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

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Abstract

This work measures CEO depression levels and relate it to firm performance. The first hypothesis we test is that negative exogenous shocks to a company foster depression sentiments in the CEO. And the second hypothesis we assess in this paper is how after a negative shock, firms with lower depressed CEO 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 use text analysis on the Earnings Conference Call transcripts. And regarding the exogenous shocks, we 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 obtain are going in the direction we expect following our argumentation.

I. Introduction

Depression is a common and serious medical illness that negatively affects the way a person feels, acts and behaves. We often see cases of how depression disorders affect the performance of students at university or employees at work. According to the American Psychiatric Association one in six people will experience depression at some time in their life. And some studies show that for the case of women one-third will experience a major depressive episode in their lifetime. The rise of depression is generally associated with negative environmental factors. Negative events in live are promoting the activation of depressive mood.

A natural question in a firm context is, how adverse circumstances are affecting the emotional well-being of the managers, in particular the CEO. This study hypothesize (First Hypothesis) and test that negative event to a company fosters depressive feelings to its CEO. Moreover, a more relevant question, in terms of economic interest, is how

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the depression tolerance of the CEO affects the firm. To answer this question we test the second hypothesis of this paper; After the firm experience a negative shock, firms with more vulnerable to depression CEOs show lower subsequent performance.

To measure depression we analyze the word usage of the CEOs during the Earnings Conference Calls to capture language patterns associated with depression. And as a negative and exogenous shocks to the company we use the Financial Crisis and industry shocks, in addition we also consider the abnormal tone approach. The results we obtained in this work support the two hypothesis we mentioned, the present paper gives evidence on the CEO's emotional state affecting the firm and vice versa. In the following sections we can see developed the argumentation and analysis employed to answer these questions.

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 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 more complete 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 crucial 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 current risk by only considering the fundamentals. As (Mayew and Venkatachalam (2012)) 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 recent years. We can think on the work of (Tetlock et al. (2008)), where it investigates how information contained in language can be used to predict individual firms' accounting earnings and stock returns. Also (Tetlock (2007)) 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 and Wang (2017)), 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 deceptive CEO realizes some news. A working paper by (Hrazdil et al. (2018)), also uses text analysis to determine the personality of the CEO. With this measure the paper 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 and Mason (1984)) 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 and March (1963)). 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.

There are also more recent works that support this idea like (Bertrand and Schoar (2003)), 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 traits. 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 frequent and serious medical illness that negatively affects how a person feels, the way he thinks and how he acts. 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 analyze the verbal content of the earnings conference calls transcripts[1]. Previous literature has already found evidence on language usage characteristics of depressed people. In the paper of (Rude et al. (2004)) 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.

[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.

D. Hypothesis

One of the reasons of depression are environmental factors, negative shocks in live could be the cause of becoming depressed. We can cite here the paper by (Rude et al. (2004)): “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 dies or an unexpected illness arises, all these are circumstances that can induce a person becoming depressed.

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 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 lower levels of depression) would be more able to handle the situation and in consequence the firm recovers from the shock in a better way. This is the second hypothesis we test:

H2: After a negative shock, firms with more resilient CEO (lower levels of depression) 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 the CEO to absorb negative news is affecting future firm’s ability to handle the crisis.

II. Data

In this section we describe the characteristics of the data we use during the current research. 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 that makes it easy for parsing the text. In addition, we use data from WRDS[3] in order to obtain firm fundamentals, in particular the data-sets of CRSP, Compustat and Segments.

A. Description of the ”Raw” Data

Our most primitive data-set, regarding the transcripts, contains 311,658 files. From these files, there are some that are a brief version of the transcripts, we only consider

[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.

[3]Wharton Research Data Services

the full transcripts. Therefore our sample becomes a total of 240,827 documents. Within this later sample we have different types of meetings, see panel A of table 1.

Table 1: Descriptive Statistics.

Panel A: Conference Calls by Event Type				Panel B: Conference Calls by Industry Sector		
Type ID	Event Type	Freq.	Percent	Industry Classification	Freq.	Percent
1	Earnings Conference Call	172,593	71.67	Agriculture, Forestry, And Fishing	150	0.17
5	Conference Call	11,290	4.69	Construction	1,139	1.27
7	Conference	36,179	15.02	Finance, Insurance, And Real Estate	15,087	16.76
25	Federal Goverenment	6,639	2.76	Manufacturing	37,145	41.27
33	Sales Conference Call	4,733	1.97	Mining	4,125	4.58
	Other	9,393	3.9	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	240,827	100	Total	90,003	100

Panel C: Summary Statistics

Variable	Source	Num. Obs.	Mean	Std. Dev.	Min	Max
Returns	CRSP	91,293	0.012	0.147	-0.526	0.917
Shares Outstanding	CRSP	91,701	171,463	454,132	3,578	6,725,000
Long Term Debt	Compustat	93,975	1,731	4,715	0	37,707
Debt in Current Liabilities	Compustat	88,567	538	2,166	0	18,994
Cash	Compustat	56,517	499	1,413	0	10,977
Retained Earnings	Compustat	91,512	1,437	4,508	-3,950	35,774
Total Assets	Compustat	94,769	11,812	39,522	0.832	371,933
Market Value	Compustat	63,753	4,533	10,940	2.80	77,450
Common Shares Outstanding	Compustat	94,181	240	810	0	29,206
Price Close - Quarter	Compustat	95,297	26	21.3	0	127.6
Common/Ordinary Equity	Compustat	94,403	2,534	6,080	-529	52,454
Number of Business Segments	Segments	25,640	5.5	3.83	1	20

This table presents some descriptive statistics of the data we use in this paper. In panel A we have the different types of meetings we can find in the former data, as we mentioned in section II.A in this paper we only consider type 1 events, Earnings Conference Call. In panel B we can see the industry distribution of our data, the industry classification variable is obtained after the merge of the transcripts with WRDS, then the number of observations is lower than the previous panel. Lastly, the panel C is a summary statistic of the variables we use from WRDS in the paper, all of them are winzorized at the 1st and 99th percentiles.

For our analysis we 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 when running the codes. This means that our sample is reduced to 172,593 documents, all of them being transcripts of Earnings Conference Calls.

B. Earnings Conference Calls

Now we 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. There are few observations from 2002 and backwards, thus we exclude data below 2003 in all our analyses. Also seems that 2012 is incomplete because the data comes that year, in fact from 2012 we only have data on the first six months.

We use the sample of Earnings Conference Calls to analyze the tone of the text. The first step is to count the frequency of each word in all the texts, to find out the likelihood of a word to appear. This measure calibrates the usage of words in

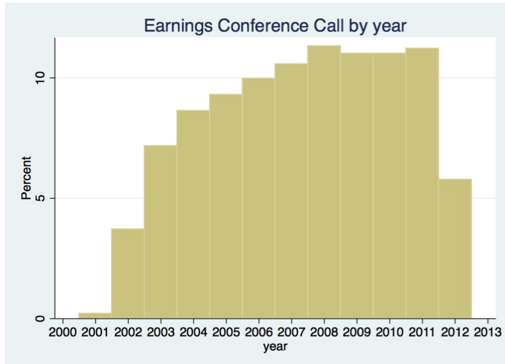


Figure 1: Frequency of Earnings Conference Call per year

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

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

C. Earnings Conference Calls merged with Compustat and CRSP

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 identifier we are able to match 3,751 CUSIPs with Compustat, 3,441 CUSIPs with CRSP and 3,287 CUSIPs with both data-sets. Finally, we end up with a sample of 90,003 observations with data on both CRSP and Compustat. We can see in panel C of table 1 the summary statistics of the variables we use during this research. We winzorize the variables coming from WRDS at the 1st and 99th percentiles also all the variables we create during the paper.

