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The CARES Quality Index

Preliminary Report

24th January '16

(1) Overview

In November 2014, the Competition and Markets Authority (CMA) board launched an investigation into the supply of banking services to personal current account (PCA) customers and to small and medium sized enterprises (SMEs) in the UK. The provisional findings were published in October 2015.

One of the issues highlighted in the provisional report is the 'lack of responsiveness by PCA customers to variations in price and quality' (para 47, p.13 of the summary of the provisional findings[1]). In particular, The Summary of Findings devotes two full pages (spread over pp. 14-16) to the issue of switching behaviour, which it notes is 'low'.

There is a particular concern that in general there is an inverse relationship between survey-based measures of quality of service and market share. In other words, higher market share is associated with lower quality of service (although the relationship is not statistically significant (para 5.85)).

We have been developing indicators of consumer attitudes towards individual companies expressed in social media conversations. We have used the approach in, for example, analysis of conversations about airlines.

We used this approach to construct quality scores for individual banks. These predict switching behaviour out of the sample period over which the conversations were analysed.

The quality scores were developed using a multi-dimensional indicator of consumer emotions towards individual banks, as expressed in social media conversations. The emotions analysed were based on the so-called SCARF model of human social behaviour[2]. This model has its roots in social neuroscience, which explores the biological foundations of the way humans relate to each other and to themselves.

The emotion-based quality scores of individual banks are:

- Predictive of bank switching behaviour by PCA holders
- Can be estimated and deployed through computational analysis of banking-related social media conversations

In addition, our analysis found that not only do economically rational considerations appear to have little predictive power (a finding which supports those reported in the Summary of Findings[3]), but even customer perceptions of rational factors have only weak predictive power.

We must stress that this submission summarises the work of a preliminary study. It should be thought of as a proof of concept rather than a finished product. There are many ways in which the analysis can be refined, but the results appear to be well determined.

[1] Retail banking market investigation: Summary of provisional findings report, CMA, 22 October 2015
[2] Rock, D., 2008. SCARF: A brain-based model for collaborating with and influencing others. NeuroLeadership Journal, 1(1), pp.44-52.
[3] And also in the main report

(2) Quality scores measured from social media conversations

Social media conversations are of course very much cheaper as a source of information about consumer attitudes than are surveys, which are expensive in terms of design and execution. The question is whether they can be transformed into a tool of practical value. Here, we collect tweets which mention one of more of six large banks, and see if they can be used to predict customer switching data from Bacs[4]. The banks are Barclays, HSBC, Halifax, Nationwide, NatWest and Santander.

A standard approach to measuring emotion in text data is based upon counts of words in the relevant text. Loughran and MacDonald of the University of Notre Dame, for example, developed a set of words to reflect tone in financial text. They linked[5] the word lists to 10 K filing returns, trading volume, return volatility, fraud, material weakness, and unexpected earnings.

The words in this list are categorised as being either positive or negative, and the emotion score of any given document is based upon the difference between the counts of positive and negative words in the text. Other approaches attach scores to words, based on the degree to which they are perceived as having positive or negative emotional content (or 'valence', the technical term which is used).

A widely used set constructed on these lines is the Affective Norms for English Words (ANEW)[6].

We identify five basic emotions:

C: Certainty	- How secure is my data and money? (Example: cyber security.)
A: Autonomy	- How convenient / efficient is the bank? (Example: online banking.)
R: Relatedness	- Does the bank share my values? (Example: attitude toward crime)
E: Equity[7]	- How fairly am I treated? (Example: fairness of bank charges.)
S: Status	- Am I important as a customer? (Example: responsive customer service.)

Our approach for developing the set of words associated with each of the emotions in the CARES framework is based on the same principles which underlie the construction of word lists such as those in ANEW, but takes advantage of modern internet technology.

[4] http://www.bacs.co.uk/bacs/corporate/resources/pages/factsandfigures.aspx

[5] Tim Loughran and Bill McDonald, 2011, "When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks," Journal of Finance, 66:1, 35-65.

[6] Bradley, M.M., & Lang, P.J. (1999). Affective norms for English words (ANEW): Instruction manual and affective ratings Technical Report C-1, The Center for Research inPsychophysiology, University of Florida.

[7] We use 'E' for equity rather than the 'F' for fairness, which is the term used in the neurobiological literature

(3) The CARES Quality Index for individual banks

We compute the CARES index for each of the six banks in two steps. First, we score the bank's performance in each of the CARES element areas. This is based on analysis of bank-related social media posts over a period of several weeks.

We then form a weighted combination of the individual element scores to construct the CARES index for each bank. The weights of the individual emotions in the overall index are estimated by out of sample prediction of actual bank switching behaviour by customers, using advanced machine learning algorithms[8].

We predict net normalised switching of the six banks using data in 2015 Q1 and 2015 Q2. By this we mean the net gains/losses figure for each bank, divided by the total number of gains and losses for the bank.

The out of sample predictions identify with complete accuracy the winners and losers. In other words, customers switch from banks which have low scores on the CARES Quality Index to banks which have higher scores.

The most important emotions appear to be status and certainty. The 'report card' for each bank in terms of how customers feel about their status with the bank is as follows:

Barclays	1.4
HSBC	2.2
Nat West	2.2
Santander	3.0
Halifax	3.2
Nationwide	3.4

For comparison, a study which we carried out for a client on major airlines concluded that in terms of Status, a typical score for the individual companies was around 5 (on a scale of 1 -10). Airlines are hardly perceived as being the most customer oriented customers, so this indicates how poorly banks are regarded.

[8] R Colbaugh and K Glass, "Practical Predictability of Human Behaviour", Invited talk, University College London, June 2015

(4) Comments and conclusions

We must stress that this should be seen as a proof of concept piece of work rather than a definitive study. However, the results which we obtain are strong. Customer switching between banks can be analysed and predicted, but it is driven by multi-dimensional emotional quality factors rather than by rational ones.

Our preliminary analysis indicates that:

- The CARES Quality Index has predictive power for bank switching activity
- A combination of machine learning algorithm and social media data can be used to construct and deploy the Index
- Rational considerations appear to have little predictive power for this phenomenon (even customer perceptions of rational issues have little predictive power).

Status and certainty are the critical indicators of quality, and are the most important predictors of switching.

We believe that banks will take interest because they can increase their CARES Quality Index, if they behave in a way that demonstrates how much they care about their customers.

We believe that customers will be interested because they can see a simple score and table telling them which banks care for their customers the most. This could give them the confidence they need to switch.

We believe that regulators should be interested because the pilot study provides evidence that analysis of social media conversations, mediated through a theoretical filter, can provide reliable evidence on the quality of service provided by banks.