Firms suffering from Sadness: A study of CEO Shock Tolerance and Firm Performance.

Proposal for the XIV International Accounting Symposium

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This work tries to measure CEO depression levels and relate it to firm performance. The first hypothesis we are going to test is that negative exogenous shocks to a company foster depression sentiments in the CEO. And the second hypothesis we would like to test in this paper is how after a negative shock, firms with less depressive CEO are going to show higher subsequent performance.The variable depression is going to be measured capturing differences in language usage that might reveal cognitive operations associated with depression. For this we will use text analysis on the Earnings Conference Call transcripts. And regarding the exogenous shocks, we are going to consider the financial crisis and the mean performance of the industry. Moreover we also test our hypothesis using the abnormal tone approach. The results we obtained are going in the direction we expect following our argumentation.

I. Introduction

A. *Importance of Qualitative Information*

Traditionally research has focused on the analysis of information from a rational point of view mainly through a quantitative framework. We may think that quantitative information is more precise and follow the universal laws of mathematics making it more appropriate for business decision-making or academic discussions. But reality is more complex than numbers and many times qualitative information is able to reveal a better picture of the world.

Firm fundamentals reflect hard verifiable information about the firm, and extant research shows that analysts use these key data to build firm forecasts of future performance. But, oftentimes, soft information of a qualitative nature may be fundamental in equity valuation. For example, a company may have problems in the negotiations with its most important customer. The uncertainty that exists on the possibility of losing its main customer is neither reflected in the value of earnings nor in other fundamentals. So analyst could not observe this idiosyncratic risk by only considering the fundamentals. As (Mayew et al., 2012)[19] considered, we may expect that the CEO in this company is more likely to exhibit uncertain affective state when he speaks about the company in a public meeting (e.g. in an earning conference call). Therefore if analysts are able to detect this qualitative information revealed by managers they would internalize it in their forecast and make better decisions.

Language is one of the most important tools that humans use to communicate and transmit qualitative information (e.g. sentiments). For these reason, a literature trying to study the information carried through words has been increasing in the recent years. We can think on the work of (Tetlock, 2008)[25], where it investigates how information contained in language can be used to predict individual firms' accounting earnings and stock returns. Also (Tetlock, 2007)[24] in another paper studies how the pessimism in the media affects the stock market prices and trading volumes. We can also direct our attention to some current works. For example, a paper by (Hope et al., 2017)[10], that uses text analysis to measure the truthfulness of managers. And later uses this qualitative dimension to conclude that deceptive CEOs that announce big baths generate bigger information asymmetry than less deceptive CEOs. These may be reflecting the distrust that investors have when a CEO realizes some news. A working paper by (Hrazdil et al., 2018)[11], also uses text analysis to determine the personality of the CEO. With this measure the paper could conclude that audit fees are higher for companies with risk tolerant CEOs.

B. CEO as an Important Actor in a Company

A company is composed by human beings, and human beings in a firm are structured within an organization. In every organization there is a degree of hierarchy where some individuals influence in a greater manner than others. In the classic literature, the upper echelon theory (Hambrick et al., 1984)[8] has strengthened the view that in the organizations exist some key members, which are predictors of the organization outcomes. In other words, this theory states that strategic choices and performance levels are partially predicted by managerial background characteristics. Supporting this theory the Carneige School have argued that complex decisions are largely the outcome of behavioural factors rather than mechanical quest for economic maximization (Cyert & March, 1963)[6]. So in a context of complexity, the view that CEO's characteristics affecting the firm actions would be more applicable. Usually when a CEO is facing choices of "strategic" nature -complex and with major significance to the organization- assuming the echelon theory would be especially apt.

We can also direct our attention to more recent works like (Bertrand & Schoar, 2003)[5], where they have shown empirical evidence on how individual managers affect corporate behaviour and performance. In their paper the authors found how a significant extent of the heterogeneity in investment, financial, and organizational practices of firms can be explained by the presence of manager fixed effects.

C. Our Variable of Interest

There are many CEO characteristics that can serve to predict the firm behaviour, according to previous literature we can divide them in two groups. One group being, observable characteristics as: age, education, socioeconomic roots, etc. And another group is psychological characteristic. In this research we would focus on the second group, particularly on a specific sentiment, which is depression.

According to the American Psychiatric Association, depression is a common and serious medical illness that negatively affects how you feel, the way you think and how you act. Depression causes feelings of sadness and/or a loss of interest in activities once enjoyed. It can lead to a variety of emotional and physical problems and can decrease a person's ability to function at work and at home. For example, difficulty thinking, concentrating or making decisions are some of the consequences produced by depression, which leads directly to under-perform at work.

To have a measure on the level of depression of the CEO we are going to analyze the verbal content of the earnings conference calls transcripts[1]. Previous literature has already find evidence on language usage characteristics of depressed people. In the paper of (Rude et al., 2004)[20] the authors examined linguistic patterns of depressed persons in the context of an essay task. The following linguistic dimensions are related to depression: first person singular I, me, my); first person plural we, us, our); social references e.g., mention of friends, family, or communication); negatively balanced e.g., gloom, fight, sad, homesick, inadequate); and positively balanced e.g., joyful, accept, best, play, share) words. Overall usage level for these word categories give an approximation of the level of depression a person exerts.

D. Hypothesis

One of the reasons of depression are environmental factors, negative shocks in live could be the cause of becoming depress. We can cite here the paper by (Rude et al., 2004)[20]: "An episode of depression may come about when losses or other stressful events trigger the activation of depressive schemas, leading the individual to begin perceiving events in negative ways". For example, when a person losses a job, some close relative die or an unexpected illness arise, all these are circumstances that can induce a person becoming depress.

The CEO is commonly viewed as the most responsible individual in a firm decision process. This can make us think that for a CEO, negative shocks to the company that they are running could also be considered as a negative shock for them as a person. Then, if for example a company losses a big customer this may induce a depressive state in the CEO. Following this reasoning we are going to set our first hypothesis:

H1: Negative events for a company foster depression feelings in the CEO.

To follow our study within the framework of the echelon theory we would like to see how the state of a CEO affects the organization functioning. So in some sense the CEO's resilience[2] to absorb negative shocks coming from the company may be a quality that is reflected in the company itself. Then, we should expect that after a negative shock happens, CEOs that are able to assimilate this negative income in a better way (exerting less levels of depression) would be more able to handle the situation and in consequence the firm is going to recover from the shock in a better way. This would be the second hypothesis we like to test:

H2: After a negative shock, firms with more resilient CEO (lower levels of depression) are going to show higher subsequent performance.

Finally as a conclusion we would like to point out that if hypothesis 2 holds then it goes in line with the echelon theory. Meaning that we are able to see reflected some characteristics of top managers in the organization performance. In this particular case the capacity of CEO to absorb negative news is affecting future firm's ability to handle the crisis.

[1] Earnings calls are conference call between the management of a public company, analysts, investors and the media to discuss the financial results during a given reporting period such as a quarter or a fiscal year.

[2] In this research we understand by resilience as the capacity of a person to absorb negative events in her live without falling into a depressive state.

II. Data

In this section we are going to describe the characteristics of the data we have. The main data-set is composed by transcripts of Conference Calls. This data comes from Thomson Reuters and it is structured in .xml format in a way which is easy to parse the text.

A. Description of the "Raw" Data

Our most primitive data-set contains 311,658 files. From these files, there are some that are a brief version of the transcripts, we are going to focus our attention on the full transcripts only. Therefore our sample will be a total of 240,827 documents. Within this later sample we have different types of meetings, see table 1.

