

The Effect of Financial Regulation on Reputation

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Abstract—Recent high profile breaches of regulation by prominent UK financial institutions suggest that self-regulation is ineffective. Intuitively, regulatory breaches should result in a tarnished reputation, but that conjecture is unsubstantiated. With objective measurement of reputation, we demonstrate that reputational damage is not a significant deterrent against regulatory breaches. Imposing regulatory fines is also no deterrent. We speculate that customers are prepared to tolerate large regulatory breaches: retail customers provided they are not affected personally, and corporate customers as long as investments do not devalue. Regulation has not previously been linked to reputation, and this result is significant because it adds to the argument that external regulation remains necessary. Note is also made of recent unsuccessful initiatives on self-regulation.

Index Terms—Reputation, reputation index, regulation, regulatory breaches, correlation.

I. INTRODUCTION

The United Kingdom has been prominent in advancing banking regulation since the 1979 UK Banking Act became law. Since then, each new banking crisis has been followed shortly after by new banking legislation or a reorganisation of the regulatory environment. That pattern is not unique to the UK, and some discussion may be found in [1]. The current regulatory environment was established in 2013 with the creation of parallel authorities. The Financial Conduct Authority (FCA) was responsible for regulating consumer protection, banking integrity and competition. The Prudential Regulation Authority (PRA) is responsible for monitoring the soundness of financial firms, assessing current and possible future risks, and overseeing the overall stability of the UK financial system.

In this paper we examine the particular aspects of regulation that are concerned with money laundering, fraud and conduct. We conjecture "Is regulation necessary if financial institutions can regulate themselves by seeking to maintain a positive reputation?" The argument is that a positive reputation is something that any institution strives to maintain. They cannot do so if they are subject to persistent regulatory breaches (or even a single serious regulatory breach). Therefore they would be persuaded not to breach regulations in order to maintain a positive reputation. The conjecture is examined by linking data on regulatory breaches with reputation. As a preliminary, we trace the main types of regulatory breach that could affect reputation.

A. Structure of This Paper

Following a summary of the categories of regulatory breaches (Section II), section III contains a brief literature review of research on links between reputation and regulation. In that section two major deficiencies are highlighted: a lack of evidence, coupled with only a loose idea of what 'reputation' means. These deficiencies are addressed in Section IV, where 'reputation' is defined formally, and is associated with regulatory events in a mathematically rigorous way. Results and discussion of them are presented in Sections V and VI. Section VII contains an analysis of recent reputational events in the light of regulation.

II. REGULATORY BREACHES

This section is a brief summary of the categories of regulatory breach that are relevant for this analysis.

A. Anti-money Laundering (AML)

Money laundering refers to making money that has been acquired from criminal activity such that it appears to have been lawfully acquired. Since 2015, UK law on money laundering has been governed by the 4th EU Money Laundering Directive (<http://researchbriefings.files.parliament.uk/documents/SN02592/SN02592.pdf>), which provided a more risk-based approach to anti-money laundering. The largest recent instance of a money laundering fine was the largest ever imposed by the FCA: £163m against Deutsche Bank in January 2017.

B. Market Abuse

Market abuse covers two main areas. *Insider dealing* is where a person who has information not available to other investors makes use of that information for personal gain. *Market manipulation* is where a person knowingly gives out false or misleading information in order to influence the price of a share for personal gain. In the UK they are regulated under the Financial Services and Markets Act 2000 (Market Abuse) Statutory Instrument Regulations 2016 (www.legislation.gov.uk/uksi/2016/680/pdfs/uksi_20160680_en.pdf). Interbank rate and foreign exchange market manipulation fines against US and EU banks have exceeded \$9bn up to 2016 [2].