Once merged with WRDS we can also have further characteristics of the firm like the industrial sector it belongs to. In panel B of table 1 we can see the distribution of observations by sector.

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 and Abramson (1983)) 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)) 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 (Jeanne et al. (1998)) 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)). 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 consists 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[4]. 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)). 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)). 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

[4]Cognitive load task; is an attention-demanding secondary task that the participants needs to perform simultaneously with the main task.

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)) 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 and Greenberg (1981)) 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 this 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 examined the linguistic patterns of depressed and depression-prone individuals. A paper by (Stirman and Pennebaker (2001)) 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 theory 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 non-suicidal poets. Although they do not measure depression directly, it seems reasonable to think that suicidal poets were more depressed than the non-suicidal ones.

We can also find papers that do focus their study into depression, one example is the paper by (Rude et al. (2004)), 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 section part A, we end up with a sample of 172.593 Earnings Conference Calls of type 1. These sample is the one we work with text analysis. There are different text analysis techniques, but we focus on the one that uses dictionaries in line with (Loughran and McDonald (2011)). 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 occurrence 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 we calculate the tone of a given text coincides with the paper we just mentioned but the dictionaries are different. The dictionaries are coming from the LIWC (Linguistic Inquiry and Word Count; see, Tausczik and Pennebaker (2010)), which contains a set of dictionaries for different dimensions. Since we are interested in measuring depression using text analysis we focus our attention on (Rude et al. (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.

We calculate two variables and later, using this two variables, we characterize the level of depression. Our first variable is one that measures the level of pessimism of a text. In this case we 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 use three dictionaries one that contains words that are negative balanced, another with words that are positive balanced and lastly a bag of social related words. To have a normalized measure we group by 1000 as if

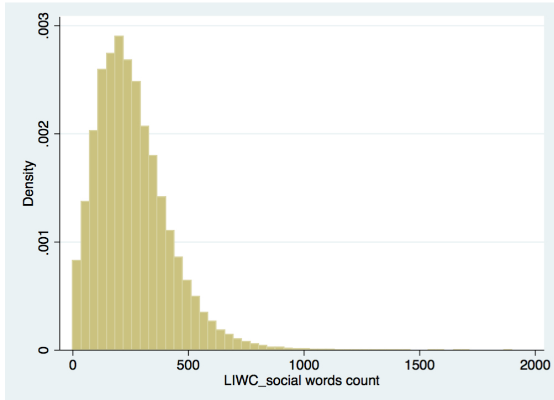


Figure 2: Distribution of Social words count per document

percentiles these measures and divide by 1000, then we obtain normalized variables that range from 0 to 1. This way of normalizing variables have appeared in previous works, see (Bernard and Thomas (1990)). Finally, after we have normalized all our variables we calculate a total measure of the tone using the formula 2:

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

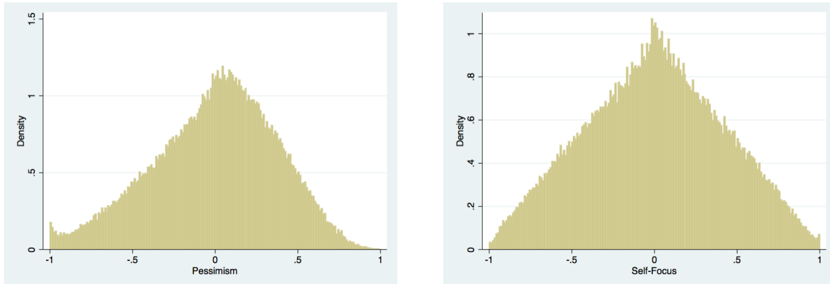
The second variable captures the self-focus attention. In this case we consider the 1º person of singular words and the 1º person of plural words. The difference from the previous one is that now we work with the raw count rather than the weighted one. The reason is that now we are counting words like ”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 remains similar to the previous one, we normalize and then we calculate the self-focus attention using the following equation:

$$SelfFocusAttention = 1^{st} personofsingularwords - 1^{st} personofpluralwords \tag{3}$$

With these two measures we 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. In figure 3 we can observe the distribution of our variables across all the transcripts.

IV. Shocks Inducing Negative Mood

The main idea of finding a negative shock is to have a framework where the level of stress is higher. According to the literature of depression we reviewed during periods of normal times we may not be able to distinguish depressive patterns in vulnerable CEOs because these are dormant. To detect heterogeneity in our measures of depression, it is important that we measure depression in the appropriate moment. Moreover we need to take into account that the negative shock to the company could be caused by a prior



(a) Distribution of Pessimism (b) Distribution of Self-Focus

Figure 3: Distribution of our variables of depression

bad performance of the CEO, we can think the CEO perform poorly due to depression and thus the firm experience a negative shock which will reinforce the depression level of the CEO. This fact raises endogenous problems since we are not able to disentangle the pure cause of the negative shock into the depression sentiments of the CEO. For this reason we consider two exogenous shocks, in this way we can identify causality of the shock on depression.

The first shock is going to be the Financial Crisis shock, based on the paper by (Lins et al. (2017)). In this paper the authors study how firm trust is more valued when the general level of trust in corporations and markets decrease. One of the challenges they face is to find an exogenous variation of trust. To solve this problem they consider the crisis period from August 2008 through March 2009 as an exogenous variation of public trust in corporations, capital markets and institutions. We also can use this big universal shock to see how interacts with our measures of text analysis, in our case the financial crisis would be a period where the levels of pessimism and stress are higher.

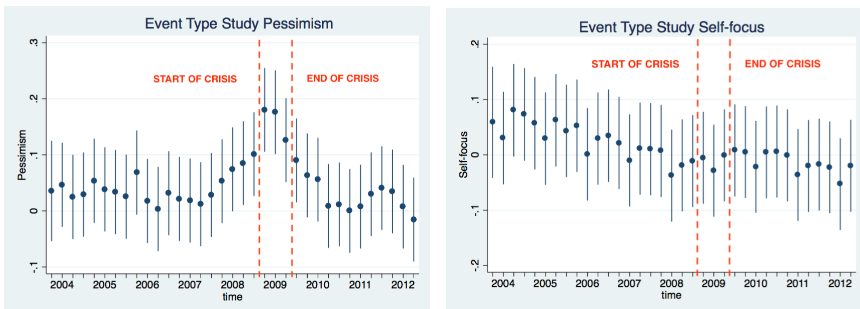
In addition, we also consider another shock, the mean performance of the industry, following the paper by (Bertrand and Mullainathan (2001)). In this paper they analyze if the pay received by the CEO is not tied to luck, being luck an observable shock to performance beyond the CEO's control. One of the 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 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. As the paper by (Jeanne et al. (1998)) 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. Therefore one way we can see if our shocks are valid is considering if they induce pessimism.

