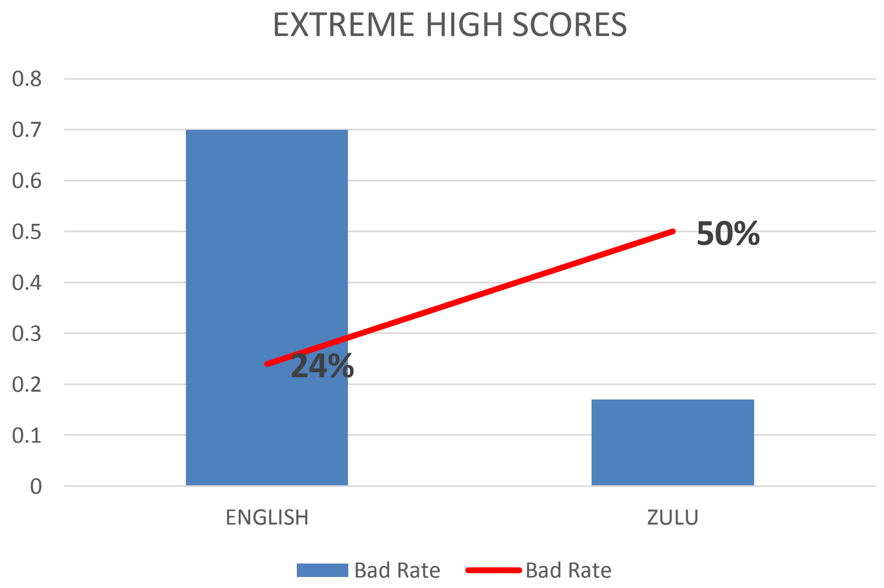
THE UNIVERSITY OF EDINBURGH

CRC Credit Research Centre

'PECULIAR' RESPONSE PATTERNS

57% English
30% Zulu
10% Sepedi
3% Venda





- Zulu-speakers less likely to strongly agree?
- Strongly agreeing English speakers lower risk?

THE UNIVERSITY OF EDINBURGH

CRC Credit Research Centre

EXPLORATORY FACTOR ANALYSIS

- Explore possible underlying structure of interrelated variables without imposing any preconceived structure on the outcome (Child, 1990)

- Data reduction: Replace many collinear "manifest variables" with fewer latent variables (Bates, 2012)

$$\boldsymbol{\Sigma}_{zz} = \boldsymbol{B}\boldsymbol{\Phi}\boldsymbol{B}' + \boldsymbol{U}^2$$

Σ_{zz} = covariance matrix of observed variables
B = matrix of common factor weights
Φ = matrix of common factor correlations
U^2 = diagonal matrix of unique variance

(Tucker and MacCallum, 1997)

Credit Research Centre

EXPLORATORY FACTOR ANALYSIS

Too few subjects for number of items

- 5:1 recommended (we have 3:1)
- Degrees of freedom with 98 items are 4,758
- Kaiser-Mayer-Olkin Test of Sampling Adequacy of 0.71

Drop items:

- Skewness > 2 *(EFA assumes variables are multivariate normal)*
- Less than 2% of responses in any category
- With Measurement of Sampling Adequacy (MSA) < 0.5

- Choose Number of Items to Extract:
  - Parallel Analysis: 10 factors recommended
    eigenvalues > than expected by chance when extracted from random datasets with identical characteristics (Bates, 2012)

THE UNIVERSITY OF EDINBURGH

CRC Credit Research Centre

EXPLORATORY FACTOR ANALYSIS

Alternative 9 or 10-factor solutions attempted on all items characterized by:

1. Positive and negatively keyed (worded) items loading on separate factors
2. Tested construct items mixed on the ‘latent’ factors
3. No interpretable simple structure for 9 or 10-factor model – perhaps because sample was too small
4. Logistic regression of factor scores on loan status AUC range: 0.60 to 0.68 (in-sample)

EFA OF NEGATIVE ITEMS SEPARATELY

FACTOR	DESCRIPTION
1	Law Abindance (Conscientiousness)
2	Social Desirability
3	Emotional Stability*
4	Trust
5	Problem Solving
6	Orderliness (Conscientiousness)

Example Solution: Pearson correlations, Parallel Analysis, ML extraction, oblimin

* Significant ($p < 0.1$) in logistic regression of factors scores on good/bad status

EFA OF POSITIVE ITEMS SEPARATELY

FACTOR	DESCRIPTION
1	Problem Solving
2	Social Desirability/ Emotional Stability
3	Integrity *
4	Self-Reported Intelligence
5	Trust *
6	Conscientiousness
7	Conscientiousness*
8	Manipulation

Factor 5: Trust

1. I trust what people say.
2. I believe that people are basically morally good.
3. I trust others.
4. I believe in human goodness.
5. I believe that others try to do the right thing.

Example Solution: Pearson correlations, Parallel Analysis, ML extraction, oblimin

* Significant ($p < 0.1$) in logistic regression of factor scores

CRC Credit Research Centre

OBSERVATIONS FROM PILOT

- Small sample, noisy data, too many items with low discrimination
- ‘Ready-made’ scales are unlikely to be easy to use in developing markets

But….

- Trust, Conscientiousness, Integrity and Emotional Stability appear most promising of items tested
- Response styles themselves may be a source of prediction.

SUGGESTIONS FOR PRACTITIONERS

- Explore psychometrics in the context of ongoing marketing research (share costs).
- Cooperate with a university or other research partner (farm out the work).
- Adapt existing scales with domain knowledge.
- Try other modelling methods*.

* Liberati C & Camillo F (2013). Satisfaction, human values and other intangible dimensions as drivers of new credit scoring models. 6th ECRIM conference

QUESTIONS

Dean Caire, CFA