C. Mis-selling

Mis-selling is the deliberate, reckless, or negligent sale of products or services in circumstances where the contract is either misrepresented, or the product or service is unsuitable for the customer's needs. In the UK mis-selling is governed by the Consumer Rights Act 2015 (<http://www.legislation.gov.uk/ukpga/2015/15/contents/enacted>). The UK has been hit hard by the practice of mis-selling payment protection

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insurance (PPI), and payouts have totalled £40.2bn up to the end of 2016 (<https://www.theguardian.com/money/2016/oct/27/ppi-mis-selling-scandal-bill-tops-40bn-pounds>).

D. Tax Evasion

Tax evasion is the intentional and fraudulent underpayment or non-payment of taxes, and is governed in the UK by the Finance Acts of 2015 and 2016. Large corporate tax evasion cases are rare, but the notorious case of HSBC emerged in 2015 (<http://www.bbc.co.uk/news/business-31248913>). HSBC helped wealthy clients evade tax by setting up 'secret' bank accounts in Switzerland, and was fined £28m. A full account may be found in [3].

E. Competition

UK competition law is governed by Chapters I and II of the Competition Act 1998 and the Enterprise Act 2002. Those chapters cover anti-competitive agreements and abuse of a dominant market position respectively. Competition attracts relatively few regulatory fines, although a significant one was £270m against British Airways in 2007 for price fixing on fuel surcharges.

F. Bribery and Corruption

Bribery and corruption concerns illegal activities designed to benefit an individual or an organization. They are covered in UK law by the Bribery Act 2010 (<http://www.legislation.gov.uk/ukpga/2010/23/contents>). Regulations range from rules on accepting hospitality to corporate finance for drug and arms trafficking. Fines have been relatively mild. A recent case where an unusually large fine was levied is that of JP Morgan for bribery \$264m in 2016. This case is surprising for JPM's disregard of the law. Children of influential Chinese figures were bribed to secure business deals. (See, <https://www.sec.gov/news/pressrelease/2016-241.html>).

III. LITERATURE: THE REGULATION-REPUTATION LINK

Most work on reputational effects has either been qualitative or has assumed (with little justification) that a suitable proxy for reputation is share price (e.g. Perry and de Fontnouvelle [4], and Fiordelisi *et al.* [5]). They locate 'significant' reputational events by subjective judgement, and measure their effect by stock price movements immediately following. We consider that these considerations are unsafe, first because of the subjective nature of what constitutes a reputational event, and second, because of the assumption that reputation can be equated with share price. In contrast, the author's paper on reputation measurement and the link between reputation and sales [6] makes neither of these assumptions.

Shapira [7] also uses share price to argue that the reputational outcomes of legal disputes is approximately 7 times the cost of legal outcomes themselves. With large capitalizations this is perhaps not surprising: the larger the capitalization, the larger the loss of equity when the share price falls. However, Shapira does make the point that there is no correlation between the size of the legal sanction and reputation (as measured by loss of capitalization).

Chovanculiak *et al.* [8] stress a different aspect of

regulation: that it does not always help to protect customers. They argue that regulators can be too heavily influenced by the organizations that they regulate. This is unlikely to be a significant factor in banking unless there is hitherto undiscovered corruption.

Nienaber *et al.* [9] report on their meta-analysis of trust in financial services, treating 'trust' as a concept distinct from reputation. Their study pre-dates the period when direct measurement of reputation became commonplace (approximately 2013), and therefore relies on subjective and non-comprehensive assessments of reputation via surveys. They concluded that customers want direct evidence in order to trust a financial institution, and that such evidence may be derived either from their own experience or from external endorsement. That view has not yet been validated using the data mining and sentiment analysis methods summarized in this paper.