Table 1: Conference Calls by Event Type

Event Type ID	Event Type	Freq.	Percent
1	Earnings Conference Call	172,593	71.67
5	Conference Call	11,290	4.69
7	Conference	36,179	15.02
25	Federal Goverenment	6,639	2.76
33	Sales Conference Call	4,733	1.97
	Other	9,393	3.9
Total		240,827	100

In our first analysis we are going to focus our attention to the first type of documents. There are three reasons to do this. The first one is that this is the most frequent type of document in our sample. Secondly, since there maybe different styles of narrative in different types of meetings, we would like to compare transcripts that comes from the same context. And the final reason is that the structure of the transcripts may differ across types which may produce some errors in the text analysis process in python.

The reasons we just mentioned does not mean we cannot work with different types of documents, in fact in further steps of the research we can use more event types. But first, for simplicity, we are going to consider only type 1. This means that our sample will be reduced to 172,593 observations, all of them being transcripts of Earnings Conference Calls.

B. Earnings Conference Calls

Now we are going to analyze the sample of 172,593 Earnings Conference Calls. In this sample we have 5,601 different companies. These companies are identified by the CUSIP number. Moreover we have observations from 2001 to 2012, we can see the distribution of data along time in figure 1.

We use this sample to analyze the tone of the text, as we mentioned before this sample only considers the type 1 of meetings, Earnings Conference Calls. The first step is to count the frequency of each words in all the texts, to find out the likelihood of a word to appear. This measure calibrates the usage of words in a given context. For this reason makes sense what we mentioned before about the importance of calibrating the words in a similar context. Because if there are some other type of meetings where the narrative is more informal and a certain type of words which contains a high emotional content are more frequent, then this may create less sensitivity in the sense that the appearance of emotional words in a formal text would have less power. Since we are only considering

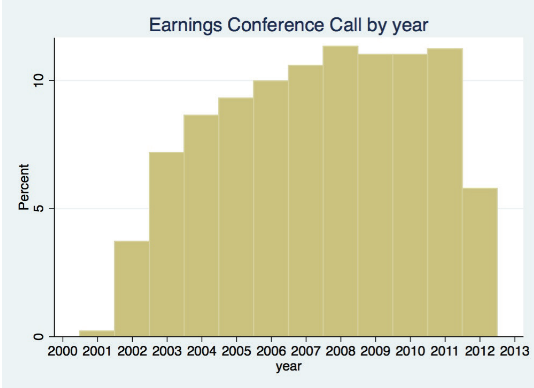


Figure 1: Histogram by year

the Earnings Conference Calls we are having an homogeneous type of meetings and we reduce this problem.

So far we have talked about our first data-set but we need to match it with other data sources in order to have more variables, e.g. prices, returns, etc. To do this we are going to use the CUSIP identifier, in the next section we are going to see the results of the merging process.

C. Earnings Conference Calls merged with Compustat and CRSP

In this section we are going to review the process of merging with WRDS, mainly to see what are the losses we make during the process. First of all we need to consider that 44,141 observations of the Earnings Conference Call sample have no CUSIP identifier meaning that we cannot merge them with WRDS. Furthermore, from the 5,322 distinct companies with CUSIP we are able to match 3,751 CUSIPs with Compustat, 3,441 CUSIPs with CRSP and 3,287 CUSIPs with both data-set. Finally, after we consider all of this, we end up with a sample of 90,003 observations with data on both CRSP and Compustat. We can see in table 2 the summary statistics of some variables from Compustat and CRSP after merged with the Earnings Conference Call data.

Table 2: Summary Statistics.

Variable	Source	Num. Obs.	Mean	Std. Dev.	Min	Max
Returns	CRSP	92,078	0.013	0.163	-0.85	7.87
Shares Outstanding	CRSP	92,490	197,498.2	709,204.9	60	29,200,000
Long Term Debt	Compustat	94,763	3,101.11	20,300.56	0	653,766.9
Debt in Current Liabilities	Compustat	89,315	2,131.07	20,835.06	0	562,857
Cash	Compustat	57,010	640.59	3,009.96	-21.89	102,002
Retained Earnings	Compustat	92,251	1,851.95	9,625.68	-102,362	340,762
Total Assets	Compustat	95,565	18,558.79	109,853.3	0.09	2,756,019
Market Value	Compustat	64,248	5,632.36	20,329.32	0.29	560,568.5
Common Shares Outstanding	Compustat	94,964	241.38	809.85	0	29,206.44
Price Close - Quarter	Compustat	96,115	26.83	27.55	0	686
Common/Ordinary Equity	Compustat	95,191	3,117.97	10,714.99	-28,904	217,213
Number of Business Segments	Segments	25,837	5.58	4.063	1	36
Number of Geografic Segments	Segments	25,837	1.62	0.483	1	2

Once we merged with WRDS we can also have further characteristics of the firm like the industrial sector it belongs to. This is interesting because the negative shock we are trying to find may be sector specific. In table 3 we can see the distribution of observations by sector:

Table 3: Conference Calls by Industry Sector

Industry Classification	Freq.	Percent
Agriculture, Forestry, And Fishing	150	0.17
Construction	1,139	1.27
Finance, Insurance, And Real Estate	15,087	16.76
Manufacturing	37,145	41.27
Mining	4,125	4.58
Public Administration	653	0.73
Retail Trade	6,069	6.74
Services	15,002	16.67
Transportation, Communications, Elect.	8,122	9.02
Wholesale Trade	2,511	2.79
Total	90,003	100

Also we can have information on other firm characteristics that may be relevant to our study like firm size, leverage, returns, etc.

III. Depression

A. Some Theories of Depression

There is a considerable number of papers supporting the idea that depressed individuals tend to focus their attention on negative information, to interpret neutral information in a negative way, and hold pessimistic beliefs about the future. For this we can look the work by (Hamilton & Abramson, 1983)[9] where they assessed cognitive patterns of individuals suffering depression during their period of depression and after they were healed.

Nevertheless cognitive models of depression claim that negative thinking is not only a symptom of depression but a cause of it. Following the work of (Beck, 1967)[3] people who are vulnerable to depression posses depressive schemas and dysfunctional beliefs that produce depressive thinking (”automatic thoughts”). According to Beck, these depressive schemas may be dormant during periods of times but difficult periods in live may activate them and give rise to depression symptoms. We can see works in this direction like (Miranda, Gross, Persons & Hahn, 1998)[18] where they test how negative mood may activate the latent dysfunctional attitudes in depressive-prone individuals. In this paper they perform an experiment with a sample of one hundred women where one third are vulnerable to depression. The level of dysfunctional attitude is measured before and after a film negative mood induction. The results show how vulnerable subjects that reported increased levels of negative mood also reported increased dysfunctional attitudes as opposed to non-vulnerable ones. In this case a stressful event that causes negative mood would activate the depressive schemas.

The induction of a sad mood may not be the only way we can capture the latent depressive schemas. Other papers have realized that persons who suffered depression have developed different mechanism in order to maintain emotional well being. Thought suppression as a way of controlling unwanted thoughts that may threat emotional stability is proved to be more present in individuals with previous depression experiences. Therefore circumstances that reduce volitional control of depressive-prone people may bring up latent depressive thinking. Following this argument goes the paper of (Wenzlaff et al., 2001)[26]. This paper is an experiment with a group of participants vulnerable and non-vulnerable to depression. It uses a measure of information processing bias that consits on a grid of words where some are negative balanced and other positive balanced. Participants needs to find words in the grid, with the particularity that some participants are subject to a cognitive load task which require respondents to perform an attention-demanding secondary task simultaneously. The results of this paper show that depressive-prone individuals have a bias in selecting negative words from the grid when subject to the cognitive load task but without cognitive load they perform the task in the same way as non-vulnerable participants. This suggest the presence of thought suppression mechanism in individuals at risk of depression.