B. *Validating Financial Crisis Shock*

First we 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 mentioned before, we can observe some interesting movements, see picture 4. 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. In the case of the self-focus attention variable, there is no change during the crisis, what we can observe is a negative trend all along the time horizon of our data.



(a) Event Type Study Pessimism

(b) Event Type Study Self-focus

Figure 4: Event type study of the two variables

To see more clearly the effect of the financial shock in the level of pessimism[5] 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 variables 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. (2009)), 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 (EARN). We also include firm characteristics that may be important for stock returns like Size, and Book-to-Market ratio (BTM). Moreover we add a dummy for firms with a negative Book to Market ratio (BM), as those firms are likely distress and their returns may behave more like high book to market firms. Finally we control for firm's Idiosyncratic Risk with measures of volatility of stock returns (STD_RET) and earnings (STD_EARN) that proxy for operating and business risk environment of the company. The definition of the variables we have mentioned and all the ones we use during the current research are described in table 2.

Is important to take into account that we want to see how the financial crisis induces negative mood. One of the components of our measure of pessimism is the 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

[5]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 3 as well.

Table 2: Definition of Variables we have used during the paper

Variable Name	Definition
Pessimism:	Variable of pessimism we described previously it uses dictionaries from LIWC of negative balanced words, positive balanced words and social references words
self-focus Attention:	Variable of self-focus we described previously it uses dictionaries from LIWC of 1º person of singular and 1º person of plural
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 scaled by Total Assets
Short-Term Debt:	Short term debt scaled by Total Assets
Cash Holdings:	Total Cash scaled by Total Assets
Profitability:	Retained Earnings scaled 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 scaled 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 3-Factor Model (see, Fama and French (1992))

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 analyses.

We 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[6]. Thus the model we test follows equation 4.

$$Pessimism_{jt} = \alpha + \beta FinancialCrisis + Controls_{jt} + Industry + \epsilon_{jt} \qquad (4)$$

Looking at table 3 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 including controls we still have a positive and significant effect. The correlation of our measure of depression and the Loughran's negative tone measure is positive, this is correct because we mentioned that they share some common words. Regarding other controls we can see as an example that cash is negatively correlated to our measure of depression,

[6]These is consistent in all the models we test in this paper.

a way to understand this is to think that enjoying a higher edge of cash may reduce the negativeness exhibited by the CEO. On the other hand, for the self-focus variable we have a negative correlation but with no significance. The negative sign makes sense if we think that the CEOs have a tendency to talk less about themselves when things are going wrong to attribute the negative events away from them. The explanatory power of the model when we add the controls for the variable of pessimism increases considerably (from 9% to 21%), meaning that our variable of tone is related to some of the controls we add. For the case of self-focus this effect is much smaller.

Table 3: 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	0.1408***	0.0747***	-0.0080	-0.0057				
	(0.0054)	(0.0052)	(0.0060)	(0.0066)				
Industry Shock 2					0.0126**	0.0053	0.0003	-0.0008
					(0.0061)	(0.0057)	(0.0065)	(0.0064)
Industry Shock 3					0.0228***	0.0138**	-0.0042	-0.0042
					(0.0072)	(0.0068)	(0.0079)	(0.0079)
Industry Shock 4					0.0351***	0.0201***	-0.0041	-0.0070
					(0.0082)	(0.0075)	(0.0087)	(0.0087)
Industry Shock 5					0.0438***	0.0282***	-0.0028	-0.0064
					(0.0087)	(0.0081)	(0.0096)	(0.0097)
L&M Negative Tone		0.4380***		0.0937***		0.4266***		0.0907***
		(0.0103)		(0.0147)		(0.0105)		(0.0149)
Size		0.0110***		0.0329***		0.0102***		0.0322***
		(0.0026)		(0.0039)		(0.0027)		(0.0039)
Book-to-Market, BTM		-0.0033***		-0.0008		-0.0031***		-0.0008
		(0.0010)		(0.0016)		(0.0010)		(0.0016)
BM		-0.1080***		-0.0466		-0.1041***		-0.0466
		(0.0282)		(0.0433)		(0.0283)		(0.0434)
Long-Term Debt, LTD		0.1201***		0.0394		0.1202***		0.0423
		(0.0250)		(0.0373)		(0.0251)		(0.0373)
Short-Term Debt, STD		-0.0034		0.2070**		-0.0063		0.2079**
		(0.0604)		(0.0913)		(0.0605)		(0.0913)
Cash Holdings, CH		-0.1160***		0.0590		-0.1160***		0.0619
		(0.0318)		(0.0429)		(0.0319)		(0.0431)
Profitability		0.0150***		0.0023		0.0137***		0.0018
		(0.0046)		(0.0067)		(0.0046)		(0.0067)
Idiosyncratic Risk, STD_RET		-0.0768*		-0.1082*		-0.1577***		-0.1621**
		(0.0392)		(0.0565)		(0.0482)		(0.0703)
Idiosyncratic Risk, STD_EARN		0.0123		0.0402**		0.0117		0.0405***
		(0.0100)		(0.0156)		(0.0100)		(0.0157)
Constant	0.0411	-0.2861**	-0.0854	-0.4146*	0.2915*	-0.0793	-0.1398	-0.4736*
	(0.1253)	(0.1265)	(0.2562)	(0.2251)	(0.1542)	(0.1409)	(0.3115)	(0.2847)
Quarter Fixed Effects	NO	NO	NO	NO	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES	YES	YES	YES	YES
N	39,145	39,145	39,145	39,145	39,132	39,132	39,132	39,132
Adjusted R^2	0.0815	0.2078	0.0574	0.0786	0.0934	0.2116	0.0589	0.0800

This table presents regression estimates for the dependent variables Pessimism and self-focus on Financial Crisis/Industry Shock and control variables. The dependent variables are calculated using text analysis on the Earnings Conference Calls as described in Section III, they measure the level of Pessimism and self-focus Attention in a given Earning Conference Call. The Financial Crisis Dummy takes value 1 from August 2008 through March 2009, and 0 otherwise. The Industry Shock is the weighted average rate of return in a given quarter in the one-digit industry that firm belongs to, excluding the firm itself from the calculation. For the case of the industry shock we consider the shock one quarter before. We run several regressions with and without controls. We include industry fixed effects for all the models and time fixed effects by quarter for the models with the industry shock. Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * p<0.10, ** p<0.05, *** p<0.01.

C. Validating Industry Shock

For the industry shock case we group our variable of shock in 5 quantiles, we reverse the order of the groups in order to have the most negative shocks in the highest group (Industry Shock 5). In this case we consider the shock one quarter before the measure of tone, because the Earning Conference Call may be happening during the period and the contemporaneous shock may not be finished. To see if industry shocks play the same roll as the financial crisis, in the sense of inducing negative emotions, we are going to test the following model:

$$\begin{aligned} Pessimism_{jt} = \alpha + \sum_{i=0}^{5} \beta_i IndustryShock_{it-1} + \\ Controls_{jt} + Quarter + Industry + \epsilon_{jt} \end{aligned} \tag{5}$$

Now we include quarter fixed effects to take into account the influence of time series trends. We are including the same controls as before. The results can be seen in table 3. For the case of industry shock there is a clear increase of the level of pessimism along with the intensity of the negative shock. This effect remains even when we add controls. For the case of self-focus there is no clear pattern after the shock.