A different view comes from Hsu and Bahar [10]. They simply regard regulation as a necessary procedure if banks are to maintain a positive reputation. They do not say how reputation is to be measured. We find this view unsatisfactory, although not uncommon, since they do not define the term 'reputation'. We attempt to redress the balance using the methodology in the following section

IV. METHODOLOGY: LINKING REPUTATION TO REGULATION USING INDICATORS

The methodology for measuring reputation is explained in [11], and a fuller account of the physical setup for appropriate data mining is given in [6]. In the discussion that follows, the daily reputation measure for a bank G on a day t , $R_G(t)$, can be expressed as a real number in $[-1,1]$, sourced from the business intelligence organization *alva* (*alva-group.com*). *Alva* provides a reliable and comprehensive reputation metric, mostly clustered around the mode zero (the neutral value). A positive/negative reputation measure represents positive/negative sentiment respectively. Our analysis considers ten UK retail banks, and the time period is from 1 January 2014 to 1 January 2016. Data are proprietary, and only a limited amount, sufficient for this study, was available for this study. The same reputational data is currently restricted to the English and Spanish languages due to the confines of natural language processing.

In the general context of regulation, a "regulatory event" is an event at which a breach of regulations is noted in some form or other. In most cases this amounts to a fine from a bank's regulatory authority. A good data source for regulatory events is the FCA fines tables at <http://www.fca.org.uk/news/fines-table-yyyy> (where yyyy = 2014 or 2015). Otherwise, fines and sanctions are regularly reported in the financial press.

A. Sentiment and Reputation

As a prelude to developing a formal link between reputation and regulation, we first define terminology rigorously. Text (reports, articles, blogs, tweets etc.) sourced via electronic feeds are subjected to natural language processing (*NLP*). *NLP* techniques are summarized in, for example, the texts by Liu, [12] and Jurafsky and Martin [13].

The output of any NLP process is an assessment of *sentiment*. Informally, *sentiment* is “a thought, opinion, or idea based on a feeling about a situation ...”. (<https://dictionary.Cambridge.org/dictionary/english/sentiment>). It may be assumed that any NLP output is a real number. This provides a formal definition of *sentiment* as mapping at time t from a section of text, c , to a real number s via a function S , which encapsulates the NLP algorithm. We often normalize s to the interval $[-1,1]$.

Definition: Sentiment $S(c, t) = s \in \mathbb{R}$

Informally, reputation is “the opinion that people in general have about someone or something...” (<https://dictionary.cambridge.org/dictionary/english/reputation>). Formally, reputation is derived from one or more sentiments. The Local Reputation, $R_G(t)$, of an organisation G is a weighted average of the n text components c_1, c_2, \dots, c_n received in a time slot of duration t . Let w_i be a weight associated with text component c_i , applicable for all times, and dependent on the originator and means of transmission of c_i . Then the following is a definition of *Local Reputation*.

Definition: Local reputation $R_G(t) = \frac{\sum_{i=1}^n w_i s_i(c_i, t)}{\sum_{i=1}^n w_i}$

The *Local Reputation* of G is the reputation metric used for the indicator analysis in this paper. Then, for a range of values of t in a set T , the *Reputation* of G , is a significantly long (advisedly 6 months) time series of *Local Reputations*.

Definition: Reputation $\hat{R}_G = \{R_G(t)\}_{t \in T}$

Reputation, as opposed to *Local Reputation* is used in the section VII of this paper.

B. Methodology: Indicators

The intuition behind the reputation-regulation association is to locate the dates of regulatory events, and trace the values of $R_G(t)$ for several organizations G , for specified times t . We first formulate a general hypothesis for the effect of adverse regulatory events (principally fines) on the $R_G(t)$ values. The hypothesis, hereinafter referred to as \mathcal{H} , is

An adverse regulatory event at a given time t' has a detrimental effect on the reputation of G by reducing the values of $R_G(t)$ for immediate subsequent times $t > t'$.

Indicators, calculated using values of $R_G(t)$, are used to measure an expected reduction (or otherwise) following an adverse regulatory event. Other factors also affect reputation, so a reduction is not expected to follow every event. Hypothesis \mathcal{H} asserts that it is more likely that a reduction will be observed than not. A suitable indicator is the

gradient of the linear regression line of $R_G(t)$ values (with time as the independent variable), for the period immediately following an adverse regulatory event. This ‘gradient’ indicator summarizes a response to the event, and can be lagged by a time l to measure a delayed response.