Another model to understand depression within the cognitive theory is the attributional reformulation of learned helplessness and depression (Abramson et al., 1978)[1]. This model suggests that individual differences exists in attributional styles and claims that certain attributional styles are more likely to be associated with depression. Particularly, when confronted with the same negative event, people who display a generalized tendency to attribute negative outcomes to internal, stable or global factors should be more likely to experience a depressive mood reaction than people who typically attribute negative outcomes to external, unstable, or specific factors. Some previous studies worked in this line, as (Metalsky et al., 1982)[18]. This paper tested the attributional theory in a naturalistic setting, they measured the different attributional styles in college students and found that students with a tendency to attribute negative events to internal factors where more likely to exhibit higher negative moods with a subsequent low midterm grade.

So far we have seen the two major cognitive theories of depression Beck's model and the attributional theory. A core feature of both major theories is the concept of a traitlike depressive cognitive style that characterizes some individuals vulnerable to depression and it remains latent even when the person is in a period of health. Within this context, some previous research suggested that self-focused attention maybe an important component of depressive cognition. There is empirical evidence that individuals with a chronic tendency of self-focus attention are more likely to react in a depressive manner when confronting negative events. A paper by (Ingram et al., 1987)[13] perform a test where they measure the level of self-focus attention in a group of depress people and a control group of non-depressed individuals. The results this study obtains are that depressed individuals, whether subclinically or clinically depressed, have a significantly greater proportion of self-focused attention than do non-depressed individuals. One of the mechanism they suggest in their paper is that in an individual who has latent negative schemas, self-focus attention may trigger their activation by turning the attention inward. This process may exacerbate depression when it is there or induce it when it is not.

We turn into a paper by (Smith & Greenberg, 1981)[21] where it gives three reasons why self-focused attention is related to depression. The first argument is related to self-steem, low self-steem is one of the main factor when depression arises. Self-focus attention has been suggested to be present in individuals that are more self-critical. For these reason, a dispositional tendency to be self-focus has been found to be correlated with lower levels of self-steem. The second argument they give has to be with attributions. As we mentioned above attributional theory claims that depressive-prone individuals tend to attribute negative events to internal factors. Similarly self-focus attention leads to an increase in attribution to internal factors. Lastly, the third argument relies in the fact that self-focus attention exacerbates the intensity of affects. Thus, when suffering depression self-focus attention have been demonstrated to produce more extreme depression. With this being said, it is well established the role of self-focused attention in maintaining and exacerbating depression.

B. *Lenguage use and Depression*

Some existing literature have already try to examine the linguistic patterns of depressed and depression-prone individuals. A paper by (Stirman & Pennebaker, 2001)[22] analyses if there exists distinct features of language used by poets in their poems that are associated to suicide. In this paper the authors test the model of social integration in suicide. The results they found are in line with the model in the sense that writings of suicidal poets contain more words related to the individual self and fewer words pertaining to the collective than did those of nonsuicidal poets. Although they do not measure depression directly, it seems reasonable to think that suicidal poets were more depressed than the nonsuicidal ones. We can also find papers that do focus their study into depression, one example is the paper by (Rude, Gortner & Pennebaker, 2004)[20], here they explore the use of first person singular pronouns as well as the use of negative emotional tone in an essay task performed by college students where some are currently depressed some are formerly depressed and some are never depressed. In line with the cognitive load concept we described in the previous section, they divided the text in three parts and noticed that the last part should be expected to be more revealing for the case of formerly depressed people. They found that depressed individuals use more words associated to self-focus attention as well as negative balanced words. In keeping with the notion that individuals vulnerable to depression struggle to keep depressive thoughts at bay, formerly depressed participants show a greater use of the self-focus words in the third part of the essay. This makes sense, since as the essay goes by, the writer gets tired and the amount of resources devoted to suppress self-preoccupations decreases.

C. *Our Measure of Depression*

From the last white paper, we end up with a sample of 172.593 Earnings Conference Calls of the type 1. These sample is the one we are going to work with text analysis. There are different text analysis techniques, but we are going to focus on the one that uses dictionaries in line with Loughran, T., & McDonald, B. (2011)[18]. This technique consists in counting the number of words appearing in a given text that belong to a specific dictionary. These dictionaries classify words into a certain categories, e.g. negative emotions, social relationships, etc. Apart from the raw count we calculate a weighted measure following the paper of Loughran, see equation 1:

$$w_{i,j} = \begin{cases} \frac{(1+log(tf_{i,j}))}{(1+log(a))} * log\frac{N}{df_i} & \text{if } tf_{i,j} \geq 1 \\ 0 & otherwise \end{cases} \tag{1}$$

Where, df_i is the number of documents containing at least one accurrence of the i^{th} word, $tf_{i,j}$ the raw count of the i^{th} word in the j^{th} document, a is the average word count in the document and N is the total number of documents. The first term has the purpose of attenuating the impact of high frequency words with a log transformation. The second part of the equation calibrates the impact of a word depending of its frequency.

The way to calculate the tone of the text is the same with the paper we just mentioned but the dictionaries are going to be different. The dictionaries are coming from the LIWC[23] (Linguistic Inquiry and Word Count), which contains a set of dictionaries for different dimensions. Since we are interested in measure depression using text analysis we focus our attention on (Rude, Gortner & Pennebaker, 2004). As mentioned previously, they measure depression patterns from written essays and compare it with actual medical reports. They found evidence that people who are more vulnerable to suffer depression are more likely to use: 1º person of singular (e.g. I, me, my, myself, etc.) and negative balanced words (e.g. anxious, bad, careless, sad, rude, etc.). On the other hand they are less likely to use: 1º person of plural (e.g. us, we, our, let's, etc), social related words (e.g. ally, counsel, mates, together, etc.) and positive balanced words (e.g. attract, beautiful, happily, magnificent, etc.) in their language. As an example We can see in figure 2 the distribution of raw words count in our data-set, the average of social words per document is around 250.

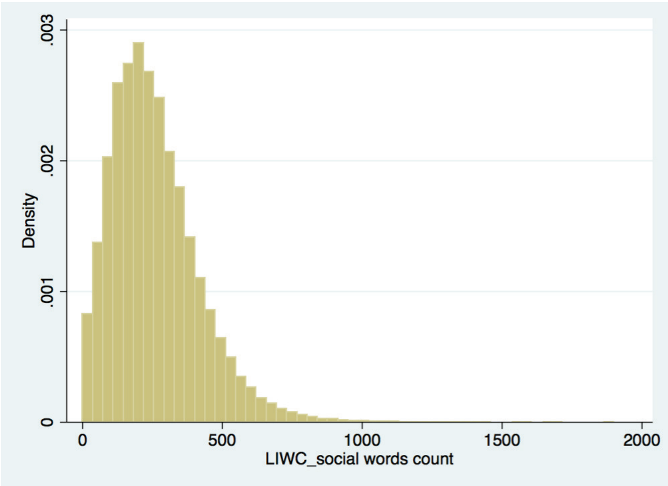


Figure 2: Histograms of word count per document

We are going to calculate two variables and later, using this two variables, we will try to characterize the level of depression. Our first variable is going to be one that measures the level of pessimism of a text. In this case we are going to consider the measure of negativeness and subtract the average value of positive and social measures (these measures are calculated using the weighting formula mentioned above). The idea is that the pessimism of a text is counterbalanced by positive and social references words, we assume that negative words are canceled by positive or social words. Basically, we create three dictionaries one that contains words that are negative balanced and another two with words that have the positive balanced and social related words. To have a normalized measure we group by 1000 as if percentiles these measures and divide by 1000, then we obtain normalized variables that range from 0 to 1. Finally we calculate a total measure of the tone using the formula 2 with the tones mentioned above:

