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Author(/s): **Mariano González and María Encina Morales**

Date: **October-2017**

WORKING PAPER SERIES: 2/2017

CÁTEDRA CEU-MM
Madrid (Spain)
ISSN online: 2530-0237

BOUNDARIES OF THE EFFECTS OF REPUTATIONAL RISK ON SHAREHOLDER WEALTH: EVIDENCE FROM SPAIN[♣]

Mariano González Sánchez
Associate professor of accounting and finance
Business Department, Universidad CEU San Pablo
Julian Romea, 23. 28003 Madrid (Spain)
+34.914566300 (ext. 5457)
gonsan@ceu.es

María Encina Morales de Vega
Assistant professor of accounting and finance
Business Department, Universidad CEU San Pablo
Julian Romea, 23. 28003 Madrid (Spain)
+34.914566300 (ext. 5519)
memorales@ceu.es

ABSTRACT:

Reputational risk is identified with a negative perception by the economic agents that can cause future effects of the same sign. Most empirical papers have identified this negative perception from bad news about companies and have tried to check their effects by explaining abnormal market returns. In this regard, this paper analyzes and selects the bad news about a sample of Spanish listed companies, to use them as an explanation of abnormal shocks in market and liquidity risk. The results indicate that there is a negative reputational effect manifested on closing prices and volume, as well as positive effects on volatility. Additionally, it implies an increase in illiquidity. Given that sometimes the effect is contemporaneous and in other cases there is a lag between the event and the loss, it has not been possible to identify homogeneous behavior among companies, so it is concluded that reputational risk is idiosyncratic.

KEYWORDS: reputational risk, abnormal return, reputation news, shareholder value.

[♣] Acknowledgement: This work has been supported by the Spanish Ministry of Economics and Competitiveness through grant MINECO/FEDER ECO2015-65826-P, and Cátedra Universidad CEU San Pablo & Mutua Madrileña insurance company (grant ARMEG 060516-USPMM-01/17). Agradecemos los comentarios recibidos de los profesores Gonzalo Rubio (UCH), Juan Nave (UCLM) y Mikel Tapia (UC3M) en el Workshop sobre riesgos financieros de la USPCEU celebrado el 15 de junio de 2017.

JEL: G14, G31, G38.

1. INTRODUCTION

Sometimes business risks are easily identifiable, and therefore their quantification is usually calculated directly from observable data, as occurs with market risk. In other cases, the identification and quantification is not so obvious. For example, in the case of operational risk, it is enough to see the definition that Basel (2002) offers for quantification, expressing it in terms of the possible occurrence of seven different events.

Within these types of risks, which are difficult to identify, the reputational risk is found. The study of this risk has been increasing in recent years, mainly in the financial sector, undoubtedly due to regulatory changes in risk matters. Basel (2003) already mentions reputational risk as part of the operational risk of financial institutions, but leaves it out of its estimation. The US Federal Reserve (2004) defines reputational risk as potential harm that negative publicity regarding an institution's business practices, whether true or not, will cause on the customer base, costly litigation or future benefit reductions. Subsequently, Basel (2009) identifies reputational risk with negative perception by the relevant economic agents that can negatively affect the viability of the banks in terms of future potential growth. In the same regard, the European Insurance Committee (Comité Européen des Assurances, 2007) states that, in relation to the insurance sector, reputational risk is identified as the loss of confidence in the integrity of an institution as a result of adverse publicity about an insurance company, whether true or not.

Within the academic sphere, interest in reputational risk can be differentiated into two large blocks. First, those studies that analyze this risk from a general perspective of the company (among others: Roberts and Dowling, 2002; Rayner, 2003; Martín de Castro et al., 2006; Walter, 2008; Bermiss et al., 2013; Sarstedt et al. 2013; Gatztert, 2015), and secondly, those interested in the financial sector as a result of the increase in regulation on this matter (Perry and De Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Soana, 2011; Fiordelisi et al., 2014; Gatzert et al., 2016).

From the analysis of this literature, it should be remarked, first, that there seems to be some consensus regarding the effects of reputational risk on the market value of a company and its future viability; that makes this risk to be identified with the set of events that could lead to loss of confidence among the different interest groups, such as clients, employees, investors and suppliers (stakeholders), as a result of news, business communication strategy or management of corporate responsibility. This would explain that in recent years the management of intangible assets and corporate reputation are becoming a primary objective for the management of a company, since the strategic potential related to good corporate reputation is identified as a key to ensuring the financial sustainability in the future.

In the second place, Deephouse (2000) and Wang and Berens (2015) emphasize the twofold aspect that is given within the literature of corporate reputation among stakeholders: internal (employees, customers, suppliers) and external (or financial). In addition to this possible double manifestation of reputational risk, it is given a multidimensional character (Dollinger et al., 1997; Martín et al., 2006; Eisenegger, 2009), which identifies three types of factors: managerial reputation, financial reputation and reputation of the product or service. This is undoubtedly an added element to the difficult task of identifying the reputational risk.

Third and finally, the published research shows that reputational risk is more difficult to manage than financial risk, as there is no generalized definition of reputation. Without a defined goal, efforts to manage risk may be unproductive. Hence, executives sometimes hesitate to classify or measure reputational risk, or even have no clear idea about how to manage reputational risk. The latter leads to the belief that efforts to improve a company's reputation imply an inefficient use of business resources, since such risk and its effects cannot be truly identified. In this context, Hogarth et al. (2016) analyze the effect of reputational risk on shareholder returns and, for a sample of 100 Australian companies and annual data (2011-2013), find that the management of this risk is positively related to shareholder wealth; by contrast, reputational risk is not statistically significant on the shareholder's total return. This may be due to different reasons: frequency of data (annual), source of reputation information (index construction) and shareholder wealth estimation method (dividend policy is considered but not market risk).