Consider two consecutive days D_1 and D_2 , when adverse regulatory events occurs. Let $T' = \{t_{l+1}, t_{l+2}, \dots, t_{l+n}\}$ be a vector of n consecutive days (n is the *horizon*), incorporating a lag l , starting on D_1 so that $D_1 = t_1$. Let the corresponding $R_G(t)$ values be $R'_G = \{R_G(t_{l+1}), R_G(t_{l+2}), \dots, R_G(t_{l+n})\}$. The next adverse regulatory event may occur before the n days have passed. In that case the period T' is truncated such that it runs from day D_1 to day D_2 . In general we define a potentially truncated period T that runs from day t_{1+l} to day t_m where $t_m = \min(D_2, t_{n+l})$. There is a similar truncation for the corresponding $R_G(t)$ values to produce a vector R_G (Equations 1 and 2).

$$T = \{t_{1+l}, t_{2+l}, \dots, t_m\} \tag{1}$$

$$R_G = \{R_G(t_{1+l}), R_G(t_{2+l}), \dots, R_G(t_m)\} \tag{2}$$

The timeline from day t_1 to day t_m is shown in Fig. 1. This figure shows two possible locations for day $D_2 (= t_m)$. The left-hand version is such that the n -day horizon is truncated, and the right-hand version is such that no truncation is needed.

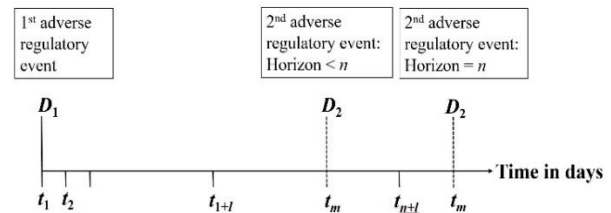


Fig. 1. Timeline from day t_1 to day t_m showing two possible locations for the 2nd adverse regulatory event at time t_m .

The ‘gradient’ indicator I_{grad} can then be written as in Equation (3), where *corr* is a Pearson correlation function for the set $\{T, R_G\}$.

$$I_{grad} = corr(\{T, R_G\}) \tag{3}$$

The indicator I_{grad} is useful because it measures a potential long term response whilst not assuming immediacy. There are two base cases, corresponding to a “downward” and an “upward” reputation trend respectively. In addition, a third case representing “no trend” can be identified.

1. $I_{grad} < 0$ (consistent with \mathcal{H});
2. $I_{grad} \geq 0$ (inconsistent with \mathcal{H});
3. $I_{grad} \sim 0$ (neither consistent nor inconsistent with \mathcal{H}).

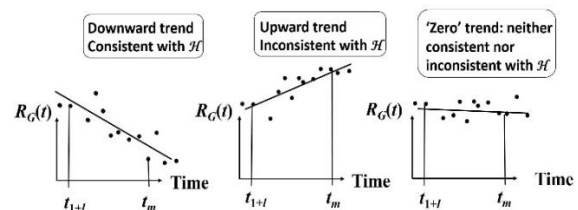


Fig. 2. Case illustrations: reputation trends with respect to \mathcal{H} .

These cases are illustrated in Fig. 2. In each case a

reputational event occurs at time t_{1+l} and the reputation metrics $R_G(t)$ (the ‘dots’) are traced until time t_m , when the next reputational event occurs.

In practice trends are not so clear. Therefore the statistical significance of the value of the Pearson correlation coefficient of the $\{T, R_G\}$ pairs is calculated. A t -test is used. We then use a binomial test to compare numbers of positive and negative correlations.