From these results we can say that the two shocks are increasing the level of pessimism in the CEO language, thus they serve for the purpose of inducing negative mood into the CEO. Therefore they are valid to create an appropriate environment, in which negative schemas are activated, and we are able to measure heterogeneity in CEO depressive tendencies. Moreover they support the first hypothesis we suggest in this work *"Negative events for a company foster depression feelings in the CEO."*

V. The Effects of Depression on Firm Performance

Now we 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 consider the degree of pessimism but more important how the CEO canalizes 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 more sensitive to become depressed[7]. Once we have classified the level of depression of the CEOs, we hypothesize that more depressed CEOs are going to exhibit lower performance which will be traduced in lower firm performance as well because the CEO is an important actor in the company and his actions have a big influence on it.

A. Financial Crisis Shock

First we consider the Financial Crisis Shock. Our variable of depression the combination of self-focus attention and negative tone. Our variable of pessimism is the same as

[7]This attitude is the opposite as the more common one called "attributional bias" which occurs when managers attribute favourable outcomes to the actions of themselves or their associates and unfavourable outcomes to uncontrollable forces (see, Bettman and Weitz (1983)).

Table 4

Panel A:Summary Statistics (for the sample of table 5, panel A)

Variable	Mean	Std Dev	25th perc.	Median	75th perc.
Pessimism	-0.013	0.361	-0.253	0.016	0.248
self-focus	-0.032	0.420	-0.346	-0.033	0.271
Raw Return	0.104	0.506	-0.200	0.056	0.315
Abnormal Return	-0.017	0.379	-0.241	-0.061	0.141
L&M Neg. Tone	0.510	0.290	0.256	0.515	0.764
Size	6.994	1.806	5.744	6.925	8.144
Book-to-Market, MTB	2.523	3.563	1.209	1.927	3.156
BM	0.027	0.162	0.000	0.000	0.000
Long-Term Debt, LTD	0.182	0.195	0.008	0.129	0.282
Short-Term Debt, STD	0.031	0.058	0.000	0.006	0.036
Cash	0.125	0.137	0.026	0.078	0.176
Profitability, Earn	-0.114	1.157	-0.074	0.129	0.356
Financial Crisis	0.093	0.290	0.000	0.000	0.000
Idiosyncratic Risk, Std. Ret	0.123	0.074	0.073	0.105	0.150
Idiosyncratic Risk, Std. Earn	0.185	0.440	0.031	0.060	0.130
Momentum	0.128	0.579	-0.196	0.053	0.321

Panel B:Correlation Matrix (for the sample of table 5, panel A)

	Pessimism	Self-Focus	Raw Ret	Ab. Ret	L&M Neg.	Size	MTB	BM	LTD	STD	Cash	Earn	Fin. Crisis	Std. Ret	Std. Earn
self-focus	0.15														
Raw Return	0.05	-0.02													
Abnormal Return	0.02	-0.01	0.84												
L&M Neg. Tone	0.35	0.05	0.07	0.03											
Size	0.02	0.12	-0.08	-0.04	-0.08										
Book-to-Market, MTB	-0.05	0.02	-0.06	-0.03	-0.12	0.15									
BM	-0.02	-0.01	0.04	0.04	-0.00	-0.06	-0.50								
Long-Term Debt, LTD	0.04	0.00	0.05	0.05	0.04	0.08	-0.11	0.37							
Short-Term Debt, STD	0.01	0.02	0.01	0.01	0.04	-0.02	-0.03	0.06	0.03						
Cash	-0.09	0.01	0.00	-0.01	-0.09	-0.20	0.16	0.03	-0.30	-0.14					
Profitability, Earn	0.10	0.01	-0.01	-0.00	0.05	0.31	-0.07	-0.20	-0.01	-0.00	-0.35				
Financial Crisis	0.11	-0.01	0.28	0.08	0.16	-0.08	-0.06	0.01	0.02	0.02	-0.01	0.00			
Idiosyncratic Risk, Std. Ret	0.01	-0.06	0.19	0.07	0.07	-0.39	-0.06	0.12	0.06	0.01	0.14	-0.27	0.09		
Idiosyncratic Risk, Std. Earn	-0.08	-0.00	-0.00	0.00	-0.07	-0.25	0.12	0.13	-0.08	-0.02	0.36	-0.75	-0.00	0.22	
Momentum	-0.08	-0.00	-0.05	-0.05	-0.16	0.09	0.12	0.00	-0.00	-0.04	0.06	-0.03	-0.21	0.07	0.04

