A Statistical Framework to Measure Reputation Risk

Tiziano Bellini and Luigi Grossi

Abstract Much of the work in the field of risk management has been focused on defining and quantifying market, credit and operational risk. Recently, there has also been recognition that organizations should measure and manage the reputation risks they are exposed to. In general, a reputation risk is any event that can potentially damage the standing of an organization in the eyes of third-parties. From a financial point of view, reputation information potentially affect firm stock value. Thus, the most important contribution of our analysis is to introduce the forward search to define lower and upper bounds (envelopes) which are likely to contain returns (at a pre-defined confidence level) when no reputation events occur.

Key words: Reputation risk, abnormal returns (AR), robust statistics.

1 Introduction

It has been recently shown that firm reputation affects the perception of firm value (Gabbi and Patarnello, 2010; Cerchiello, 2012). Cooper et *al*. (2001) show that image can affect equity pricing, even when that image has no impact upon firm profitability. Examining data from 1 June, 1998 to 31 July, 1999, they report that companies which change their name to an Internet-related *dotcom* name had a significant positive stock price reaction. Following the perspective that investors are willing to pay more for the stock of a firm that has a good reputation, Anderson and Smith (2006) support the view that a firm with good reputation outperform a firm with poor reputation. Jones et *al*. (2000) show how reputation influences financial performances and shareholder returns. On the contrary, some researchers focus on how high financial performance and low risk affect high reputation (Chung et *al*., 2003). A third research field investigates both relationship considering that financial performances have consequences on reputation and, at the same time, reputation affects financial performances (Roberts and Dowling, 2002). Almost all the above

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mentioned studies rely on a proxies of firm reputation based on indexes obtained from expert surveys.

The output of these surveys is a reputation quotient (RQ). Recently, the Reputation Institute (Ponzi *et al.*, 2011) has proposed a new measure of firm reputation called RepTrack Pulse (RTP, form now on). This is an emotion-based measure of the corporate reputation drawn on a set of beliefs about each company under investigation. Based on the above discussion, the aim of our study is to test whether the publication and changes of a RTP induce firm security prices to change. In order to investigate this phenomenon it is necessary to formalize the null hypothesis that price do not change and test it.

Following Abraham et *al*. (2008), we rely on event study analysis to investigate the relationship between the release of reputation news and equity returns. In event studies, the actual return to shareholders (given an event) is compared to a prediction of what this return would have been absent the event. In this case, the announcement of the RTP is the event. Any difference is referred to as an abnormal return (AR). However, in order to state that an effective AR occurs (the difference is statistically significant), the need to carry out a test arises. For this reason, in the next section, we apply the forward search framework, both to robustly forecast returns in the absence of reputation events and test whether reputation news lead to (statistically significant) AR.

2 Event Study Analysis: a Robust Approach

The effect of the RTP on security returns on any time t is estimated by examining the equation

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|No\ announcement), \tag{1}$$

where $AR_{i,t}$ is the abnormal return of firm i on time t due to the announcement. $R_{i,t}$ is the actual return of firm i on time t and $E(R_{i,t}|No\ announcement)$ is the expected return when there is no announcement. It is evident that $E(R_{i,t}|No\ announcement)$ must be predicted by the researcher.

The market model posits that the return to any security on time t is a function of the market as a whole and the risk of investing in that security relative to the risk of investing in the market as a whole. The ex-ante return to security i at any time period t equals

$$R_{i,t} = \beta_{0,i} + \beta_{1,i}(R_{\xi,t}) + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ is the return to security i at time t and $R_{\xi,t}$ is the return on the value-weighted index of all publicly traded stocks at time t. From the Normal theory assumptions, the errors $\varepsilon_{i,t}$ are *iid* $N(0,\sigma^2)$. Thus, in order to fit β parameters, we can exploit the well known standard least squares model

$$y = X\beta + \varepsilon, \tag{3}$$

where y is the $T \times 1$ vector of responses, X is a $T \times p$ full-rank matrix of known constants, with t^{th} row x_t^T, and β is a vector of p unknown parameters.

Many statistical approaches have been developed to detect atypical observations. Given that traditional deletion methods, due to the well known masking effect, may not lead to the identification of the contaminated observations, the forward search was proposed, originally in linear and nonlinear regression by Atkinson and Riani (2000) and extended to time series analysis by Grossi (2004), as a powerful general method for detecting multiple masked outliers and for determining their effect on inferences about models fitted to data. In the forward search the evolution of residuals and parameter estimates is monitored as the subset size increases. Results are presented as forward plots which show the evolution of the quantities of interest as a function of the subset size.

Considering Ω the set of all subsets of size m of the T observations, the forward search fits subsets of observations of size m to data. Let $S_*^{(m)} \in \Omega$ be the optimum subset of size m. This subset is obtained considering the m units with the lowest squared standardized residuals. In order to compute these residuals, we need to specify a vector of parameters to get our estimates.

Relying on $\hat{\Theta}_*^{(m)}$, the vector of parameters estimated at step m on the subset $S_*^{(m)}$, we run the regression and compute $r_t(m^*)$ for all units. The notation $r_t(m^*)$ stands for unit t residual at step m, obtained considering the parameter vector $\hat{\Theta}_*^{(m)}$. Thus, standardized residuals are calculated as follows

$$r_t(m^*) = \frac{y_t - x_t^T \hat{\beta}(m^*)}{\sqrt{s^2(m^*)\{1 + h_t(m^*)\}}} = \frac{e_t(m^*)}{\sqrt{s^2(m^*)\{1 + h_t(m^*)\}}}, \tag{4}$$

where the symbol $h_t(m^*)$ is a reminder that the leverage of each observation depends on $S_*^{(m)}$. The search moves forward considering the subset $S_*^{(m)}$ consisting of the observations with the m smallest squared standardized residuals.

Let the observation nearest to those belonging to $S_*^{(m)}$ be t_{min}, the observation with the minimum squared residual among those not in $S_*^{(m)}$, with $t_{min} = \arg\min[r_t(m^*)] \quad t \notin S_*^{(m)}$. To test whether observation t_{min} is an outlier, we rely on what follows

$$r^*_{t_{min}}(m^*) = \frac{e_{t_{min}}(m^*)}{\sqrt{s^2(m^*)\{1 + h_{t_{min}}(m^*)\}}}. \tag{5}$$

In order to obtain envelopes (lower and upper bounds) of the minimum residual of equation (5) we could use Monte Carlo simulations. Aiming to avoid a time consuming random generation procedure to simulate envelopes, Riani et *al*. (2009) study a fast procedure based on the distribution of scaled and unscaled (Mahalanobis) distances in multivariate analysis.

Thus we can exploit the forward search to:

- Estimate the returns $\hat{R}_{i,t}$ in the absence of announcement and, consequently, compute $E(R_{i,t}|No\ announcement)$.
- Test whether $AR_{i,t}$ is statistically significant.

Envelopes analysis can be a very effective graphical tool to inspect whether reputation information cause atypical consequences on firm returns.

3 Conclusions

We introduce a robust statistical framework in order to test the occurrence of AR. This is the first step of our analysis which is aimed to apply our framework to real data in order to verify whether the release of reputation information has an impact on firm returns. Anderson and Smith (2006) investigate AR at the aggregate level. In our research, we aim to extend the analysis at the firm level. In addition, our purpose is to study both the temporal lag of the impact of reputation news as well as the intensity (Bellini and Riani, 2011) of the impact of RTP release on returns. We carry out the analysis relying first of all on the forward search aiming to extend the research to other robust statistical tools emphasizing strength and weakness of each approach.

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