Thus, in order to shed light on the effects of corporate reputation on shareholder wealth, the aim of this paper is to identify reputational risk as an indirect risk, whose effects can be found on the basis of results that would initially be classified as other directly quantifiable risks, such as market and liquidity risks; and to avoid the potential problems described above, our empirical study will analyze the effects of the daily news of Bloomberg on the abnormal daily returns, estimated from the closing prices, and also on implicit volatility and the trading volume.

The rest of the paper is organized as follows: the next section reviews the most relevant literature on reputational risk. In section 3 we study the methodology followed to identify the effects of reputational risk, defining the hypotheses to be tested. Section 4 describes the data used for the empirical study. In section 5 an empirical analysis is performed on a sample of companies and finally, in the last section, the most important conclusions of the study are explained.

2. IDENTIFICATION OF THE EFFECTS OF REPUTATIONAL RISK IN THE LITERATURE

The lack of a standardized definition of reputational risk means that there is no consensus methodology for measurement. To this must be added their intangible nature, and a particular characteristic of the reputation, that is, it is inherent to each company, difficult to replicate, when integrated in the circumstances and in the historical evolution of each institution. Hence, in the literature both studies are focused on the analysis of corporate reputation using qualitative as well as quantitative information, with inconclusive results in all cases.

Regarding the methodologies that employ qualitative information (Martín de Castro et al., 2006, Gillet et al., 2010, Soana, 2011, Fryxell and Wang, 1994, Sarstedt et al., 2013, Wang and Berens, 2015), it can be pointed out that the objective is to identify the elements that shape the business reputation, such as quality management, financial stability, quality of the product or service, degree of innovation, efficiency, ability to recruit, develop and retain talented employees, social responsibility and long-term value of investments, among others. But given the lack of consensus on the method of measuring reputational losses in companies, they use different data sources, ranging from surveys to CEOs; the construction of corporate reputation indicators such as

Corporate Social Performance, against the usual indicators of Corporate Financial Performance, to collect economic, legal, ethical and philanthropic aspects that can influence the stakeholders (internal and external); and they even use indicators and rankings of business reputation published by more or less specialized magazines such as Corporate Reputational Index (Fortune).

These works perform different types of analysis on the obtained data (factorial, dependence, structural equations, Q of Tobin), but the results show that there is a financial bias, that is, opinions about business reputation are influenced by the values that take the financial variables (ROA, sales, debt, book value, ...), which requires this bias be corrected. In addition, it is not clear what the market information should have in the construction of reputational indicators, nor does it obtain empirical evidence on the effects of adverse news on companies, since they could be punctual and only appear in market data or major importance data, and present effects on accounting variables (which should be audited to avoid possible manipulation). In this sense, it is doubtful whether, despite incorporating quantitative information, such as accounting, the effects of reputational risk are fully collected.

Summing up, from the results obtained by these works that use the qualitative information, we observe a repetitive problem, consisting of the lack of relevance of the variables included in the models. In this sense, even applying different techniques, they obtain different ranking positions for the same (Soana, 2011), and show the limited utility of reputation indices (Fryxell and Wang, 1994) to estimate such risk.

Among studies that use quantitative information exclusively to identify the effects of reputational risk (Perry and De Fontnouvelle, 2005; Cummins et al., 2006; Walter, 2008; Micocci et al., 2009; Gillet et al., 2010; Fiordelisi et al., 2011; Soana, 2011; Sarstedt et al. 2013, Moosa and Li, 2013; Bermiss et al., 2013; Knittel and Stango, 2013; Wang and Berens, 2015; Pineiro-Chousa et al., 2016), we have to differentiate, first, the problem in the selection of the financial variables that best approximate the loss for reputational risk (net income, EBITDA, Free Cash-Flow, Mark-to-Book value, beta, market price), although according to Moosa and Li (2013), the lack of quality of information is an added problem, for example when using non-audited accounting data; and on the other hand, the disadvantage of determining the variable that identifies the

event that causes the loss by reputational risk. With respect to the latter, the analyzed works either use some kind of binary variable (news related to corporate reputation), either to identify the event as realized losses higher than announced, or to try to extract them from the total losses due to operational risk.

A separate case is the works whose interest is to estimate the reputational risk premium for both the valuation of assets (Walter, 2008) and its stochastic modeling.

Regarding the methodology applied, for the most part, these are regressions in which a model of asset valuation is a starting point (usually, Capital Asset Pricing Model or CAPM) and in which tries to explain as risk the excess of losses on the expected value (abnormal returns). Other variables, such as industry or interest rate, are also included to try to isolate the reputational effect (see Eckert and Gatzert, 2017). But a problem that arises when working with daily data is the so-called "stylized facts" of the assets returns (Cont, 2001), which requires correctly modeling the behavior of this, otherwise any estimation would have typical anomalous errors (for example, Canna et al., 2009 include a GARCH (1, 1) process to model volatility).

With regard to the results of the work that uses quantitative information, we must first emphasize that there is no consensus on how to analyze reputational risk separately from operational risk. Second, most papers find the stock market price as the best proxy for measuring reputational risk severity, although it is also related to other financial variables such as Free Cash Flow; also it is pointed out that the effect is usually greater in growth companies than in value ones, higher in large companies than in smaller ones, and more among European companies that among US companies. Finally, just to highlight that there is also no clear consensus on whether a company's reputational risk affects its competitors in a positive way.