Table 5: This table presents regression estimates for the dependent variables Cumulative Raw Returns in the subsequent 4 and 8 periods on the interaction of Pessimism, self-focus and negative Shocks and also control variables. The variables of Pessimism and self-focus are calculated using text analysis on the Earnings Conference Calls as described in Section III, they measure the level of Pessimism and self-focus Attention in a given Earnings Conference Call. For the case of self-focus we use dummy variables for Self quantiles such that $Self_2$ takes value 1 if the self-focus is in the second quantile and 0 otherwise, and so on for 3, 4 and 5. The Financial Crisis Dummy (panel A) takes value 1 from August 2008 through March 2009, and 0 otherwise. The Industry Shock (panel B) is the weighted average rate of return in a given quarter in the one-digit industry that firm belongs to, excluding the firm itself from the calculation. Later we convert the Industry Shock as a Dummy variable that takes value 1 for the two lowest quantiles and 0 otherwise. For the case of the industry shock we consider the shock one quarter before. Controls are the ones specified in table 3. In panel A we consider the controls one year before, for example in the case of Cash we would consider the total amount of Cash during the previous year of the observation date. In panel B we would consider the current Cash. We include industry fixed effects for all the models and time fixed effects by quarter for the models with the industry shock (panel B). Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Panel A: Cumulative Raw Return (Financial Crisis)				
	(1)	(2)	(3)	(4)
	4 quarter	8 quarter	4 quarter	8 quarter
Pessimism	0.0161	0.0442*	0.0020	0.0050
	(0.0147)	(0.0258)	(0.0153)	(0.0266)
Pessimism*FinancialCrisis	0.4023***	0.6101***	0.3925***	0.6009***
	(0.0798)	(0.1256)	(0.0780)	(0.1216)
$\text{Self}_2 * Pessimism$	-0.0088	-0.0053	-0.0167	-0.0199
	(0.0189)	(0.0317)	(0.0189)	(0.0315)
$\text{Self}_3 * Pessimism$	-0.0082	0.0178	-0.0166	0.0068
	(0.0197)	(0.0344)	(0.0200)	(0.0344)
$\text{Self}_4 * Pessimism$	-0.0221	-0.0215	-0.0306	-0.0273
	(0.0210)	(0.0348)	(0.0213)	(0.0351)
$\text{Self}_5 * Pessimism$	-0.0003	0.0052	-0.0008	0.0126
	(0.0197)	(0.0344)	(0.0202)	(0.0351)
$\text{Self}_2 * Pessimism * FinancialCrisis$	-0.1591	-0.1871	-0.1641	-0.1927
	(0.1151)	(0.1787)	(0.1116)	(0.1718)
$\text{Self}_3 * Pessimism * FinancialCrisis$	-0.3737***	-0.5071***	-0.3643***	-0.4932***
	(0.1146)	(0.1881)	(0.1111)	(0.1812)
$\text{Self}_4 * Pessimism * FinancialCrisis$	-0.2043*	-0.3424*	-0.1991*	-0.3316*
	(0.1100)	(0.1799)	(0.1075)	(0.1741)
$\text{Self}_5 * Pessimism * FinancialCrisis$	-0.3499***	-0.4065**	-0.3384***	-0.3897**
	(0.1159)	(0.1912)	(0.1130)	(0.1856)
Controls	NO	NO	YES	YES
Quarter Fixed Effects	NO	NO	NO	NO
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	49,591	49,591	49,591	49,591
Adjusted R^2	0.0888	0.0976	0.1211	0.1281
Panel B: Cumulative Raw Return (Industry Shock)				
	(1)	(2)	(3)	(4)
	4 quarter	8 quarter	4 quarter	8 quarter
Pessimism	0.0027	0.0005	-0.0066	-0.0184
	(0.0181)	(0.0307)	(0.0185)	(0.0292)
Pessimism*IndustryShock	0.1218***	0.2059***	0.1215***	0.2007*
	(0.0309)	(0.0499)	(0.0305)	(0.0663)
$\text{Self}_2 * Pessimism$	0.0001	-0.0221	-0.0076	-0.0397
	(0.0233)	(0.0375)	(0.0235)	(0.0450)
$\text{Self}_3 * Pessimism$	0.0224	0.0550	0.0161	0.0412
	(0.0244)	(0.0409)	(0.0247)	(0.0408)
$\text{Self}_4 * Pessimism$	-0.0203	-0.0265	-0.0219	-0.0273
	(0.0255)	(0.0391)	(0.0259)	(0.0340)
$\text{Self}_5 * Pessimism$	0.0041	-0.0053	0.0091	0.0041
	(0.0234)	(0.0392)	(0.0239)	(0.0286)
$\text{Self}_2 * Pessimism * IndustryShock$	-0.0660	-0.0365	-0.0647	-0.0283
	(0.0434)	(0.0712)	(0.0430)	(0.0369)
$\text{Self}_3 * Pessimism * IndustryShock$	-0.1308***	-0.2445***	-0.1264***	-0.2304**
	(0.0438)	(0.0728)	(0.0435)	(0.0404)
$\text{Self}_4 * Pessimism * IndustryShock$	-0.0933**	-0.1423**	-0.0897**	-0.1336
	(0.0462)	(0.0715)	(0.0457)	(0.0598)
$\text{Self}_5 * Pessimism * IndustryShock$	-0.1438***	-0.1796**	-0.1459***	-0.1777***
	(0.0429)	(0.0728)	(0.0424)	(0.0224)
Controls	NO	NO	YES	YES
Quarter Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	37,808	37,808	37,808	37,808
Adjusted R^2	0.3039	0.2801	0.3122	0.2955

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 in analyzing how the depression level is affecting the firm performance after a negative shock. To measure firm performance we consider the raw cumulative returns during one and two year buy-hold strategy [8]. We have also test the model using as dependent variable a shorter period of time (6 months), the results are less clear even-though follow the same trends. The fact that the effect of the depression the CEO suffers affect the performance of the firm should be understood under the channel of strategic decisions that are the ones more dependent on CEO characteristics as mentioned in the first section. For this logic is reasonable to consider one year performance (12 months) and two year performance (24 months) after the shock takes place.

$$\begin{aligned} RawReturns_{jt+n} = \alpha + \sum_{i=0}^{5} \beta_{1i} self_i * Pessimism_{jt} * Shock + \\ \sum_{i=0}^{5} \beta_{2i} self_i * Pessimism_{jt} + \beta_3 Pessimism_{jt} * Shock + \\ \sum_{i=0}^{5} \beta_{4i} self_i * Shock + \beta_5 Shock + \beta_6 Pessimism_{jt} + \\ Controls_{jt} + Quarter + Industry + \epsilon_{jt} \end{aligned} \tag{6}$$

Our research strategy to estimate the effect of depression during the crisis period in subsequent performance is a triple interaction. We interact the variables Self-Focus, Pessimism and Financial Shock. In the model we present in equation 6 the coefficients of interest are the β_1's. These coefficients measure the differential effect of CEO self-focus and pessimism levels during the crisis period compared with non-crisis period.

In this case we use the same controls as in the previous section, with the particularity that the financial health proxies (Cash Holdings, Short-Term Debt, Long-Term Debt, and Profitability) are yearly data and lagged one period as (Lins et al. (2017)). The reason is that when the crisis started firms that where financially strong where less exposed. Thus instead of considering the current measures of financial health we consider the ones exhibited before the crisis begins. We also add a Momentum variable to control from past returns tendency, see (Jegadeesh and Titman (1993)). We exclude the observations where the CEO speaks fewer than 150 words, we do this for all the analysis along the paper. The results can be seen in panel A of table 5.

From the table we can observe a significant negative effect of the estimates β_1 when the level of self-focus increases. When self-focus attention is high and we are in crisis period the level of pessimism is negatively correlated with the subsequent firm performance. As we go further in time this effect diminishes, when we take into account the subsequent 8 quarters (2)-(4) we still keep significance but with lower intensity. An interesting point is that, during the crisis time, exhibiting pessimism is associated with higher subsequent returns as observed in the estimate β_4. These may tell us that reacting in a negative manner is something understandable when the

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

firm is going through bad times, the problem may emerge in the way CEOs canalize this negative emotions, if CEOs attribute this negativeness to themselves then bad performance comes. This effect endures even after we add controls.

An interesting test would be to consider what would happen if we measure depression when there is no crisis. We treated the crisis as a good setting to measure depression due to the negativeness it induces and the activation of the latent negative schemas in the vulnerable CEOs. But if we measure depression out of the crisis, when the negative schemas 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 for all observations that are not in 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 form of equation 7 and the results are presented in table 6, where we consider as independent variable the Cumulative Raw Returns.

$$\begin{gathered} RawReturns_{jt+n} = \alpha + \sum_{i=0}^{5} \beta_{1i} self_i * Pessimism_{jt} + \\ \sum_{i=0}^{5} \beta_2 self_i + \beta_3 Pessimism_{jt} + Controls_{jt} + Q + I + \epsilon_{jt} \end{gathered} \tag{7}$$

We can see that the results are as we expected, in the crisis time the measure of depression has relevance in identifying subsequent firm performance but when 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 decrease of the Adjusted R^2 when we are not in crisis period, the Adjusted R^2 assess the amount the dependent variable is explained by our model. 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 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 same model we presented before for the financial crisis, see equation 6.

