CEO Overconfidence and the Probability of Corporate Failure: Evidence from the United Kingdom.

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Abstract

This paper investigates the impact of CEO overconfidence on the probability of corporate bankruptcy. Using a large dataset of UK firms, we find that firms with overconfident CEOs face a greater risk of failure. The presence of overconfident CEOs leads to a higher risk of bankruptcy in innovative environments, while the impact is insignificant in non-innovative environments. Moreover, overconfident CEOs can increase the bankruptcy risk of firms with less conservative accounting. We find that banks, as major creditors, seem to play an important role in constraining CEO overconfidence, and hence in reducing the likelihood of bankruptcy. Finally, the impact of overconfidence on the probability of bankruptcy is stronger in firms with generalist CEOs than specialist CEOs.

Keywords: CEO Overconfidence; Hazard Model; Corporate Bankruptcy; Corporate Governance.

JEL Classification: G02, G14, G30, G33

1. Introduction

This paper investigates whether psychological traits can help explain the probability of corporate failure[i]. In doing so, we focus on the impact of CEO overconfidence, which is one of the most prominent among CEOs biases (Graham et al. 2013). Overconfidence is observed when an individual's subjective confidence in her judgements is greater than the actual accuracy of those judgements (Alicke 1985). Despite much research into exploring the consequences of managerial overconfidence for corporate policies and outcomes (for a review, see Malmendier and Tate [2015]), the question of how managerial overconfidence impacts the likelihood of corporate bankruptcy remains unaddressed. Motivated by this gap in the literature, we investigate the interplay between CEO overconfidence and the probability of bankruptcy.

Overconfident CEOs are known of their tendency to overestimate future cash flows and engage in value-destroying investment and financing decisions (Malmendier and Tate 2015; Hackbarth 2008; Malmendier and Tate 2005; Malmendier et al. 2011; Huang et al. 2016; Ho et al. 2016). Prior studies also show that overconfident CEOs delay their reaction to privately received negative feedback and news (Kim et al. 2016; Ahmed and Duellman 2013; Hsu et al. 2017; Astebro et al. 2007). Considering sub-optimal investment and financing decisions of overconfident CEOs, i.e., the dark side of CEO overconfidence, we argue that overconfident CEOs are likely to increase the likelihood of corporate failures.

However, there might be also a bright side to CEO overconfidence. Previous literature argues that overconfident CEOs have strong self-belief in their leadership, which makes them viewed as more competent, and therefore more respected and influential (e.g., Anderson et al. [2012]). Phua et al. (2018) provide evidence that overconfident CEOs induce greater supplier commitments leading to lower input costs and higher profitability. Further, they can enhance innovation and increase R&D productivity (Hirshleifer et al. 2012). Considering the likely benefits of CEO overconfidence, we argue that overconfident CEOs can reduce the likelihood of corporate failures. Overall, we predict that the ultimate impact of overconfidence on the likelihood of bankruptcy would depend on whether the 'effective leadership' or the 'suboptimal decision-making' aspect of CEO overconfidence dominates. It is also possible that the expected costs and benefits of overconfidence can offset each other to lead to an insignificant observed relation between overconfidence and the probability of bankruptcy.

For our empirical analysis, we employ a large sample of non-financial UK firms, out of which 235 fail during our sample period from 1999 until 2017. The UK offers an interesting set-up to conduct a study on the impact of behavioural biases on corporate decisions. As prior studies argue, CEOs in UK firms have more leeway in their corporate decision-making compared to managers in other countries, e.g., Germany (Hambrick 2007; Crossland and Hambrick 2011; Li and Tang 2010). Notably, Crossland Hambrick (2011) provide evidence that the UK next to the USA provides managers with a high degree of discretion, which stems from the nation's formal and informal institutions (i.e., individualism, tolerance of uncertainty, cultural looseness, dispersed firm ownership, a common-law legal origin, and employer flexibility).

While both the UK and the US share the main characteristics of the Anglo-Saxon model of the corporate governance system, the UK has some distinct corporate governance features that may influence the relation between managerial discretion and firm survival. First, the UK corporate sector suffers from insufficient external market discipline (Poletti-Hughes and Ozkan 2014; Ozkan and Ozkan 2004). Although financial institutions have significant shareholdings in UK firms, evidence suggests that they do not take an active role in corporate governance. For example, they fail to impose discipline on managers (Franks et al. 2001, Cosh and Hughers 1997) and have lower tendency to engage in voting at shareholders' meetings than those institutional investors in the US firms (Malli 1996, 2001; PIRC 1998).