In any case, the problem lies in the very nature of the risk to be measured. As Cruz (2002) points out, reputational risk is part of operational risk, and its quantification requires, first, to know the event that causes it, using a discrete distribution that would measure the frequency of the event, and on the other hand, the loss that originates such event, modeled by a continuous distribution conditioned to the first and, that would measure the severity of the event (frequency-severity models).

However, since ethical concepts are not easily and objectively measurable, within the estimation of reputational risk, it must be considered as an indirect risk whose severity is observed from the losses caused by other risks (market, credit, liquidity), when they are higher than expected, and therefore affect different agents or stakeholders (for example, market-shareholder, credit-creditor). The drawback is the need to identify what events are causing such excess losses. In this line, Knittel and Stango (2013) highlight that the measure of Google Insight is key to delimiting the pattern of observed abnormal returns.

3. METHODOLOGY FOR IDENTIFYING THE EFFECTS OF REPUTATIONAL RISK

From the review of literature above, we have to define a model and its variables that allow defining reputational risk in the most objective way possible and according to the following general principles:

- Consider the behavior of financial variables.
- Collect the event or news that may lead to such reputational risk.
- Analyze the effect of reputational risk on the severity of other observable risks.
- Measure the effect of reputational risk in terms of abnormal returns.

Thus, we define the variables used below as the following: x_t is the value at moment *t* of the variable that is used as reference to estimate the abnormality of the results. For example, in a CAPM model it would be the return of the market portfolio; y_t is the value at moment *t* of the variable that represents another observable risk and on which it is intended to measure the effect (severity) of reputational risk, therefore, it is an indirect measurement. Finally, d_t is the value at time t of the variable that shows whether the event (news) of reputational risk has occurred ($d_t = 1$) or not ($d_t = 0$).

Then the general model, considering the behavior of financial variables (stylized facts) is:

$$y_t = \alpha + \beta \cdot x_t + \sum_{j=0}^{J} \lambda_{j,m} \cdot d_{t-j} + \varepsilon_t \qquad \varepsilon_t \sim iid\left(0, \sigma_t^2\right)$$
$$\sigma_t^2 = \delta_0 + \delta_1 \cdot \varepsilon_{t-1}^2 + \delta_2 \cdot \sigma_{t-1}^2 + \lambda_v \cdot d_t \tag{1}$$

In expression (1) note, on the one hand, the reputational risk effect on the mean (on the risk *y*) has occurred in the delay *j*, i.e. from contemporaneous (j = 0) until the lag (j = J); on the other hand, we only measure the contemporary effect of reputational risk on the variance equation of such risk (λ_v), since the GARCH process includes lags, which, in the case that it includes the reputational dummy variable, it could generate multicollinearity problems.

We then detail the variables for each of the risks on which we study the reputational risk effect on shareholder wealth and, for each of the companies ($i = 1,...,N$):

– Market risk: in this case we analyze the effect on two variables, first on the excess of daily returns (CAPM) estimated from daily market closing prices (*P*) of both the asset and the market portfolio (*Mkt*) and, the daily risk free rate (*Rf*):

$$y_{i,t} = R_{i,t} - Rf_t = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - Rf_t$$
$$x_t = R_{mkt,t} - Rf_t = \ln\left(\frac{P_{mkt,t}}{P_{mkt,t-1}}\right) - Rf_t \tag{2}$$

And also, on the daily implicit volatility of each company's options market ($y_{i,t} = vol\_impl_{i,t}$) and the daily realized volatility of the market portfolio ($x_t = \sqrt{R_{mkt,t}^2}$).

– Liquidity risk: in this case the effect is analyzed on two variables for each company. The first is the daily frequency of the volume (*vol*) of the securities traded during each daily session. So, the variables are estimated as:

$$y_{i,t} = \ln\left(\frac{vol_{i,t}}{vol_{i,t-1}}\right)$$
$$x_t = \ln\left(\frac{vol_{mkt,t}}{vol_{mkt,t-1}}\right) \tag{3}$$

In this way, we check if the reputational effect that may exist on the closing price is the same on volume prices, or conversely, whether a reputational event has a different effect. In addition, we study the effect that reputational news has on a commonly used measure of illiquidity (see Amihud, 2002). Thus, if *J* is the period in which reputational news has shown effects on market risk and volume, then we define the illiquidity index for this frequency as:

$$\ln\left(A_{i,t}\right) = \ln\left(\frac{1}{J}\sum_{j=1}^{J}\frac{\left|R_{i,t,j}\right|}{dvol_{i,t,j}}\right) \tag{4}$$

where *R* is daily return and *dvol* is daily volume expressed in monetary units. So, the closer to zero the value of the index, the less liquid the active is. Thus, *D* takes value 1, if for *J* consecutive days no reputational news has emerged, and 0 otherwise, then we test reputational effect on illiquidity index by:

$$\begin{aligned} &\ln\left(A_{i,t}\right) = \alpha + \beta\cdot\ln\left(A_{market,t}\right) + \lambda_m\cdot D_{t,J} + \varepsilon_t \qquad \varepsilon_t \sim iid\left(0,\sigma_t^2\right) \\ &\sigma_t^2 = \delta_0 + \delta_1\cdot\varepsilon_{t-1}^2 + \delta_2\cdot\sigma_{t-1}^2 + \lambda_v\cdot D_{t,J} \end{aligned} \tag{5}$$

4. DATA

The research works that use qualitative information apply data provided by specialized journals and rankings (Fortune, Forbes, KLD stats, KWIC, LWIC, Pulse Scores Reputation Institute, Stats Axia, AEI and Ethibel), or it is obtained from surveys carried out among professionals.