$$Pessimism = NegativeWords - \frac{1}{2}(PositiveWords + SocialWords) \tag{2}$$

The second variable is going to capture the self-focus attention. In this case we consider the 1º person of singular words and the 1º person of plural words. The difference from the previous one is that now we are going to consider the raw count rather than the weighted one. The reason is that now we are counting words like "I" or "We" which are very frequent, so it is better to use the absolute number of times these words appear and divided by the length of the text. Apart from that the process remain similar to the pessimism one, we normalize and then we calculate the self-focus attention using the following equation:

$$SelfFocusAttention = 1^{st} person of singular words - 1^{st} person of plural words \quad (3)$$

With these two measures we are going to characterize the depressive state of the CEO in the Earning Conference Call. Based on the theory we have reviewed we should expect that CEOs that use higher pessimism tone and higher self-focus attention are the ones with greater depression levels.

IV. Shocks Inducing Negative Mood

For this paper we consider two exogenous shocks, the exogenous nature of the shock is important because we do not want it to be a consequence of the CEO's actions, otherwise we may not be able to identify causality of the shock on depression. The first shock is going to be the Financial Crisis shock, based on the paper by (Lins, Servaes & Tamayo, 2017) [16]. In this paper the authors try to study how firm trust is more valued when the general level of trust in corporations and markets suffers a negative shock. They consider the crisis period from Augoust 2008 through March 2009 as an exogenous variation of public trust in corporations, capital markets and institutions. We can use this big universal shock to see how interacts with our measures of tone.

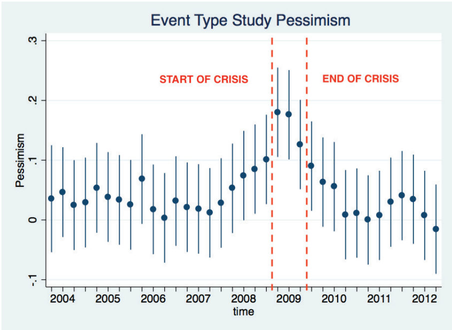
In addition, we also consider another shock, the mean performance of the industry, following the paper by (Bertrand & Mullainathan, 2001) [4]. In this paper they are interested in analyze if the pay received by the CEO is not tied to luck, being luck an observable shock to performance beyond the CEO's control. One of the exogenous shocks they consider is the mean performance of the industry, which meant to capture external shocks that are experienced by all firms in the industry. These shocks are calculated as the weighted average rate of accounting return in a given quarter in the one-digit industry that firm belongs to, excluding the firm itself from the calculation. We will also consider this shock in our study.

A. Are these Shocks Valid for our Purpose?

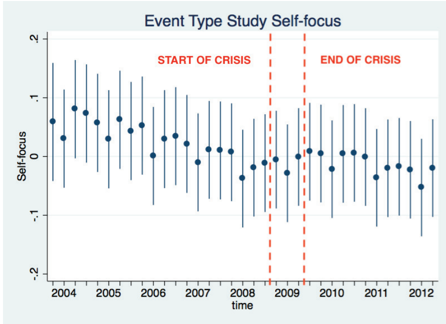
Since our intention is to measure depression variation among CEOs we need to find a period where the activation of depressive schemas in vulnerable CEOs are more likely to happen. During normal times we may not be able to distinguish depressive patterns in depressive CEO because these are dormant, so a period characterized by stress and negativeness would be a good context for our measures of depression. As the paper by (Miranda, Gross, Persons & Hahn, 1998)[18] noticed, negative mood triggers the activation of dysfunctional thinking, so if our shocks are inducing pessimism then they will activate depressive schemas and that would be a good set-up for measuring heterogeneity in depression levels.

B. Validating Financial Crisis Shock

First we are going to see what happen with the financial shock. If we consider an event type study with the average values of the variables of text analysis we mention before we can see some interesting movements, see picture 3. In the case of pessimism there is a big increase during the crisis period, which goes in line with validating the shock, because the crisis period would be a context where negative mood is higher. We can also



(a) Event Type Study Pessimism



(b) Event Type Study Self-focus

Figure 3: Event type study of the two variables

see the self-focus attention variable, here there is no change during the crisis, what we can observe is a negative trend during the time horizon of our data.

To see more clearly the effect of the financial shock in the level of pessimism[3]. A first model we can test is an OLS where the dependent variable is our measure of pessimism and as the explanatory variable we have a financial crisis dummy (FinCrisis) which takes value one when the observation belongs to the crisis period and zero otherwise.

We control for firm characteristics that may be correlated with the financial crisis intensity and thus the level of pessimism. During the crisis firms with liquidity poor situations would be more stroked than financial healthy firms, see (Almeida et al., 2012)[2], so we employ several proxies to measure a firm's financial health: Cash Holdings (CH), Short-Term Debt (STD), Long-Term Debt (LTD), and Profitability (Profit). We also include firm characteristics that may affect during the crisis like Size, and Book-to-Market ratio (BTM). Finally we control for firm's Idiosyncratic Risk with measures of volatility of stock returns (STD_RET) and earnings (STD_EARN).

Is important to take into account that we want to see how the financial crisis induces negative mood. We are measuring negative mood by the raw count of negative words, but this negative words may be associated to a financial context rather than an emotional mood, for example the word ”restructuring” it is considered a negative word in a financial context but it is hard to think how it may be related to a negative mood. In our case, to measure pessimism we use LIWC which contains negative words in a psychological context rather than financial context as Loughran's dictionaries. If the LIWC negative dictionary contains 1,159 words only 292 of them are shared with Loughran's dictionary, meaning that only a quarter of the words are in both dictionaries. To isolate our measure of negative mood from financial negative terms we also control for the Loughran's negative tone measure (neg_L&M) in our analysis.

We also include industry dummies (defined at the two-digit SIC level) because some industries may be affected by the crisis in a different way than others and all standard errors are robust and clustered by firm. Thus the model we are going to test follows equation 4.

$$Pessimism = \alpha + \beta FinancialCrisis + Controls + Industry + \epsilon_{jt} \quad (4)$$

[3]We also run the same test for the variable Self-Focus even-though the validity of the shock for our approach relies on the effect it has on inducing pessimism. The results can be seen in table 5 as well.