C. Statistical Tests

The statistical significance of a correlation derived from a pair taken from $\{T, R_G\}$ may be assessed by a binomial test based on the number of number of negative and positive correlations ($n_{(-)}$ and $n_{(+)}$ respectively). The test statistic is the probability, p , of recording a negative correlation, for which the null and alternative hypotheses (H_{null} and H_{alt} respectively) are:

$$\left. \begin{aligned} H_{null}: & \quad p = \frac{n_{(-)}}{n_{(-)}+n_{(+)}} = \frac{1}{2} \\ H_{alt}: & \quad p < \frac{1}{2} \end{aligned} \right\} \quad (4)$$

The probability of obtaining r instances of a negative correlation coefficient in n binomial trials is $P(n, r) = \binom{n}{r} p^r (1-p)^{n-r}$. The probability of obtaining not more than r successes out of n trials is then $\sum_{r=0}^n P(n, r)$. In our analyses, n is sufficiently large for the normal approximation to the binomial to apply. In that case, with mean μ and variance σ^2 as in equation (5), a z -test can be used.

$$\left. \begin{aligned} \mu &= np \\ \sigma^2 &= np(1-p) \\ z &= \left| \frac{n_{(-)} - \mu}{\sigma} \right| \end{aligned} \right\} \quad (5)$$

H_{null} is rejected if $z > z_c$, where z_c is the 1-tail critical normal ordinate at significance level c (1.645 for $c = 5\%$).

V. RESULTS

The results of the analysis of the previous section are based on considering horizons (m in Equations 1 and 2) of between 3 and 21 days. These are sufficiently long to calculate correlations with reasonable confidence, and give an indication of any sustained effect of an adverse regulatory event. The lags (l in Equation 2) range from 0 to 16 days. Figure 3 shows a typical result which has a 14 day lag with a 14 day horizon. The plotted points shown indicate the adverse regulatory events with the t -values for the appropriate $\{T, R_G\}$ pair. The dotted horizontal line shows the 5% 1-tail significance level at approximately $t = -1.703$. Points above the dashed horizontal line ($t = 0$) do not indicate support for \mathcal{H} . Points below the dashed horizontal line do indicate support for \mathcal{H} , but only those below the dotted ($t = -1.703$) line are statistically significant.

The plot in Fig. 3 shows a case where the number of positive correlations exceeds the number of negative correlations. That applies in approximately 50% of horizon-lag combinations. A few broad generalizations can be made. There are *usually* more negative than positive correlations in the cases when the horizon is between 3 and 7 and the lag is between 7 and 14 (i.e. 1-2 weeks). These

cases indicate support for \mathcal{H} . However, statistically significant results are not forthcoming (see the following section). There are *usually* more positive than negative correlations in the cases when the horizon is greater than 7. These cases indicate a lack of support for \mathcal{H} .

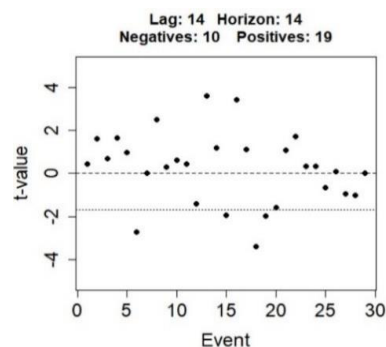


Fig. 3. Indicator significance example: Lag 14 days; horizon 14 days.

A. Statistical Significance

In Fig. 3, the points that lie below the critical t -value line are the ones that are statistically significant, and it is clear from Fig. 3 that there are very few of them. A more extensive investigation confirms this view.

Fig. 4 shows a contour plot of the results (significance level as a %) of applying the binomial test to the reputation data, with the lags plotted horizontally and horizons plotted vertically. The darkest entries indicate positive correlations that do not support \mathcal{H} . Entries marked in white are negative correlations (supporting \mathcal{H}) that are significant at 5%, and the intermediate grey entries are negative correlations that support \mathcal{H} but at a significance level greater than 5%. The figure in the Appendix has specific details of the elements of this contour plot,

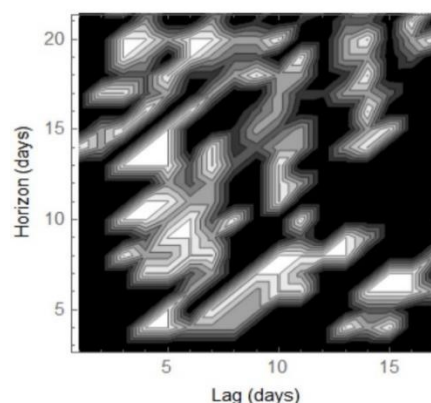


Fig. 4. Statistical significance contour plot of the slope of the linear regression line (reputation against time) following reputational events.