On the other hand, the previously referenced studies that use quantitative information in the analysis of reputational risk get the date from different databases. On the one hand, there are those who analyze reputational risk as part of operational risk, especially with samples from financial sector companies, using databases on losses as ALGO OpData™, OpVantage FIRST and DataLossDB. Others directly employ reputational risk databases (RepTrak™ Pulse), if only to test its reliability (Ponzi et al., 2011). However, as pointed out Micocci et al. (2009), operational risk databases are usually constructed according to the type of events that cause them, and in most cases they conform to normative classifications that do not collect reputational risk separately.

For all this, most studies obtain quantitative information on severity (loss) from financial variables extracted from one of the usual databases (Bloomberg, CSRP, Compustat, BankScope[c] and Datastream[c]); while information related to the event is usually obtained from news in the media or Google Insights and Google Finance. Regarding this form of identification of the event within the news, it should be noted that the keyword filter should be treated with special care, as Loughran and McDonald (2011) show that a general listing of words that imply a negative feeling may not be adequate to analyze the effects on accounting and financial information, since these words do not necessarily have the same negative meaning in the financial context.

Thus, as do Lauterbarch and Pajuste (2017), our study also analyzes the reputation of firms based on information provided by the media, but instead of considering the news of specialized and generalist newspapers (Wall Street Journal, Financial Times, Washington Post, USA Today, New York Times, among others), we take a source closer to the analysts and financial experts (Bloomberg), which shows a more rapid diffusion, that can better show the reaction of the economic agents according to the news about the reputation of companies.

Firstly, we selected the sample space, specifically the non-financial companies that were part of the Spanish market index IBEX-35 as of December 31, 2015. The reasons for this choice are: first, to isolate the study of the effects of financial institutions marked by the recent financial crisis and its particular regulations on risks, which could bias the results; and second, to select companies whose reference portfolio is identified and defined, in order to be able to estimate our model of abnormal returns on this market portfolio, avoiding bias by other factors. The final sample consisted of 24 non-financial companies for a daily frequency period from January 1, 2010 to December 31, 2015 both inclusive.

The search for keywords among Bloomberg daily news for selected companies and the sample period was done by grouping them into six groups (see Annex): *legal* (16 keywords), *fraud* (2 keywords), *economic-financial* (46 keywords), *personnel* (10 keywords), *irresponsible behavior* (4 keywords) and *analysts* (8 keywords).

As Loughran and McDonald (2011) points out, due to the fact that the keywords introduced are general and cover a multitude of different situations that do not

necessarily have to involve reputational risk, it was necessary to individually review each news item, even reading the full content, in order to debug the information and classify the events correctly. The total number of news items reviewed was 36,572 (compared to approximately 1,000 news in Lauterbarch and Pajuste, 2017). All news reviewed are distributed as follows: *legal* (13,548 or 37.04%), *fraud* (253 or 0.69%), *economic-financial* (9,517 or 26.02%), *personnel* (6,045 or 16.53%), *irresponsible behavior* (17 or 0.05%) and *analysts* (7,192 or 19.67%).

After reviewing all the news, we selected those that could have reputational character for each one of the companies in the sample. Table-1 shows the number of news items finally selected by company and category:

[Insert around here TABLE-1]

From the data in Table 1 we can verify that only 492 of the 36,572 (1.35%) are finally considered as a possible reputational event, which shows the important effect of not reviewing the news individually. By categories, we can highlight *fraud* with no news finally selected and *analysts* with the highest percentage of selected news (312), which would show the role of these economic agents as intermediaries between the news of a company and the final investor, although in our case only if the news is negative.

Next, we obtain the financial variables from Bloomberg. Table 2 shows a summary of the statistical analysis of financial variables, on which, we intend measure the effect or reputational risk severity.

[Insert around here TABLE-2]

Note in Table 2 that all variables for their minimum, mean and maximum values are stationary. In addition, in most cases the so-called stylized facts are observed, that is, non-normality, autocorrelation, heteroscedasticity and conditional heteroscedasticity. Therefore, the proposed model is fully justified.

5. RESULTS

First, we study the effect that reputational news has on two variables used in the analysis of market risk, such as the excess of return on daily closing prices and the

excess of the daily implicit volatility of options on the daily realized volatility of market returns.

Table 3 shows the significant lags of reputational news on daily excess returns.

[Insert around here TABLE-3]

Note that there is only one company for which there is no effect of reputational risk on its daily closing prices (ACS). For those that show reputational effects, it should be emphasized that all of them show significant results on the mean equation and, as one would expect, with a negative sign. For the most firms the effect is contemporaneous, although there are many cases in which significant lags appear, which indicates that economic agents do not automatically discount reputational news. The highest contemporaneous effect is observed in INDRA with -2.06%, and in lags AENA shows -3.09% with 1 day of lag since the appearance of the reputational news.

As regards the other variable related to market risk, the excess of daily volatility, Table 4 shows that only four companies have a reputational effect by increasing their implicit volatility: Abertis, Ferrovial, Iberdrola and OHL. Again, only on the mean equation, and with two different temporal effects, first, for some lags (Abertis and Ferrovial), and second, both contemporaneous and lagged parameters during 2 weeks (Iberdrola and OHL). The largest increases in volatility due to the reputational effect are 0.18% contemporaneous and 0.57% lagged, both at OHL.

[Insert around here TABLE-4]

As for as the other risk analyzed, liquidity risk, first, we have analyzed the possible reputational effects on the daily volume trade variations excesses on the market portfolio.