Table 4: Definition of Variables we have used during the paper

Variable Name	Definition
Financial Crisis:	Dummy variable 1 from Augoust 2008 through March 2009, 0 otherwise
Industry Shock:	The weighted average rate of return in that quarter in the one-digit industry that firm belongs to, excluding the firm itself from the calculation. Divided in 5 quantiles, where 5 are the most negative shocks.
L&M Negative Tone:	Variable of negative tone using Loughran's dictionaries.
Size:	log(Market Value of Equity)
Book to Market Value:	(Price Close * Common Shares Outstanding) / Common Ordinary Equity
BM:	Dummy for firms with a negative Book to Market Ratio
Long-Term Debt:	Long Term Debt divided by Total Assets
Short-Term Debt:	Short term debt divided by Total Assets
Cash Holdings:	Total Cash divided by Total Assets
Profitability:	Retained Earnings divided by Total Assets
STD_RET:	Standard deviation of Returns over the last 6 months
STD_EARN:	Standard deviation of Earnings over the last 5 years
$\Delta EARN$:	Change in earnings before extraordinary items divided by Total Assets
Age:	log(1+number of years a firm appears in CRSP)
Loss:	Dummy variable 1 if EARN negative, 0 otherwise
Busseg:	log(1+number of Business Segments)
SUE:	firms currently quarterly earnings minus earnings of same quarter last year scaled by its standard deviation.
Momentum:	Cumulative returns over the last 4 quarters
Raw Returns:	Cumulative returns over the subsequent quarters
Abnormal Returns:	Realized Returns - Predicted Returns Fama&French 3-Factor Model [7]

Looking at table 5 we can see the results of the model. For the case of the pessimism variable the results are as we expected, the financial crisis works as a negative event and it fosters negative emotions. Moreover, we can observe that even if we include the control of Loughran's negative tone we still have a positive and significant effect. On the other hand, for the self-focus variable we have a negative correlation but the effect is not strongly significant as before. These result makes sense if we think the CEOs have a tendency talk less about themselves to attribute the negative shock away from them.

C. Validating Industry Shock

For the industry shock variable we group it in 5, where more negative shocks are in the highest group (Industry Shock 5). To see if these shocks plays the same roll as the financial crisis, in the sense of inducing negative emotions, we are going to test the following model:

$$Pessimism = \alpha + \sum_{i=0}^{5} \beta_i IndustryShock_{it-1} + Controls + Quarter + Industry + \epsilon_{jt} \quad (5)$$

Now we include quarter fixed effects to take into account the influence of time series trends. The results can be seen in table 5. For the case of industry shock there is a clear increase of the level of pessimism along with the intensity of the negative shock. We can also observe that the power explanation of the model increase when we add the control variables, meaning that the controls we considered are related with our variable of Pessimism and Self-Focus. After we observe all of this we can say that the shocks are inducing negative mood into the CEO, therefore they are valid to create a context to measure heterogeneity in CEO depressive tendencies.

Table 5: OLS where the dependent variable are Pessimism and Self-Focus.

	Financial Shock				Industry Shock			
	Pessimism	Pessimism	Self Focus	Self Focus	Pessimism	Pessimism	Self Focus	Self Focus
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Crisis Dummy	0.1251***	0.0634***	-0.0121**	-0.0100				
	(0.0049)	(0.0048)	(0.0057)	(0.0062)				
Industry Shock 2					0.0092	0.0035	-0.0014	-0.0033
					(0.0056)	(0.0053)	(0.0062)	(0.0062)
Industry Shock 3					0.0233***	0.0134**	-0.0021	-0.0031
					(0.0066)	(0.0062)	(0.0074)	(0.0074)
Industry Shock 4					0.0323***	0.0171**	-0.0025	-0.0063
					(0.0075)	(0.0070)	(0.0083)	(0.0083)
Industry Shock 5					0.0427***	0.0266***	0.0006	-0.0029
					(0.0079)	(0.0074)	(0.0094)	(0.0094)
L&M Negative Tone		0.4368***		0.0965***		0.4264***		0.0941***
		(0.0093)		(0.0139)		(0.0095)		(0.0142)
Size		0.0077***		0.0324***		0.0077***		0.0322***
		(0.0022)		(0.0035)		(0.0022)		(0.0036)
Book-to-Market, BTM		0.0000		0.0000		0.0000		0.0000
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Long-Term Debt, LTD		0.0498***		0.0165		0.0488***		0.0170
		(0.0181)		(0.0261)		(0.0181)		(0.0261)
Short-Term Debt, STD		-0.0186		0.1075*		-0.0230		0.1073*
		(0.0392)		(0.0615)		(0.0390)		(0.0615)
Cash Holdings, CH		-0.1472***		0.0376		-0.1479***		0.0387
		(0.0266)		(0.0376)		(0.0267)		(0.0377)
Profitability		0.0066***		-0.0039		0.0063***		-0.0039
		(0.0022)		(0.0025)		(0.0021)		(0.0025)
Idiosyncratic Risk, STD_RET		-0.0458***		-0.0262		-0.0594***		-0.0343**
		(0.0106)		(0.0163)		(0.0115)		(0.0173)
Idiosyncratic Risk, STD_EARN		-0.0005		0.0026		-0.0006		0.0026
		(0.0018)		(0.0031)		(0.0017)		(0.0032)
Constant	0.0503	-0.2411*	-0.0816	-0.4074*	0.3426**	-0.0158	-0.1035	-0.4249
	(0.1340)	(0.1346)	(0.2550)	(0.2255)	(0.1520)	(0.1452)	(0.2969)	(0.2716)
Year Fixed Effects	NO	NO	NO	NO	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES	YES	YES	YES	YES
N	42.627	42.627	42.627	42.627	42.620	42.620	42.620	42.620
Adjusted R^2	0.0839	0.2155	0.0563	0.0756	0.0949	0.2186	0.0576	0.0768

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01.

V. The Effects of Depression on Firm Performance

Now we are going to analyze how each CEO faces this negative shock from the models of depression we considered. We have seen in previous section how the shocks we used were fostering negative mood into the CEO. As the theory of depression would predict this negative mood induction activates depressive schemas in the vulnerable CEOs, for this reason the periods after the shocks are a good setting for distinguishing non-vulnerable to depression CEOs from vulnerable to depression CEOs. We can consider the shocks as a natural experiment that creates a context were we can distinguish better among depressed CEOs from non depressed ones. To measure depression we are going to consider the degree of pessimism but more important how the CEO canalize this pessimism using the variable of Self-Focus Attention. According to the theory under the same levels of pessimism CEOs with dysfunctional thinking would have a tendency to focus on themselves. Therefore we can say that when facing stress the individuals that uses higher levels of Self-Focus Attention would be considered as depressed. Once we have classified the level of depression of the CEOs, we hypothesize that more depress CEOs are going to exhibit lower performance which will be traduced in lower firm performance as well.

A. *Financial Crisis Shock*

First we consider the Financial Crisis Shock. Our variable of depression is going to be the combination of self-focus attention and negative tone. Our variable of pessimism is the same as in the previous section, for the case of Self-Focus variable we group it in 5 being more self-focus CEOs in the highest group (5) and the shock variable is a dummy as before that takes value 1 when we are in the crisis period. We are interested into analyze how the depression level is effecting the firm performance afterwords. To measure the firm performance we are going to consider the raw cumulative returns during one and two year buy-hold strategy.[4]. To estimate the effect of depression during the crisis period in subsequent performance the primary coefficient is going to be the triple interaction of Self-Focus, Pessimism and the Financial Shock, in our model see equation 6, are the coefficient β_1. This coefficient measures the differential effect of CEO self-focus and pessimism levels during the crisis period compared with non-crisis period. Therefore the regression has the following form:

$$\begin{aligned} RawReturns = \alpha + \sum_{i=0}^{5} \beta_{1i} self_i(t) * Pessimism(t) * Shock + \\ \sum_{i=0}^{5} \beta_{2i} self_i(t) * Pessimism(t) + \beta_4 Pessimism(t) * Shock + \\ \sum_{i=0}^{5} \beta_{3i} self_i(t) * Shock + \beta_5 Shock + \beta_6 Pessimism(t) + \\ Controls + Quarter + Industry + \epsilon_{jt} \end{aligned} \tag{6}$$

In this case we use the same controls as in the previous section, also we add the Momentum (the firm's raw return over the four periods before the Earnings Conference Call) and dummy for firms with a negative Book-to-Market ratio to take into account that this firms are likely distressed and hence their returns behave more like those of high book-to-market firms as (Lins, Servaes & Tamayo, 2017) [16]. We include industry dummies and cluster the standard errors by firm, this is going to be consistent during the paper.