The results in Fig. 4 show that significant negative correlations based on a generous test (“negative correlation supports \mathcal{H} , positive correlation does not”) are rare. Out of 323 lag/horizon combinations, only 2.2% are negative and significant. Overall only 50.8% are negative and 49.2% are positive. Clearly, if the more stringent condition for the binomial test, that a correlation should be *significantly* negative, is applied, even fewer lag/horizon combinations would qualify.

Overall, the results show that there is no clear lag/horizon combination that can be used to support \mathcal{H} . There is a small

cluster corresponding to horizon = 14 and $4 \leq \text{lag} \leq 7$. It is tempting to consider this cluster as a region of support for \mathcal{H} , but the presence of neighboring regions that do not support \mathcal{H} makes this conclusion unsafe.

VI. DISCUSSION

The statistical analysis in section V points to the conclusion that hypothesis \mathcal{H} cannot be justified, and we conclude that there is no statistical evidence that adverse regulatory events have a detrimental effect on reputation. At first sight the relationship between regulation and reputation might appear to be the same as the relationship between conduct regulation and any other adverse event (e.g. fraud). However, there is an important difference. Data on regulatory events, fines in particular, are publicly available and significant ones are reported in the press. However, not all of this data is immediately absorbed by the public. One would have to actively seek much of it rather than have it delivered to you. Reporting in the financial press is most likely minimal, and it is unlikely that consumers will get to hear of them. On the other hand, some regulatory events are heavily reported in the press and thereby invite consumer comment. Regulatory events that are effectively hidden from the public domain have very little impact on reputation.

It seems counter intuitive that customers should continue to use a bank that incurs large regulatory fines, particularly if that bank is a serial offender, or if a single regulatory breach is very serious. We speculate on reasons for this, but stress that we cannot justify such speculations on current evidence. Those reasons are:

- 1) Retail customers value quality of personal service above misdemeanors that affect the bank as a whole. They are very concerned about issues that affect them personally, so they tolerate even quite serious crimes.
- 2) Retail customers consider that “all banks are the same”, and they have no choice but to tolerate misdemeanors.
- 3) Corporate customers are more concerned with a bank’s support for their business. They tolerate misdemeanors in the same way that retail customers do.
- 4) Investors are primarily concerned with the returns on their investments. They will not object unless misdemeanors compromise those returns, or they think that their own reputation will be compromised if their relationship with a particular bank continues.

VII. REGULATION AND REPUTATION: WIDER ISSUES

A. The Purpose of Regulation in 2020

The future of financial regulation appears set to continue as it is. The Bank of England has issued a report [14] on what it considers to be the major issues for 2020 onwards. They split into three principal themes: *Resilience*, *Transition* and *The Digital Economy*. Notably, reputation is omitted from the BoE document.

B. Can Reputation Drive Self-regulation?

Financial regulation has been at a national or international level, and financial self-regulation has not been considered

adequate. There is little evidence to support the general effectiveness of self-regulation, and cases are somewhat anecdotal. In this section we consider one such case which can be considered a success, and another which is a definite failure.

The study by Malhotra [15] argues that a current view, “corporate social responsibility”, of the reason for employing self-regulation is incorrect. This view states that that companies can project a favorable image to stakeholders, and thereby maintain their position in the marketplace. Malhotra found that stakeholders preferred modest self-regulation to more extreme external regulation, but only if nearly all companies within an industry do the same. This study was conducted by survey, so it measures what *might* happen, not what actually *has* happened. Therefore there is no evidence that self-regulation has worked in practice.