Table 5 shows the reputational effects on the daily volume trade variations.

[Insert around here TABLE-5]

For the volume, we observe the largest number of companies (5) which show no reputational effect: Acerinox, Gamesa, Gas Natural, Grifols and IAG. Also, note that now, the only company that has not previously shown a reputational effect (ACS), now shows one by volume, therefore, the analytical approach of this research is justified

when studying the reputational effect on different market variables. Unlike the other ones, there is no preponderance of the contemporaneous effect on the volume. In any case, the reputational effect is negative, that is, there is a drop in the daily volume of securities traded after a reputational event. It is also noteworthy that for this variable, we obtain the highest number of cases with a positive reputational effect on the variance equation (FCC, Ferrovial, Iberdrola, Inditex, OHL and Técnicas Reunidas). The highest contemporaneous and lagged effects on the mean equation are -40.44% in INDRA, and -90.81% (8 day lag) in AENA, respectively. Regarding the variance equation, the highest contemporaneous effect is 23.56% in OHL.

Finally, Table-6 shows results for log-illiquidity index:

[Insert around here TABLE-6]

Note that no company shows simultaneous effects on the mean and variance equations and, as with volume, there are a high number of companies (9) that show no reputational effect on the illiquidity index: ACS, Acerinox, Aena, Enagas, Gas Natural, Grifols, Inditex, REE and Tecnicas Reunidas. By contrast, 12 companies (Amadeus, DIA, Endesa, FCC, Ferrovial, Gamesa, IAG, Iberdrola, Indra, Mediaset, OHL and Repsol) show a reputational effect on illiquidity, and since the sign of the parameter is positive in all the cases, this means that illiquidity increases as a consequence of the effect of news on their reputation. There are also 3 firms (ACS, Acciona and Telefonica) whose reputational effect is on the variance equation, that is, news about their reputation increases the volatility of the illiquidity index.

6. CONCLUSIONS

Reputational risk is not a directly quantifiable risk, but its effects can be seen through variables that are identified a priori with other types of risks, and therefore are hidden with other risks. Nevertheless, there is financial literature that tries to measure the effect of reputational risk on shareholder wealth, which beforehand would be more related to market risk, among others. Most of this literature uses asset pricing models in which reputational events are added to empirically explain abnormal returns. This approach shows several disadvantages, such as the selection and behavior of market variables and the identification of reputational events based on news.

Starting from the previous studies, this paper is the first to test if there is a reputational effect on variables that are identified with both market and liquidity risk.

In general, the empirical evidence of this work shows that the reputational effect is hidden under different market variables that affect shareholder wealth. This effect is negative for return excesses and trading volume variation, while it is positive for implied volatility. Moreover, this effect is not always contemporaneous, that is, the market sometimes takes several days to discount the reputation event. Additionally, reputational risk implies an increase in illiquidity. From the results obtained, it is not possible to identify a unique pattern of behavior related with reputational risk, although it is important to remark that the closing price reflects a higher significance of the reputational effect. Thus, reputational risk is more likely to be an idiosyncratic component of companies.

In particular, regarding the sample of Spanish listed companies, note that the firm with the least number of reputational effects is ACS, since it only shows so through volume variations and illiquidity index variance. Among the companies most affected by reputational risk, it should be noted that the main contemporaneous reputational effect is shown by Indra. With respect to the lagged effect, AENA and OHL show the highest incidence of reputational news. In the volatility case, OHL is again the company with a higher and sustained reputational effect over time. Finally, Amadeus, FCC and OHL suffer the highest reputational effects on the illiquidity index.

Acknowledgements and Declaration of Interest:

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

This work has been supported by the Spanish Ministry of Economics and Competitiveness through grant MINECO/FEDER ECO2015-65826-P, and Cátedra Universidad CEU San Pablo & Mutua Madrileña insurance company (grant ARMEG 060516-USPMM-01/17). We appreciate comments from professors Gonzalo Rubio (UCH), Juan Nave (UCLM) and Mikel Tapia (UC3M) in Financial Risk hold at USPCEU (June, 15 2017).

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ANNEX: CATEGORIES OF KEYWORDS (BLOOMBERG)

- *Legal* (16 words): Legal Affairs, Litigation (NI LAWUPD), Verdicts, Settlements (NI VERDICTS), Regulatory Investigations (NI REGPROBE), Government Health Agencies (NI HEAGVT), Antitrust (NI ANTITRUST), Civil Procedure (NI CIVPRO), Criminal Practice &Procedure (NI CRIMPRO), Litigation (NI LITIGATE), Employment Law, Labor Issues (NI EMPLAW), Legal Practice Areas (NI LAWPRAC), Bankruptcy Law (NI BCYLAW), Possible Reg. Investigations (NI PREPROBE), Conflict Resolutions (NI ARBITRATE), Mortgage Litigation (NI MORLIT), Trade Sanctions (NI TRADESANC), and Lawsuits (NI LAWSUITS).

- *Fraud* (2 words): Investment Fraud (INVFRAUD) and Money Laundering (NI LAUNDER).