The results can be seen in table 6. From the table we see how there is clear pattern, when we increase the level of self-focus attention the increase of pessimism worsen and translates in significant lower returns for the following quarters. As we go further in time this effect diminishes, when we take into account the subsequent 8 periods we still keep significance but with lower intensity. An interesting point is that when crisis time exhibiting pessimism is associated with higher subsequent returns as observed in variable β_4. These may tell us that reacting in a negative manner is something understandable and the problem may raise in the way CEOs canalize this negative emotions, if CEOs attribute this negativeness to themselves then bad performance comes.

An interesting test would be to consider what would happen if we measure depression when there is no crisis. We considered the crisis as a good setting to measure depression due to the negativeness it induces an the activation of the negative schemas in the vulnerable CEOs, but if we measure depression out of the crisis, when the negative schemas

[4] We also have considered in our analysis the Fama and French 3 and 5-factor model, see (Fama et al., 1992) [7]. We are not including the results in the present paper because they are very similar to the ones exposed here.

Table 6: OLS where the dependent variable are the Cumulative Raw Returns in the subsequent 4 and 8 periods.

	Cumulative Raw Return			
	(1)	(2)	(3)	(4)
	4 quarters	8 quarters	4 quarters	8 quarters
Pessimism	0.0364**	0.0704***	0.0138	0.0170
	(0.0156)	(0.0273)	(0.0162)	(0.0284)
Pessimism*Shock	0.4983***	0.7835***	0.4942***	0.7819***
	(0.0903)	(0.1497)	(0.0892)	(0.1471)
$\text{Self}_2 * Pessimism$	-0.0306	-0.0503	-0.0356*	-0.0587*
	(0.0204)	(0.0356)	(0.0204)	(0.0356)
$\text{Self}_3 * Pessimism$	-0.0284	-0.0104	-0.0313	-0.0156
	(0.0214)	(0.0372)	(0.0216)	(0.0373)
$\text{Self}_4 * Pessimism$	-0.0364	-0.0461	-0.0338	-0.0398
	(0.0229)	(0.0374)	(0.0231)	(0.0378)
$\text{Self}_5 * Pessimism$	-0.0287	-0.0403	-0.0228	-0.0289
	(0.0215)	(0.0398)	(0.0220)	(0.0408)
$\text{Self}_2 * Pessimism * Shock$	-0.2725**	-0.2496	-0.2785**	-0.2545
	(0.1390)	(0.2087)	(0.1373)	(0.2040)
$\text{Self}_3 * Pessimism * Shock$	-0.5141***	-0.5670***	-0.5131***	-0.5646***
	(0.1301)	(0.2119)	(0.1282)	(0.2075)
$\text{Self}_4 * Pessimism * Shock$	-0.3384**	-0.4523*	-0.3298**	-0.4356*
	(0.1436)	(0.2320)	(0.1417)	(0.2275)
$\text{Self}_5 * Pessimism * Shock$	-0.4331***	-0.6067*	-0.4246***	-0.5916*
	(0.1440)	(0.3127)	(0.1428)	(0.3092)
Controls	NO	NO	YES	YES
Quarter Fixed Effects	NO	NO	NO	NO
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	53.605	53.605	53.605	53.605
Adjusted R^2	0.0769	0.0823	0.0887	0.0976

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01. The omitted variables are the ones with i=1 and shock dummy equal 0. Thus the ones with low levels of self-attention and not in crisis times.

are dormant, would be difficult to identify the dysfunctional thinking. To consider this setting we create three samples, one for the observations that belong to the financial crisis period, another for observations after the financial crisis period and the last one all observations that are not during the financial crisis. In this case we consider the same model as before but now since we are separating samples the variable of shock is not necessary. The model therefore has the following form of equation 7 and the results are presented in table 7, where we consider as independent variable the Cumulative Raw Returns[5].

$$RawReturns = \alpha + \sum_{i=0}^{5} \beta_{1i} self_i(t) * Pessimism(t) + \sum_{i=0}^{5} \beta_2 self_i(t) + \beta_3 Pessimism(t) + Q + I + \epsilon_{jt} \tag{7}$$

Table 7: OLS where the dependent variable are the Cumulative Raw Returns in the subsequent 4 periods.

	Cumulative Raw Return subsequent 4 quarters			
	(1)	(2)	(3)	(4)
	During Crisis	During Crisis	Post-Crisis	Out-Crisis
Pessimism	0.3305***	0.3432***	0.0533**	0.0222
	(0.1029)	(0.0992)	(0.0242)	(0.0199)
$\text{Self}_2 * Pessimism$	-0.3790**	-0.3915***	-0.0406	-0.0320
	(0.1530)	(0.1468)	(0.0309)	(0.0256)
$\text{Self}_3 * Pessimism$	-0.5678***	-0.5804***	-0.0260	-0.0223
	(0.1382)	(0.1312)	(0.0324)	(0.0268)
$\text{Self}_4 * Pessimism$	-0.4137**	-0.3744**	-0.0323	-0.0298
	(0.1633)	(0.1497)	(0.0333)	(0.0280)
$\text{Self}_5 * Pessimism$	-0.4613***	-0.4288***	-0.0321	-0.0188
	(0.1676)	(0.1623)	(0.0335)	(0.0281)
Controls	NO	YES	YES	YES
Quarter Fixed Effects	NO	NO	NO	NO
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	4.239	4.239	23.177	33.388
Adjusted R^2	0.2491	0.3247	0.0280	0.0183

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01. The omitted variables are the ones with i=1 and shock dummy equal 0. Thus the ones with low levels of self-attention and not in crisis times.

We can see the results are as we expected, when we are in the crisis time the measure of depression has relevance in identifying subsequent firm performance but when we are not in a crisis period the fact that CEOs show greater Self-Focus Attention and pessimism does not allow us to distinguish vulnerable from non-vulnerable individuals. The fact that we lose significance when we are out of the crisis period goes in the argumentation we just exposed. Another aspect to take into account is the fact that the Adjusted R^2 which can be interpreted as the amount the dependent variable is explained by our model, we can see that when we are in crisis the ability to explain the subsequent abnormal returns is greater. This may be interpreted as the depression dimension being more relevant during crisis periods than in normal times.

B. Industry Shock

Now instead of considering the financial crisis shock that may be interpreted as a big universal shock into the market we can think about a more specific shock, like industry

[5]For simplicity we only consider the Cumulative Raw Returns in the subsequent 4 quarters but we can obtained similar results for the subsequent 2 and 8 quarters. We exclude the firms that are in the financial sector for this analysis as the paper by (Lins, Servaes & Tamayo, 2017) [16]

shock. In this case the shock is industry specific and also exogenous to the CEOs previous performance. To see how depression is affecting the firm with this new shock we are going to use the the same model as we presented before for the financial crisis, see equation 6.

Table 8: OLS where the dependent variable are the Cumulative Raw Returns in the subsequent 4 periods.