Our variable of shock now comes from the weighted average rate of return in a given quarter in the one-digit industry that firm belongs to, meaning that now we have a continuous variable of shocks. As we did in the preceding section we divide it into 5 quantiles and we consider the two bottom quantiles as the ones receiving a shock. Consequently, we would have a dummy variable that takes value 1 when we are in the two most negative quantiles and zero otherwise. One particularity is that the shock now varies in time $Shock(t)$, so 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 as

Table 6: 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	0.2573***	0.2472***	0.0342*	0.0097
	(0.0829)	(0.0702)	(0.0199)	(0.0172)
$\text{Self}_2 * Pessimism$	-0.2599**	-0.1974**	-0.0050	-0.0031
	(0.1210)	(0.0995)	(0.0250)	(0.0215)
$\text{Self}_3 * Pessimism$	-0.4404***	-0.3412***	-0.0118	-0.0034
	(0.1176)	(0.0986)	(0.0262)	(0.0226)
$\text{Self}_4 * Pessimism$	-0.2082*	-0.2131**	-0.0357	-0.0340
	(0.1159)	(0.0952)	(0.0277)	(0.0244)
$\text{Self}_5 * Pessimism$	-0.3504***	-0.2993***	-0.0169	0.0015
	(0.1188)	(0.0997)	(0.0269)	(0.0234)
Controls	NO	YES	YES	YES
Quarter Fixed Effects	NO	NO	NO	NO
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	3,839	4,627	24,297	34,721
Adjusted R^2	0.3946	0.4883	0.0356	0.0452

This table presents regression estimates for the dependent variables Cumulative Raw Returns in the subsequent 4 and 8 periods on the interaction of Pessimism and Self-Focus, and also control variables. The variables of Pessimism and self-focus are calculated using text analysis on the Earnings Conference Calls as described in Section III, they measure the level of Pessimism and self-focus Attention in a given Earnings Conference Call. For the case of self-focus we use dummy variables for Self quantiles such that $Self_2$ takes value 1 if the self-focus is in the second quantile and 0 otherwise and so on for 3, 4 and 5. We test the same model for different samples; observations during the crisis (from August 2008 through March 2009), post-crisis (after March 2009) and not in the crisis period (excluding observations from August 2008 through March 2009). Controls are the ones specified in table 3. We consider the controls one year before, for example in the case of Cash we would consider the total amount of Cash during the previous year of the observation date. We include industry fixed effects for all the models. Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * p<0.10, ** p<0.05, *** p<0.01..

before. These coefficients are the $\beta_1's$, which measures the differential effect of CEO self-focus and pessimism levels after an industry shock compared with non-industry shock ones, see panel B of table 5.

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, this effect continues after we add controls. 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, afterwards firms 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 7. The results follow our argumentation, 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. The financial crisis is one of the main shock for most of the industries along the period we are considering from 2003 to 2012, for this reason the importance of the financial crisis in our industry shock variable is evident.

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)	(5)	(6)
	After Shock	After Shock	After Shock	After Shock	No Shock	No shock
Pessimism	0.1312***	0.1099***	0.0564**	0.0480**	-0.0024	-0.0052
	(0.0292)	(0.0289)	(0.0227)	(0.0230)	(0.0192)	(0.0196)
$\text{Self}_2 * Pessimism$	-0.0725*	-0.0849**	-0.0397	-0.0436	0.0076	0.0068
	(0.0404)	(0.0399)	(0.0336)	(0.0337)	(0.0246)	(0.0246)
$\text{Self}_3 * Pessimism$	-0.1291***	-0.1345***	-0.0335	-0.0362	0.0336	0.0316
	(0.0398)	(0.0397)	(0.0332)	(0.0334)	(0.0260)	(0.0259)
$\text{Self}_4 * Pessimism$	-0.1184***	-0.1160***	-0.0705*	-0.0695*	-0.0039	-0.0041
	(0.0428)	(0.0420)	(0.0367)	(0.0367)	(0.0266)	(0.0266)
$\text{Self}_5 * Pessimism$	-0.1541***	-0.1525***	-0.0690**	-0.0707**	0.0106	0.0116
	(0.0421)	(0.0411)	(0.0337)	(0.0338)	(0.0251)	(0.0250)
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	14,434	14,434	11,022	11,022	20,781	20,781
Adjusted R^2	0.3284	0.3504	0.2997	0.3034	0.2370	0.2380

This table presents regression estimates for the dependent variables Cumulative Raw Returns in the subsequent 4 quarters on the interaction of Pessimism, self-focus and negative Shocks and also control variables. The variables of Pessimism and self-focus are calculated using text analysis on the Earnings Conference Calls as described in Section III, they measure the level of Pessimism and self-focus Attention in a given Earnings Conference Call. For the case of self-focus we use dummy variables for Self quantiles such that $Self_2$ takes value 1 if the self-focus is in the second quantile and 0 otherwise and so on for 3, 4 and 5. The Industry Shock is the weighted average rate of return in a given quarter in the one-digit industry that firm belongs to, excluding the firm itself from the calculation. Later we convert the Industry Shock as a Dummy variable that takes value 1 for the two lowest quantiles and 0 otherwise. For the case of the industry shock we consider the shock one quarter before. We test the same model for different samples; observations after experiencing an industry shock (observations where dummy variable of industry shock is equal to 1), after experiencing an industry shock excluding Financial Crisis (same case as before but excluding observations from August 2008 through March 2009) and observations that not experienced a shock (observations where dummy variable of industry shock is equal to 0). Controls are the ones specified in table 3. We include industry fixed effects and time fixed effects by quarter for all the models. Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * p<0.10, ** p<0.05, *** p<0.01.

C. Abnormal Tone Strategy

Lastly we consider another strategy. Now instead of looking for a shock we can try to see which CEOs are exhibiting higher levels of pessimism relative to the mean 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 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 et al. (2013)). 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)), this determinants are measures for current available fundamental information, growth opportunities, operating risks, and complexity. Specifically, the regression is:

$$
\begin{aligned}
Tone(Pessimism)_{jt} = \alpha + \beta_0 EARN_{jt} + \beta_1 RET_{jt} + \beta_2 SIZE_{jt} + \beta_3 BTM_{jt} + \\
\beta_4 STD\_RET_{jt} + \beta_5 STD\_EARN_{jt} + \beta_6 AGE_{jt} + \\
\beta_7 BUSSEG_{jt} + \beta_8 LOSS_{jt} + \beta_9 \Delta EARN_{jt} + \\
\beta_{10} FinCrisis + \epsilon_{jt}
\end{aligned} \tag{8}
$$

Table 8: OLS where the dependent variable is Pessimism.

Pessimism					
Indep. Variable	Coefficient	s.e.	Indep. Variable	Coefficient	s.e.
α	-0.1376***	(0.0107)	STD_EARN	-0.0146***	(0.0052)
EARN	0.0161***	(0.0023)	AGE	0.0156***	(0.0023)
RET	-0.0948***	(0.0106)	BUSSEG	0.0377***	(0.0030)
FinCrisis	0.1220***	(0.0056)	LOSS	-0.0425***	(0.0042)
SIZE	0.0001	(0.0011)	Δ EARN	-0.0381***	(0.0134)
MTB	-0.0034***	(0.0005)			
STD_RET	0.2390***	(0.0242)			
Number of obs: 48,622 ; Adjusted R^2 : 0.0354					

This table presents regression estimates for the dependent variable Pessimism on tone determinants. The variable of Pessimism is calculated using text analysis on the Earnings Conference Calls as described in Section III, it measures the level of Pessimism in a given Earnings Conference Call. Controls are the ones specified in equation 8. Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * p<0.10, ** p<0.05, *** p<0.01.