- *Economic-financial* (46 words): Distressed Corporate Bonds (NI DBON), Worldwide Refinery Outages (NI REFOUT), Corporate Bond Redemption (NI RED), Price Target Decreases (NI BMRTGTDWN), Credit Crunch, Crisis (NI CRUNCH), Bond Alert (NI BONDALERT), Negative Earnings Preannouncement (NI NEGPRE), Fund Withdrawal Suspensions, Fund Phase outs (NI FNDHLT), Payment Defaults (NI DEFAULT), Bankruptcy/Restruct Newsletter (NI BCYBRIEF), Distressed Debt, Leverage, Etc. (NI DISTRESSED), BFW U.S. Pre-Market Movers (NI PMMOVUS), Bankruptcies (NI BCY), Chapter 11 Bankruptcy (NI BCYCH11), Trading Halts, Imbalances (NI HLT), Loan Loss Provisions (NI LOANLOSS), Subprime Lending (NI SUBPRIME), Corrections (NI CORRECT), Energy Mkt Integ Transparency (NI REMIT), Investment Risk (NI RISK), Default Probability (NI DEFPROB), Defaulted Bond Payments (NI DEFPAY), Electric Utility Outages (NI VOLTOUT), Market Crashes & Corrections (NI CRASH), bankruptcy filings (NI BCYFILE), Bankruptcies (NI BCYUPD), Charges, Writedowns (NI CHARGES), High Volatility Research (NI BMRHIVOL), Debtor-in-Possession Financing (NI DIP), Critical Natural Gas Pipeline Outages (NI GASOCRIT), Income Inequality (NI INCINEQ), Trading Halt Cos Announcements (NI HALTED), Possible IPOs (NI PREIPO), Trading Imbalances (NI IMBAL), Dividend Cuts (NI DIVCUT), Trading Halts Pending News (NI NEWSHLT), To Be Announced Securities (NI TBA), Default Notices (NI DEFNOTICE), Dividend

Suspension, Elimination (NI DIVHALT), Store, Plant Closings (NI CLOSINGS), Pipeline Outages (NI PIPOUT), Accounting Standards Board (NI FASB), Bankruptcy Reorganization Plans (NI BCYREORG), Possible Bankruptcies (NI PREBCY), Bank Failures (NI BANKFAIL), and Emergence From Bankruptcy (NI BCYEMERGE).

- *Personnel* (10 words): Job Cuts, Firings, Layoffs (NI JOBCUTS), Executive Compensation (NI PAY), Obituaries (NI OBIT), Labor & Unions (NI LABOR), Restructuring, Turnarounds (NI RESTRUCT), Protests, Demonstrations, Riots and Civil Unrest (NI PROTESTS), Strikes and Pay Disputes (NI STRIKE), Workplace Safety (NI WORKSAFETY), Structured Fin Staff Changes (NI SFPEEP), and Unemployment and Jobs (NI UNEMPLOY).

- *Irresponsible Behavior* (4 words): Genetically Modified Food (NI GMFOOD), Airplane Crashes & Accidents (NI AIRCRASH), Air Pollution (NI AIRPOLLUTE), Counterfeit Products (NI CNTRFEIT).

- *Analysts* (8 words): Analyst Rating Changes (NI ANACHANGE), Analyst Downgrade (NI ANACUT), Analyst Tgt Price Changes (NI ANATGTCHG), Estimate Downgrades Research (NI BMRESTDWN), Credit Rating Downgrades (NI CREDITDN), Analyst Target Price Downgrades (NI ANATGTDWN), Analyst Ratings, Estimates and Target Price Changes (NI ANAMOVES) and Analyst Rating Downgrades (NI BMRANADWN).

TABLES

Table 1. Number of news items analyzed by firm and category

Firms	Economic-Financial	Legal	Analysts	Irresponsible behavior	Personnel	Fraud	Total reputational
Abertis Infraestructuras	0	0	18	0	3	0	21
Grupo ACS	1	0	6	0	3	0	10
Acerinox	0	0	5	0	6	0	11
AENA	0	0	3	0	4	0	7
Amadeus IT Group	0	0	7	0	3	0	10
Acciona	2	1	9	0	3	0	15
Distribuidora Internacional de Alimentación (DIA)	0	0	8	0	3	0	11
Endesa	3	4	15	0	3	0	25
Enagás	0	0	19	0	3	0	22
Fomento de Construcciones y Contratas (FCC)	0	0	0	0	3	0	3
Ferrovial	0	0	4	0	3	0	7
Gamesa Corp. Tecnológica	0	0	17	0	4	0	21
Gas Natural SDG	0	6	15	0	3	0	23
Grifols	0	0	9	0	3	0	12
International Consolidated Airlines Group (IAG)	1	2	18	1	25	0	46
Iberdrola	3	6	28	0	4	0	41
Indra Sistemas	1	0	10	0	3	0	14
Industria de Diseño Textil (INDITEX)	0	2	19	0	4	0	25
Obrascón Huarte Lain (OHL)	0	0	0	0	3	0	3
Red Eléctrica de España (REE)	1	1	18	0	3	0	23
Repsol	5	2	23	0	18	0	47
Mediaset España Comunicación	0	0	18	0	4	0	22
Técnicas Reunidas	0	0	10	0	3	0	13
Telefónica	6	8	33	0	13	0	60
NEWS ANALYZED	**9.517**	**13.548**	**7.192**	**17**	**6.045**	**253**	**36.572**
NEGATIVE NEWS	**23**	**32**	**312**	**1**	**127**	**0**	**492**
RATIO NEGATIVE/ANALYZED	**0,24%**	**0,24%**	**4,34%**	**5,88%**	**2,1%**	**0,00%**	**1,35%**