	Cumulative Raw Return			
	(1)	(2)	(3)	(4)
	4 quarter	8 quarter	4 quarter	8 quarter
Pessimism	0.0109	0.0084	-0.0051	-0.0236
	(0.0206)	(0.0356)	(0.0211)	(0.0368)
Pessimism*IndustryShock	0.1593***	0.2660***	0.1588***	0.2652***
	(0.0362)	(0.0605)	(0.0359)	(0.0600)
$\text{Self}_2 * Pessimism$	-0.0131	-0.0455	-0.0220	-0.0617
	(0.0262)	(0.0426)	(0.0263)	(0.0429)
$\text{Self}_3 * Pessimism$	0.0212	0.0468	0.0153	0.0350
	(0.0285)	(0.0470)	(0.0287)	(0.0470)
$\text{Self}_4 * Pessimism$	-0.0248	-0.0300	-0.0186	-0.0195
	(0.0299)	(0.0444)	(0.0300)	(0.0445)
$\text{Self}_5 * Pessimism$	-0.0138	-0.0444	-0.0060	-0.0307
	(0.0271)	(0.0497)	(0.0277)	(0.0503)
$\text{Self}_2 * Pessimism * IndustryShock$	-0.1019*	-0.0972	-0.0975*	-0.0895
	(0.0530)	(0.0908)	(0.0523)	(0.0899)
$\text{Self}_3 * Pessimism * IndustryShock$	-0.2142***	-0.3110***	-0.2071***	-0.2965***
	(0.0514)	(0.0853)	(0.0510)	(0.0843)
$\text{Self}_4 * Pessimism * IndustryShock$	-0.1383**	-0.2183**	-0.1362**	-0.2143**
	(0.0562)	(0.0939)	(0.0555)	(0.0927)
$\text{Self}_5 * Pessimism * IndustryShock$	-0.1684***	-0.2299**	-0.1675***	-0.2283**
	(0.0544)	(0.1088)	(0.0538)	(0.1074)
Controls	NO	NO	YES	YES
Quarter Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	40.223	40.223	40.223	40.223
Adjusted R^2	0.2209	0.2002	0.2313	0.2156

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01. The omitted variables are the ones with i=1 and shock dummy equal 0. Thus the ones with low levels of self-attention and not in crisis times.

Our variable of shock now comes from the weighted average rate of accounting return in a given quarter in the one-digit industry that firm belongs to, meaning that now we have a continuous variable of shock. To convert it into a dummy variable we divide it into quantiles of five and we consider the two bottom quantiles as the ones receiving a shock, then this observations would have one in the dummy variable shock and the other ones zero. One particularity now is that the shock now varies in time $Shock(t)$, also we include time fixed effects. To estimate the effect of depression after a negative shock in subsequent performance the primary coefficient is going to be the triple interaction of Self-Focus, Pessimism and the Industry Shock. These coefficients are the β_1, which measures the differential effect of CEO self-focus and pessimism levels after an industry shock compared with non-industry shock ones, see table 8.

We can see similar patterns as in the case of financial crisis, when firm receives a shock higher levels of pessimism are associated with higher subsequent returns. But when we interact the effect of self-focus attention with the pessimism we observe that when a CEO is focused in himself the impact in subsequent returns are negative. This results support the depression theory as well, when stressful events occur the dysfunctional thinking are activated and we are able to distinguish vulnerable from non-vulnerable CEOs, subsequently fimrs with depressive CEOs are associated with lower performance. We can also consider what would happen if we do the analysis considering different samples, one for the observations that experienced a shock and another for the ones that did not. In this case we consider the same model as before, see 7, and the results are presented in table 9. The results follow our intuition regarding the theory of depression, when we are under the effect of a shock the relevance of our estimates appear to matter as oppose to the case of normal times. We also run the regression for the sample excluding the financial crisis period (3)-(4) and we still keep significant values though we observe a reduction of it, this may tell us about the relevance of the financial crisis as a shock.

Table 9: OLS where the dependent variable are the Cumulative Raw Returns in the subsequent 4 periods.

	Cumulative Raw Return subsequent 4 quarters					
	(1)	(2)	(3)	(4)	(5)	(6)
	After Shock	After Shock	After Shock	After Shock	No Shock	No shock
Pessimism	0.1600***	0.1274***	0.0755***	0.0666***	0.0040	0.0042
	(0.0317)	(0.0315)	(0.0223)	(0.0229)	(0.0202)	(0.0207)
$Self_2 * Pessimism$	-0.1121**	-0.1229***	-0.0658*	-0.0681*	-0.0026	-0.0057
	(0.0450)	(0.0447)	(0.0356)	(0.0352)	(0.0259)	(0.0260)
$Self_3 * Pessimism$	-0.1927***	-0.1951***	-0.0753**	-0.0755**	0.0311	0.0290
	(0.0428)	(0.0425)	(0.0340)	(0.0341)	(0.0281)	(0.0280)
$Self_4 * Pessimism$	-0.1605***	-0.1516***	-0.0833**	-0.0798**	-0.0248	-0.0243
	(0.0470)	(0.0461)	(0.0369)	(0.0369)	(0.0295)	(0.0294)
$Self_5 * Pessimism$	-0.1834***	-0.1734***	-0.0682**	-0.0659*	-0.0084	-0.0067
	(0.0500)	(0.0489)	(0.0343)	(0.0342)	(0.0274)	(0.0273)
Controls	NO	YES	NO	YES	NO	YES
Quarter Fixed Effects	YES	YES	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES	YES	YES
Sample including Financial Crisis Period	YES	YES	NO	NO	YES	YES
N	17.588	17.588	13.358	13.358	24.036	24.036
Adjusted R^2	0.2249	0.2497	0.2647	0.2702	0.2029	0.2048

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01. The omitted variables are the ones with i=1 and shock dummy equal 0. Thus the ones with low levels of self-attention and not in crisis times.

C. Abnormal Tone Strategy

Lastly we are going to consider another strategy. Now instead of looking for a shock we can try to see which CEOs are exhibit higher levels of pessimism relative to other within the same circumstances, this may give us some information about some individual negative events that CEOs are experiencing. Then we test how the Self-Focus Attention interacts with CEOs that show abnormal degrees of pessimism. For this, we are going to calculate the abnormal tone, understood as the difference of the reaction of the CEO with the reaction of the average CEO in his circumstances, following the paper by (Huang, Teoh & Zhang, 2013) [12]. Here they first estimate the model parameters where the dependent variable is the text tone (in our case would be the level of pessimism) and the independent variables are firm characteristics. After they have calculated the values of the parameters in the model they are able to predict for a given firm characteristics what would be the Normal Tone using this model. And the difference between this Normal Tone predicted by the model and the Tone actually observed in the data is called the

Abnormal Tone. To predict the tone they use an annual cross-sectional regression of Tone on tone determinants suggested by (Li, 2010)[15], this determinants are measures for current available fundamental information, growth opportunities, operating risks, and complexity. Specifically, the regression is:

$$\begin{aligned} Tone = \alpha + \beta_0 EARN + \beta_1 RET + \beta_2 SIZE + \beta_3 BTM + \\ \beta_4 STD\_RET + \beta_5 STD\_EARN + \beta_6 AGE + \beta_7 BUSSEG + \\ \beta_8 GEOSEG + \beta_9 LOSS + \beta_{10} \Delta EARN + \beta_{11} FinCrisis + \epsilon_{jt} \end{aligned} \tag{8}$$

The model determinants are selected to control for information about firm fundamentals, we consider profitability (EARN) and earnings performance benchmarks (LOSS and ΔEARN) to capture the cashflows generated during the current period. We also exploit the forward-looking property of market variables, stock returns (RET) and book-to-market ratio (BTM) to capture information about growth and the present value of consequent future cash flows beyond what is conveyed by current accounting numbers. We also include some measures of idiosyncratic risk (STD_EARN and STD_RET) to proxy for operating and business risk. For include operating complexity we use the number of business and geographic segments (BUSSEG and GEOSEG). Lastly we include another determinant that is not considered in the paper by Li, the financial crisis dummy because the period of crisis is related to the average tone exert. The results of the model are presented in table 10:

Table 10: OLS where the dependent variable is Pessimism.