C. Volkswagen: Self-regulation by Reputation

In September 2015 it was found that Volkswagen (VW) software for cars with Type EA 189 diesel engines gave false emissions data. The revelation became known as ‘dieselgate’. An account may be found in [16]. VW was also the subject of a wider discussion of the use of reputation indicators in [17]. Approximately 11 million vehicles worldwide were affected, and Volkswagen set a provision of €6.5bn to redress the problem. The provision was increased to €16.2bn in April 2016. There was a dramatic impact on sales and reputation. From November 2014 to November 2015 sales of new Volkswagen registrations fell by 19.99% whereas there was a 3.8% increase in registrations for all new cars in the same period.

We argue that VW has recovered from the initial shock of ‘dieselgate’ using evidence from the VW reputation score. Fig. 5 shows the VW reputation score (on a scale from -1 representing the worst possible to +1 representing the best possible, and 0 as neutral) from immediately before ‘dieselgate’ (on day 81) to several months after. The equivalent profile for their principal rival BMW is also shown for comparison. VW’s reputation score shows a marked plunge on day 81 (marked by the upwards pointing arrow), and recovers afterwards. Approximately a year later VW’s reputation profile is similar to what it was before ‘dieselgate’, apart from subsequent downward spikes which represent repeated updates and reiterations of the original scandal. After ‘dieselgate’ VW made sound efforts to regain stakeholder trust. The result is the restored ambient reputation level.

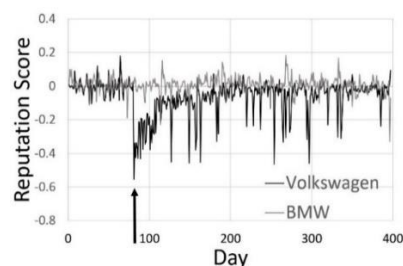


Fig. 5. Volkswagen (black) and BMW (grey) reputation scores (from 30/06/2015 to 30/07/2016).

D. Boeing: Failure of Self-regulation

Boeing suffered two major blows to its reputation with

major crashes of two of its 737 Max aircraft on October 29 2018 and March 10 2019. 189 deaths resulted. The *National Transport Safety Board* [18] concluded that, effectively, Boeing was self-regulated. Self-regulation failed in the perception of stakeholders. Figure 6 shows the sharp drops in Boeing’s reputation profile on the days of the crashes (169 and 283 - marked by the upwards pointing arrows). After the first there was some recovery, but not after the second. Boeing continued with a poor absolute reputation (shown by negative values), and a poor reputation compared to its principal rival, Airbus.

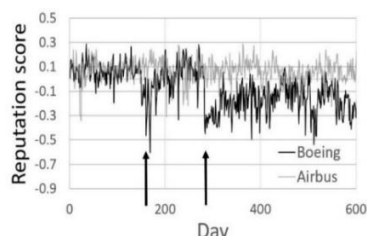


Fig. 6. Boeing (black) and Airbus (grey) reputation scores (from 01/05/2018 to 09/02/2020).

E. Regulation Initiatives 2019-20

In May 2019, most UK banks agreed to abide by a voluntary self-regulation code of practice (“Contingent Reimbursement”) to reduce the incidence of authorised push payment (APP) fraud [19]. In an APP fraud, the fraudster persuades a customer to transfer money to the fraudster’s account. Since the payment is authorized by the customer, banks had refused compensation. The signatory banks agreed to compensate defrauded customers even if the customer had authorized the payment. UK Finance reported 2019 APP fraud figures in March 2020 (<https://www.ukfinance.org.uk/uk-finance-cross-sector-cooperation-needed-tackle-rise-aut-horised-push-payment-fraud>). Of £456m lost to APP fraud, only £41m had been refunded under the voluntary code. It therefore appears that this voluntary code was unsuccessful.