Source: Own elaboration based on information from Bloomberg News

Table 2. Statistical summary of variables

Risk	Variables	Statistics	observ.	min	mean	max	std.dev.	skewness	excess kurtosis	Jarque-Bera	ARCH(5)	Box-Pierce AR(5)	Box-Pierce squared (5 lags)	ADF
Market	exc_return	Min	229	-0.6541	-0.2522	0.0591	0.0146	-0.5810	0.2254	0.3621	0.3760	3.4629	2.003	-19.636
		Median	1535	-0.0947	0.0001	0.1131	0.0187	0.0387	2.5692	301.5800	6.0762	11.4921	36.912	-16.129
		Max	1535	-0.0698	0.0026	0.2480	0.0292	0.8592	40.5210	64007.00	97.0740	27.6130	562.473	-5.988
	volat.	Min	156	0.0019	0.0122	0.0159	0.0014	-0.8689	-0.6718	4.2139	1.4760	263.4890	225.933	-42.480
		Median	1535	0.0074	0.0152	0.0311	0.0031	0.8193	1.0748	225.7150	1473.80	4558.3100	4351.495	-3.534
		Max	1535	22.6980	36.6090	100.1000	10.0290	4.2357	47.4230	23339.00	5273.70	6353.87	6261.90	-1.689
Liquidity	var_volum	Min	228	-49.6510	-0.0194	3.4030	0.5070	-0.5236	-0.2021	1.5427	2.1599	16.3284	16.319	-27.420
		Median	1535	-31.6195	-0.0005	27.9340	0.6530	0.0818	2.6018	315.8100	32.9380	195.3680	174.698	-23.250
		Max	1535	-2.3500	0.4608	54.4040	0.9122	0.3743	11.2830	2899.70	82.1720	328.83	645.21	-8.230
	log(A)	Min	22	-23.7790	-21.9220	-20.8250	0.3967	-0.9091	-1.1594	0.2891	4.8145	22.9946	22.32	-38.457
		Median	153	-20.2860	-18.8460	-17.5360	0.4818	-0.0332	0.1873	2.1149	17.4160	154.9220	152.58	-4.059
		Max	153	-17.9450	-16.6310	-15.0800	0.9093	1.0063	1.6569	7.8058	149.44	523.2570	529.71	-3.697
Market Factor	exc_ibex		1535	-0.0688	-0.0002	0.1348	0.0154	0.2537	5.0234	1629.40	32.6890	24.2492	174.36	-19.566
	log(A)		153	-25.3050	-24.2830	-22.9640	0.4276	0.2707	0.0305	1.8741	19.0370	120.1830	34.18	-4.618

Table 3. Effects of reputational risk on market risk (closing prices)

Firms	Eq. Mean	Lag(0)	Lag(1)	Lag(2)	Lag(3)	Lag(4)	Lag(5)	Lag(6)	Lag(7)	Lag(8)	Lag(9)	Lag(10)
	param.	-0.0040[*]										
Abertis	std dev.	0.0017										
	param.					-0.0042[*]						
Acerinox	std dev.					0.0021						
	param.	-0.0109[**]										
Acciona	std.dev.	0.0039										
	param.		-0.0309[**]	-0.0088[**]				-0.0193[**]				
AENA	std.dev.		0.0097	0.0024				0.0064				
	param.	-0.0122[*]										
Amadeus	std.dev.	0.0062										
									-0.0042[*]	-0.0098[**]		
DIA									0.0019	0.0028		
	param.		-0.0088[*]	-0.0039[*]	-0.0048[**]	-0.0092[*]	-0.0010[**]					
Endesa	std.dev.		0.0041	0.0020	0.0016	0.0046	0.0038					
	param.	-0.0048[**]					-0.0098[**]					
Enagas	std.dev.	0.0015					0.0032					
	param.					-0.0063[*]					-0.0074[*]	-0.0140[**]
FCC	std.dev.					0.0029					0.0036	0.0047
	param.			0.0132[**]			-0.0089[**]			-0.0038[**]		
Ferrovial	std.dev.			0.0045			0.0034			0.0013		
	param.		-0.0106[*]						-0.009475[**]			
Gamesa	std.dev.		0.0051						0.0032			
	param.	-0.0049[*]										
Gas Natural	std.dev.	0.0025										
	param.	-0.005[*]			-0.0078[*]							
Grifols	std.dev.	0.0025			0.0031							
	param.							-0.0042[**]				
IAG	std.dev.							0.0016				
	param.	-0.0019[*]	-0.0021[*]	-0.0017[*]				-0.0020[*]				
Iberdrola	std.dev.	0.0010	0.0010	0.0008				0.0009				
	param.	-0.0206[**]					-0.0057[*]				-0.0090[*]	
Indra	std.dev.	0.0068					0.0029				0.0040	
	param.	-0.004942[*]										
Inditex	std.dev.	0.0025										
	param.		-0.0071[*]			-0.0077[*]			-0.0240[*]	-0.0130[*]		
OHL	std.dev.		0.0032			0.0043			0.0118	0.0058		
	param.						-0.0063[*]					
REE	std.dev.						0.0032					
	param.									-0.0039[**]		
Repsol	std.dev.									0.0013		
	param.	-0.0090[*]	-0.0078[*]						-0.0094[**]			
Mediaset	std.dev.	0.0050	0.0039						0.0027			
	param.							-0.005474[*]			-0.0048[**]	
Tecnicas Reunidas	std.dev.							0.0028			0.0018	
	param.		-0.0025[**]									
Telefonica	std.dev.		0.0007									

Note: [**] and [*] represent statistically significant at 1% and 5% level, respectively.