		Pessimism			
Indep. Variable	Coefficient	s.e.	Indep. Variable	Coefficient	s.e.
α	-0.0840***	(0.0102)	STD_EARN	-0.0018	(0.0016)
EARN	0.0085***	(0.0012)	AGE	0.0008***	(0.0001)
RET	-0.0658***	(0.0101)	BUSSEG	0.0376***	(0.0033)
FinCrisis	0.1179***	(0.0052)	GEOSEG	0.0360***	(0.0095)
SIZE	-0.0068***	(0.0010)	LOSS	-0.0461***	(0.0036)
MTB	0.0000**	(0.0000)	Δ EARN	-0.0094***	(0.0035)
STD_RET	0.0629***	(0.0202)			
Number of obs: 52.196; Adjusted R^2 : 0.0310					

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01.

Using the previous model we can predict the Abnormal Tone which would be the residual of the regression, thus the difference between the realized tone and the predicted tone. Once we have the Abnormal Tone variable we can see how the interaction of this variable with Self-focus attention variable affects future performance of the firm. To do this we can test the regression in equation 10 for for n=4 and 8, this time we also have considered in our analysis abnormal returns calculated with the Fama and French 3-factor model, see (Fama et al., 1992) [7].

$$\begin{aligned} RawReturns = \alpha + \sum_{i=0}^{5} \beta_{1i} self_i(t) * AbnormalTone(t) + \\ \sum_{i=0}^{5} \beta_2 self_i(t) + \beta_3 AbnormalTone(t) + Controls + Q + I + \epsilon_{jt} \end{aligned} \tag{9}$$

We can see similar patterns as with the exogenous shocks in table 11, when CEO shows higher levels of Abnormal Tone, meaning levels of pessimism that are above the normal Tone. Then the Self-Focus attention by the CEO are associated with the subsequent returns. But when we interact the effect of self-focus attention with the Abnormal Tone we observe that when a CEO is focused in himself the impact in subsequent returns are negative. In this case we can see that the slope for the estimate of interest β_1 is increasing along with the intensity of Self-Focus attention variable, even if we consider abnormal returns. The theory of depression that we have exposed would be supported but this results.

Table 11: OLS where the dependent variable are the average returns in the subsequent 4 and 8 periods.

	Raw Returns		Abnormal Returns	
	(1)	(2)	(3)	(4)
	4 quarter	8 quarter	4 quarter	8 quarter
AbnormalTone	0.0619***	0.0947***	0.0488***	0.0612**
	(0.0195)	(0.0360)	(0.0164)	(0.0245)
$\text{self}_2(t) * AbnormalTone$	-0.0669***	-0.1039**	-0.0567***	-0.0871***
	(0.0247)	(0.0449)	(0.0207)	(0.0302)
$\text{self}_3(t) * AbnormalTone$	-0.0793***	-0.1058**	-0.0615***	-0.0673**
	(0.0256)	(0.0452)	(0.0219)	(0.0312)
$\text{self}_4(t) * AbnormalTone$	-0.0772***	-0.1121**	-0.0739***	-0.0912***
	(0.0268)	(0.0467)	(0.0229)	(0.0315)
$\text{self}_5(t) * AbnormalTone$	-0.0852***	-0.1411**	-0.0747***	-0.1161***
	(0.0275)	(0.0559)	(0.0233)	(0.0374)
Control variables	YES	YES	YES	YES
Quarter Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	39.690	39.690	39.690	39.690
Adjusted R^2	0.2325	0.2151	0.0358	0.0527

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01.

D. Market Reaction

So far we have think about the subsequent return in a range of one to two years, this makes sense because the effect of the depressive CEO in the firm performance should be something that takes time to consolidate. The main reason is that we are considering that one of the most important context where the CEO affects the firm is when we refer to strategic and complex decisions rather than mechanical ones. This decisions outcomes are observe in the long run. Now we need to consider the fact that analyst may anticipate the effect of CEOs depressive state in future performance of the firm, then analyst would update their valuation of the firm when attend the Earnings Conference Calls. If this happens we should expect movements in the returns around the date of the meeting. To study the ability of analyst in capturing the emotional state regarding depression of CEOs we run the following regression:

$$CR[-1,+1] = \alpha + \sum_{i=0}^{5} \beta_{1i} self_i(t) * (AbnormalTone/Pessimism) + \sum_{i=0}^{5} \beta_2 self_i(t) + \beta_3 (AbnormalTone/Pessimism) + Controls + T + I + \epsilon_{jt} \tag{10}$$

In this case the dependent variable are the cumulative results from one day before the event takes place until one day after, in this manner we can observe reactions in the returns around the date of the event. As controls we use the ones that have been considered in previous literature influencing the event price reactions , see (Huang, Teoh & Zhang, 2013) [12]. In particular we take into account the variables we mentioned before like profitability, size and idiosyncratic risk. Also, we include as proxy for the quantitative news the variable SUE (firms current quarterly earnings minus earnings of the same quarter last year, scaled by the market value of the beginning of the quarter). The results are presented in table 12.

Table 12: OLS where the dependent variable is the Cumulative Return around the Event.

	CR[-1,+1]			
	(1) Financial Crisis	(2) Industry Shock		(3) AbnormalTone
Pessimism	-0.0115	-0.0041	AbnormalTone	-0.0075***
	(0.0107)	(0.0038)		(0.0024)
$\text{Self}_2 * Pessimism$	-0.0035	-0.0005	$\text{Self}_2(t) * AbnormalTone$	-0.0057
	(0.0155)	(0.0055)		(0.0042)
$\text{Self}_3 * Pessimism$	0.0032	-0.0044	$\text{Self}_3(t) * AbnormalTone$	-0.0051
	(0.0156)	(0.0056)		(0.0035)
$\text{Self}_4 * Pessimism$	-0.0070	-0.0021	$\text{Self}_4(t) * AbnormalTone$	-0.0026
	(0.0162)	(0.0058)		(0.0037)
$\text{Self}_5 * Pessimism$	-0.0047	0.0040	$\text{Self}_5(t) * AbnormalTone$	0.0019
	(0.0177)	(0.0061)		(0.0038)
Control variables	YES	YES		YES
Quarter Fixed Effects	YES	YES		YES
Industry Fixed Effects (2-digits)	YES	YES		YES
N	5.192	22.857		43.546
Adjusted R^2	0.2019	0.3021		0.3420

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01.

The results do not show any kind of direction regarding our variable of interest. It seems that analyst are not able to extract the information about CEOs depressive tendencies. This makes sense because what we are considering as proxies for dysfunctional thinking are quite subtle for a non experienced person in this field. So the information is not updated through the market after the Earnings Conference Call but through time when CEOs actions take place.

VI. Comments

We rooted our analysis on the depression theories and we considered the negative shocks to a company as a natural experiment to test depression and how this CEO characteristic is related to the firm. The results we obtained are in line with what we expected, giving us room to keep working on this direction. But the results presented so far are preliminary, therefore in the following weeks we are going to work to refine the analysis and test the robustness of the results. Therefore is important to keep in mind that this is an early stage paper which, serves as a proposal of the work we would like to present in the XIV International Accounting Symposium, but it is going to be further developed from now until the event will take place.

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