F. The Effect of COVID-19

Police reports in April 2020 indicate that fraudsters are trying to take advantage of the Covid-19 outbreak to perpetrate APP and similar frauds (see <https://nationalcrimeagency.gov.uk/news/fraud-scams-covid-19> and <https://www.interpol.int/en/News-and-Events/News/2020/Unmasked-International-COVID-19-fraud-exposed>). UK Banks responded only by issuing warnings on the internet. The FCA has reacted, not by regulation, but by issuing a letter to UK bank CEOs (<https://www.fca.org.uk/coronavirus>), effectively ordering that corporate customers must be treated fairly. The letter, entitled “Ensuring fair treatment of corporate customers preparing to raise equity finance” points out that unfair treatment can be treated as a market abuse offence. Retail customers are not mentioned. Details of the UK Government business loan guarantee schemes (CBILS and CLBILS) are given on the same website. Banks have concentrated on procedures for facilitating transactions, internet operations, call centres and capital provisioning.

G. Conclusion

The overall conclusion from this study is that regulation

cannot be replaced by reputation. There are two parts to this conclusion. First, the evidence from our analysis of reputation trends following events that have a regulatory basis shows that there is no significant increase in reputation following such an event. If anything, the evidence is to the contrary. The reasons are likely to be the availability and mode of dissemination of information, which does not lead to a diminution of reputation. Wider circulation of information only occurs when major events are reported via news channels using social media. Significant reporting activity does not appear to occur for regulatory events. Only some (e.g. ‘dieselgate’ and the 737 Max crashes) are considered ‘newsworthy’.

APPENDIX

Fig. 7 in this appendix is a detailed form of Fig. 4. It shows an analysis of the results of applying the binomial test to the reputation data. Each cell shows the significance level (expressed as a %) obtained when the test is applied with the lags (the columns) and horizons (the rows) indicated. The darkest entries indicate positive correlations that do not support H). Entries marked in white are negative correlations (supporting H) that are significant at 5%, and the light grey entries are “near miss” negative correlations. They support H but their significance level is between 5% and 6.5%. The entries in mid grey support H but not at an acceptable level of statistical significance.

Horizon (days)	Lag (days)																	
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
3			35.5	6.3				6.3		6.3	2.5	12.9		22.8	6.3		35.5	
4				22.8			22.8		6.3		6.3		12.9	12.9	0.2		35.5	
5			35.5	35.5	22.8	35.5	35.5	22.8	22.8	35.5			22.8	35.5	2.5	22.8	35.5	
6			35.5	22.8		35.5	22.8	12.9	12.9		35.5			22.8	22.8	0.8	12.9	
7			12.9	12.9	35.5	6.3	6.3	22.8	35.5	22.8	22.8			6.3	35.5	0.8		
8		35.5	35.5	12.9	22.8		22.8		22.8	6.3	6.3	22.8	22.8	12.9				
9			35.5		35.5				12.9	22.8	2.5				35.5			
10		22.8	35.5		35.5			6.3	22.8	12.9	22.8				22.8	35.5		
11	35.5	22.8		35.5	35.5		35.5	6.3	12.9	22.8	22.8			22.8	35.5			
12			35.5	35.5	35.5	12.9	35.5	12.9		35.5								
13				22.8	12.9	22.8			35.5	22.8								
14				35.5	35.5	22.8	22.8			35.5								
15			35.5	35.5	22.8	35.5	12.9	35.5			35.5							
16			12.9	35.5	35.5	22.8				12.9			35.5	22.8				
17			35.5	22.8	22.8	35.5	35.5			35.5	35.5	35.5	35.5				22.8	
18			35.5	35.5	12.9	22.8			35.5	35.5	22.8					35.5	35.5	2.5
19				22.8		35.5	22.8	35.5	35.5						35.5	35.5	35.5	22.8
20					35.5		35.5	22.8	22.8					12.9	12.9			
21					35.5	35.5	22.8	22.8						35.5	22.8	35.5		

Fig. 7. Binomial test % statistical significance (detailed version of Fig. 4).

CONFLICT OF INTEREST

The author declares no conflict of interest.

AUTHOR CONTRIBUTIONS

All of the research reported in this paper, including the writing and approval of the paper, was done by the named author.

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