Table 4. Effects of reputational risk on market risk (implied volatiliy of options)

Firms	Eq. Mean	Lag(0)	Lag(1)	Lag(2)	Lag(3)	Lag(4)	Lag(5)	Lag(6)	Lag(7)	Lag(8)	Lag(9)	Lag(10)
	param.						0.0006[*]	0.0008[*]	0.0007[*]	0.0007[*]	0.0006[*]	0.0006[*]
Abertis	std.dev.						0.0002	0.0002	0.0003	0.0002	0.0002	0.0002
	param.		0.0005[*]	0.0006[*]					0.0007[*]			
Ferrovial	std.dev.		0.0001	0.0002					0.0003			
	param.	0.0012[*]	0.0017*]	0.0022[*]	0.0024[*]	0.00243[*]	0.0023[*]	0.0022[*]	0.0019[*]	0.0021[*]	0.0016[*]	0.0011[*]
Iberdrola	std.dev.	0.0003	0.0003	0.0002	0.0001	0.0001	0.0002	0.0007	0.0006	0.0001	0.0001	0.0001
	param.	0.0018[*]	0.0011[*]	0.0016[*]	0.0007[*]	0.0026[*]	0.0038[*]	0.0032[*]	0.0044[*]	0.0057[*]	0.0036[*]	0.0042[*]
OHL	std.dev.	0.0002	0.0001	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	0.0014	0.0017

Note: [**] and [*] represent statistically significant at 1% and 5% level, respectively.

Table 5. Effect of reputational risk on liquidity risk (volume)

Firms	Eq. Mean	Lag(0)	Lag(1)	Lag(2)	Lag(3)	Lag(4)	Lag(6)	Lag(7)	Lag(8)	Lag(9)	Lag(10)	Eq. Variance Lag(0)
	param.						-0.3408[**]					
Abertis	std.dev.						0.0914					
	param.					-0.1867[**]						
Acciona	std.dev.					0.0927						
	param.					-0.4514[**]						
ACS	std.dev.					0.1938						
	param.			-0.7309[**]					-0.9081[**]			
AENA	std.dev.			0.0152					0.0568			
	param.						-0.4636[**]					
Amadeus	std.dev.						0.1505					
	param.					-0.2614[**]						
DIA	std.dev.					0.1133						
	param.				-0.1701[**]							
Endesa	std.dev.				0.0866							
	param.	-0.3749[**]	-0.4572[**]	-0.5495[**]					-0.2489[**]		-0.4063[**]	
Enagas	std.dev.	0.0961	0.2099	0.1409					0.0687		0.0110	
	param.											0.1329[**]
FCC	std.dev.											0.0620
	param.		-0.3231[**]							-0.196568[**]		0.0927[**]
Ferrovial	std.dev.		0.1478							0.0286		0.0391
	param.											0.1305[**]
Iberdrola	std.dev.											0.0254
	param.	-0.4044[**]	-0.3854[**]				-0.2685[**]					
Indra	std.dev.	0.1717	0.1541				0.1159					
	param.				-0.187419[**]	-0.252687[**]						0.0520[**]
Inditex	std.dev.				0.0798	0.1028						0.0204
	param.		-0.4564[**]	-0.3102[**]			-0.5359[**]			-0.0625[**]		0.2356[**]
OHL	std.dev.		0.2679	0.1495			0.2005			0.0252		0.0352
	param.			-0.4906[**]	-0.1921[**]							
REE	std.dev.			0.0187	0.0717							
	param.							-0.1255[**]				
Repsol	std.dev.							0.0779				
	param.	-0.2854[**]										
Mediaset	std.dev.	0.1118										
	param.			-0.1823[**]								0.1379[**]
Tecnicas Reunidas	std.dev.			0.0693								0.0720
	param.			-0.0873[**]								
Telefonica	std.dev.			0.0438								

Note: [**] and [*] represent statistically significant at 1% and 5% level, respectively.

Table 6. Effect of reputational risk on illiquidity index

FIRMS	Effect on equation mean		Effect on equation variance	
	param.	std. dev.	param.	std. dev.
Abertis	0.0106	0.1246	0.1386 [**]	0.0501
ACS	0.0998	0.1847	0.0300	0.0485
Acerinox	0.0248	0.1123	0.0269	0.0549
AENA	0.0127	0.2564	0.2585	0.1852
Amadeus	0.5142 [**]	0.0552	0.3436	0.8112
Acciona	0.2580	0.1411	0.1081 [*]	0.0481
DIA	0.2388 [**]	0.0665	0.20151	0.5218
Endesa	0.3028 [*]	0.1219	0.0502	0.3564
Enagas	0.1171	0.3524	0.0326	0.2487
FCC	0.3753 [**]	0.1305	0.0108	0.1156
Ferrovial	0.1301 [*]	0.0643	0.1124	0.6471
Gamesa	0.2145 [**]	0.0203	0.1056	0.0905
Gas Natural	0.1386	0.0862	0.0548	0.2871
Grifols	0.2265	0.1675	0.0283	0.0763
IAG	0.1368 [*]	0.0701	0.2154	0.8476
Iberdrola	0.1289 [*]	0.0551	0.1052	0.4317
Indra	0.1071 [**]	0.0417	0.0238	0.0446
Inditex	0.0895	0.0905	0.1088	0.0472
Mediaset	0.1458 [*]	0.0748	0.0032	0.0521
OHL	0.4524 [**]	0.1604	0.0478	0.1482
Red Electrica	0.0627	0.0889	0.0815	0.0551
Repsol	0.0988 [*]	0.0511	0.0493	0.0298
Tecnicas Reunidas	0.0408	0.1102	0.0486	0.0809
Telefonica	0.0584	0.0733	0.0731 [*]	0.0314

Note: [**] and [*] represent statistically significant at 1% and 5% level, respectively.