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. To proxy operating complexity we use the number of business (BUSSEG). And (AGE) captures life cycle stage of the company. Finally we introduce a new determinant that is not considered in the paper by Li, the financial crisis dummy, because it is related to the average tone exerted as we have seen earlier. One of the main difference now is that in the paper by Li they use this model to predict Abnormal positive tone, in our case we re predicting Abnormal negative tone (Pessimism). The results of the model are presented in table 8.

Using the previous model we can predict the Abnormal Tone which would be the residual of the regression, thus the difference between the realized level of pessimism and the predicted pessimism tone. Then we interact the Abnormal Tone with the self-focus attention variable to characterize the level of depression and see how affects future performance of the firm. To do this we can test the regression in equation 9, this time we include as dependent variable the abnormal returns calculated with the Fama and French 3-factor model.

Table 9: 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	0.0455***	0.0700**	0.0339**	0.0472**
	(0.0168)	(0.0305)	(0.0143)	(0.0211)
$\text{Self}_2 * AbnormalTone$	-0.0421**	-0.0609*	-0.0346*	-0.0516**
	(0.0210)	(0.0368)	(0.0180)	(0.0253)
$\text{Self}_3 * AbnormalTone$	-0.0407*	-0.0706*	-0.0280	-0.0410
	(0.0218)	(0.0393)	(0.0190)	(0.0272)
$\text{Self}_4 * AbnormalTone$	-0.0595***	-0.0841**	-0.0545***	-0.0689**
	(0.0230)	(0.0392)	(0.0199)	(0.0275)
$\text{Self}_5 * AbnormalTone$	-0.0642***	-0.0873**	-0.0525***	-0.0702**
	(0.0222)	(0.0391)	(0.0195)	(0.0273)
Control variables	YES	YES	YES	YES
Quarter Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES
N	37,432	37,432	37,432	37,432
Adjusted R^2	0.3102	0.2933	0.0368	0.0618

This table presents regression estimates for the dependent variables Cumulative Raw Returns and Abnormal Returns in the subsequent 4 and 8 quarters on the interaction of self-focus and AbnormalTone and also control variables. The variable of self-focus is calculated using text analysis on the Earnings Conference Calls as described in Section III, it measures the level of self-focus Attention in a given Earnings Conference Call. For self-focus we use dummy variables for Self quantiles such that $Self_2$ takes value 1 if the self-focus is in the second quantile and 0 otherwise and so on for 3, 4 and 5. The Abnormal Tone is the residual of the equation 8, thus the realized pessimism level minus the predicted one by the model. Controls are the ones specified in table 3. We include industry fixed effects and time fixed effects by quarter for all the models. Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * p<0.10, ** p<0.05, *** p<0.01.

$$RawReturns_{jt+n} = \alpha + \sum_{i=0}^{5} \beta_{1i} self_i * AbnormalTone_{jt} + \sum_{i=0}^{5} \beta_2 self_i + \beta_3 AbnormalTone_{jt} + Controls_{jt} + Q + I + \epsilon_{jt} \tag{9}$$

The results are similar as with the exogenous shocks we considered before, when the CEO shows higher levels of Abnormal Tone, meaning levels of pessimism that are above the average, the subsequent raw returns increase. 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 observe that the slope of the estimate of interest β_1 becomes more negative along with the intensity of the self-focus attention variable, even if we consider abnormal returns, see table 9. After all the analyses we have considered during the last two sections our second hypothesis seems to be supported by the results, *"After a negative shock, firms with more resilient CEO (lower levels of depression) show higher subsequent performance"*.

D. Market Reaction

So far we have think about the effect of depression on the firm performance one and two years afterwords, this makes sense because the effect of the depressed CEO in the firm performance should be something that takes time to consolidate as we already pointed out. The main reason was that the effect of the CEO in the firm performance was mainly through strategic and complex decisions rather than mechanical ones, and these decisions usually have a time horizon of at least one year. 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 the Earnings Conference Calls has finished. If this happens we should expect movements in the returns around the date of the meeting. To study the ability of analyst in capturing during the meetings the emotional state of CEOs we run the following regression:

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

Table 10: OLS where the dependent variable is the Cumulative Return around the Event.

	CR[-1,+1]			
	(1) Financial Crisis	(2) Industry Shock		(3) AbnormalTone
Pessimism	-0.0056	-0.0019	AbnormalTone	-0.0063***
	(0.0110)	(0.0039)		(0.0022)
Self$_2$ $* Pessimism$	-0.0083	-0.0036	Self$_2(t) * AbnormalTone$	-0.0026
	(0.0157)	(0.0056)		(0.0031)
Self$_3$ $* Pessimism$	-0.0100	-0.0079	Self$_3(t) * AbnormalTone$	-0.0041
	(0.0161)	(0.0057)		(0.0031)
Self$_4$ $* Pessimism$	-0.0077	-0.0022	Self$_4(t) * AbnormalTone$	-0.0006
	(0.0161)	(0.0058)		(0.0033)
Self$_5$ $* Pessimism$	0.0025	0.0064	Self$_5(t) * AbnormalTone$	0.0025
	(0.0184)	(0.0059)		(0.0032)
Control variables	YES	YES		YES
Quarter Fixed Effects	YES	YES		YES
Industry Fixed Effects (2-digits)	YES	YES		YES
N	3,904	17,115		42,341
Adjusted R^2	0.2285	0.3340		0.3730

This table presents regression estimates for the dependent variables Cumulative Raw Returns CR[-1,+1], from one day before to one day after the event takes place, on the interaction of self-focus and Pessimism/AbnormalTone and also control variables. The variables of Pessimism and self-focus are calculated using text analysis on the Earnings Conference Calls as described in Section III, they measure the level of Pessimism and self-focus Attention in a given Earnings Conference Call. For self-focus we use dummy variables for Self quantiles such that $Self_2$ takes value 1 if the self-focus is in the second quantile and 0 otherwise and so on for 3, 4 and 5. The Abnormal Tone is the residual of the equation 8, thus the realized pessimism level minus the predicted one by the model. Controls are L&M Negative Tone, SUE, Size, MTB, STD_RET STD_EARN and current Returns, see table 2 for definitions. We include industry fixed effects and time fixed effects by quarter for all the models. Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * p<0.10, ** p<0.05, *** p<0.01.

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 market 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 et al. (2013)). 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).

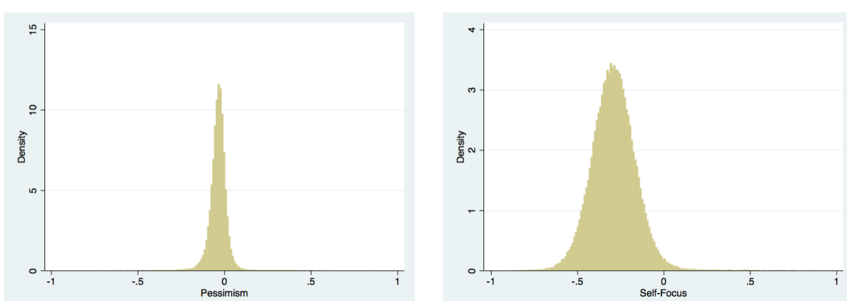
In table 10 we can see that the results are not showing any kind of direction regarding our variable of interest. It seems that analyst are not able to extract information about CEOs depression tendencies. This makes sense because what we are considering as proxies for dysfunctional thinking are language patterns quite subtle for a non experienced person in this field. So the information is not updated through the market reaction after the Earnings Conference Call but through time when CEOs actions take place.

VI. Robustness Check

One of the concerns that may arise with the measures we propose of Pessimism and self-focus is the way we normalized. As explained in the section III.C before we calculate the formula 2 and 3 we normalize the variables of tone so they take values between 0 and 1. We do this because for example in the case of self-focus the appearance of 1º person of plural words is greater than 1º person of singular then the effect of one may dilute the other variable when we add them. To normalize we rank the variable in 1000 groups and divide by 1000. Doing this we are losing the shape of the former distribution. For this reason, in this section we normalize our measure in a proportionate way, see equation 11, and check if results hold.

$$VariableScaled[0,1] = \frac{(Variable - Min\{Variable\})}{(Max\{Variable\} - Min\{Variable\})} \tag{11}$$

Variable	Num. Obs.	Mean	Std. Dev.	Min.	Max.
Tone Self not normalized (raw from text analysis)	167,319	0.012	0.006	0	0.095
Tone Self normalized (proportional)	167,319	0.127	0.065	0	1
Tone Self normalized (groups of 1000)	167,319	0.501	0.288	0	1



(a) Distribution of Pessimism (b) Distribution of Self-Focus

Figure 5: Distribution of our variables of depression normalizing proportionally

In the example of the variable of Tone Self (raw count of 1º person singular words) using this new way we proportionally calibrate our variable into 0 and 1 range. In the old case the mean and the standard deviation are modified when we normalize, but with this proportional manner we keep the proportions multiplied by ten. See the distribution of Pessimism and self-focus attention with this form of normalizing in figure 5. If we compare them to the distributions showed in section III.C figure 3 we can see how they differ.

Table 11: OLS where the dependent variable is the Cumulative Return around the Event.

	Financial Crisis		Industry Shock		AbnormalTone	
	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Returns	Ab. Returns	Raw Returns	Ab. Returns	Raw Returns	Ab. Returns
	Panel A: We rank the self-focus Variable in 3					
$\text{Self}_2 * Pessimism * Shock$	-1.9854***	-1.5960***	-0.7971	-0.5974*		
	(0.7625)	(0.5684)	(0.3854)	(0.2456)		
$\text{Self}_3 * Pessimism * Shock$	-1.7002**	-1.2663**	-0.8818*	-0.7259*		
	(0.7439)	(0.5653)	(0.2778)	(0.2840)		
$\text{Self}_2(t) * AbnormalTone$					-0.2963*	-0.2362*
					(0.1531)	(0.1306)
$\text{Self}_3(t) * AbnormalTone$					-0.4275***	-0.3591***
					(0.1494)	(0.1278)
	Panel B: Continuous self-focus Variable					
Self*Pessimism*Shock	-8.0475***	-5.8660***	-2.9763**	-2.3268*		
	(1.8704)	(1.6392)	(0.8447)	(0.8735)		
Self*AbnormalTone					-1.0052***	-0.7558**
					(0.3667)	(0.3146)
Control variables	YES	YES	YES	YES	YES	YES
Quarter Fixed Effects	NO	NO	YES	YES	YES	YES
Industry Fixed Effects (2-digits)	YES	YES	YES	YES	YES	YES
N	42,036	42,036	35,215	35,215	34,874	34,874
Adjusted R^2	0.1130	0.0191	0.2989	0.0346	0.2971	0.0340

This table presents regression estimates for the dependent variables Cumulative Raw Returns and Abnormal Returns in the subsequent 4 quarters on the interaction of Self-Focus, Pessimism and Negative Shock and also the interaction of self-focus and AbnormalTone, with Controls. The variables of Pessimism and self-focus are calculated using text analysis on the Earnings Conference Calls as described in Section VI (using the proportional way of normalizing), they measure the level of Pessimism and self-focus Attention in a given Earnings Conference Call. In panel A for self-focus we rank it in 3 groups and we use a dummy variables such that $Self_2$ takes value 1 if the self-focus is in the second rank and 0 otherwise and the same for 3. In panel A we employ the linear measure of Self-Focus. The Abnormal Tone is the residual of the equation 8, thus the realized pessimism level minus the predicted one by the model. Controls are the ones specified in table 3. We include industry fixed effects for all our models and time fixed effects by quarter for the cases of industry shock and abnormal tone. Observations with prices below 1$, length of the CEO speech below 150 words, missing data on variables and date earlier than 2003 are removed from the sample. All the variables are winzorized at the 1st and 99th percentiles. The errors are robust and clustered at the firm level and are presented in parentheses * p<0.10, ** p<0.05, *** p<0.01.

To check if the results we have presented along the paper hold using this way of normalizing, we perform again the main tests with this method. We present the results for the variable self-focus ranked in three and for the case when it is a continuous variable. Everything else remains the same as with the regressions we performed in earlier parts with the models 6 and 9. The results are in the same direction as with the former way of normalizing. See table 11.

VII. Conclusion

The CEO is often regarded as the most influential person in a firm, his decisions and the actions it takes have a big effect in the company. A natural question it may arise is how the emotional state of the CEO affects the firm. In this research we examined this question, in particular the degree of depression exerted by the CEO and the consequences on the company performance.

Depression is a common illness that disturbs the emotional well-being of a person affecting his actions, thoughts and feelings. Cognitive theories of depression suggest that negative thinking is not a consequence of depression rather a cause of it. In normal times we may not be able to find heterogeneity in cognitive patterns among non-vulnerable and vulnerable individuals but during difficult periods the activation of depressive schemas in vulnerable individuals takes place. One of the attributes associated with depressive dysfunctional thinking is the self-focus bias, meaning that under negative circumstances vulnerable individuals tend to concentrate on themselves and attribute negative events to them.

In this paper we rooted our analysis on the depression theories and considered the negative shocks to a company as a natural experiment to test depression vulnerability and how this CEO characteristic is related to the firm.

We measure the exposure to depression using two linguistic patterns, the degree of pessimism and self-focus attention. We analyze the word usage during the Earnings Conference Calls by the CEOs as a way to characterize this two dimensions. To find a proper environment for distinguishing non-vulnerable and vulnerable CEOs we consider negative and exogenous shocks to the company that foster negative emotions on the CEO and consequently activate the depressive schemas in prone-individuals. The negative shocks we employ are the Financial Crisis and industry shocks, moreover we also consider another approach with the abnormal tone.

Our evidence indicates that negative events in the company affects the emotional state of the CEO, when they take place the CEO increases the use of negative balanced words. Furthermore, once a firm experienced a negative shock firms with CEOs that show lower levels of depressive tendencies are associated with higher levels of performance. This results are consistent across the different shocks we studied and also with the abnormal tone approach. The repercussion of CEO emotional state on the firm performance is detected in a window of one to two years and we do not find evidence of a market reaction during the Earnings Conference Calls. This seems to suggest that what we are measuring is subtle and analyst are not able to notice it, as a result the actualization of this information materializes along time when the CEOs actions takes place.

This research is interesting because it gives a new method to detect depression and highlights the relevance of CEO emotional well-being on an economic framework. Further steps may go in the direction of giving more evidence to the characterization of depression using text analysis and the effect of depression on other economic outcomes apart from firm performance.

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