Second, under the UK regulatory framework, banks as major creditors of UK firms play a more important monitoring role than those in US firms. The incentives of the US banks to monitor and scrutinise financially distressed firms are limited by the lender's liability principle (Chen et al. 2018). More importantly, different from US firms, UK firms raise debt financing predominantly from banks, who therefore can be perceived as the main corporate creditors (Chen et al. 2018). Furthermore, the protection of creditors rights is stronger in the UK than in the US when it comes to insolvency procedures. UK Insolvency Act 1986, in comparison to US Chapter 11, makes it relatively easier for creditors to force financially distressed firms into insolvency (Acharya, Sundaram, and Kose 2011; Ozkan 1996).

To examine the relation between CEO overconfidence and the probability of corporate failures we use a discrete-time hazard model, which is suitable for our empirical analysis as it incorporates information from previous periods in a dynamic manner. This feature is desirable in behavioural studies as the biases are not constant over time. Furthermore, Hilary and Hsu (2011) and Hilary et al. (2016) show that the perception of CEOs can change over time depending on, for example, the success of earlier initiatives, favourable past performance, and the success in the accuracy of earnings forecast. The three overconfidence proxies we employ in our study allow the bias to vary across time at individual level. Specifically, we follow the previous studies and use three measures of CEO overconfidence (1) CEO stock purchase transactions (Kolasinski and Li 2013); (2) CEO option holdings and the decision to exercise (Malmendier and Tate 2005); and (3) CEO's media-portrayal (Malmendier and Tate 2005; Hirshleifer et al. 2012).

Our results provide evidence that firms managed by overconfident CEOs are more likely to fail. Specifically, employing the three aforementioned measures of CEO overconfidence we find that CEO overconfidence increases the probability of corporate failure among UK firms.

Our findings suggest that including CEO overconfidence measures in the bankruptcy prediction models can increase the accuracy of the forecast.

Additionally, we investigate the mechanisms that are likely to drive the positive impact of CEO overconfidence on corporate failures. In this respect, we focus on two potential mechanisms, i.e., investment environment and accounting conservatism, through which CEO overconfidence can influence the likelihood of bankruptcy.

As argued in prior research, investment environment, measured by the extent of innovative activity, could play a crucial role in explaining how overconfident CEOs influence corporate financial policies (Chen et al. 2020). Accordingly, we consider whether there are differences between innovative and non-innovative environments in terms of how overconfident CEOs can influence corporate failures. Hirshleifer et al. (2012) find that the effective leadership of overconfident CEOs is more pronounced in firms operating in innovative industries. We find that overconfident CEOs tend to increase corporate failures in innovative industries (and high R&D firms) suggesting that 'sub-optimal decision-making' aspect of CEO overconfidence dominates rather than 'effective leadership' aspect.

Additionally, we provide evidence that accounting conservatism could be an alternative channel through which overconfident CEOs increase the probability of failure. Prior research shows that overconfident CEOs tend to delay reaction to privately received negative feedback and news (Ahmed and Duellman 2013; Hsu et al. 2017). Furthermore, Kim et al. (2016) and Astebro et al. (2007) find that overconfident CEOs delay their responses to the unfavourable information about the project's interim performance until it is too late to resolve the problem. Importantly, accounting conservatism imposes stronger verification requirement for the recognition of economic gains than for losses (Gracia Lara et al. 2009; Yildiz et al. 2019). Therefore, greater accounting conservatism is associated with relatively more prompt adjustment to bad news. We examine if the differences between strong and weak accounting conservatism can help explain the association between CEO overconfidence and the probability of corporate failure. We find that overconfident CEOs tend to increase corporate failures in firms with weak accounting conservatism regime while there is no significant relation between CEO overconfidence and the likelihood of bankruptcy in firms with strong accounting conservatism.

Prior studies also highlight the importance of governance mechanisms in restraining CEO overconfidence (see e.g., Banerjee et al. [2020]; Banerjee et al. [2015]), hence we examine the effectiveness of internal and external monitoring. To test the former, we incorporate three important board characteristics, i.e., size, independence and gender diversity, into our analysis. Board members can provide expertise to balance and limit the impact of CEO overconfidence on the financial policies (e.g., Fich and Slezak [2008]; Lajili and Z´eghal [2010]). We find that the association between CEO overconfidence on the probability of bankruptcy is significant only in subsamples of firms managed by generally weaker boards, i.e. smaller, less independent and non-diverse.

To examine the effectiveness of external governance we consider the effect of monitoring by banks and institutional owners. In line with Kahnem and Lovalo (1993) and Hedon (2002) we expect the overconfidence to be moderated by an external monitoring. To test whether bank monitoring influences the relation between CEO overconfidence and the likelihood of bankruptcy, we consider the state of financial distress as a period during which banks impose greater scrutiny on firms and hence limit the discretion of CEOs (Chen et al. 2018; Franks and Sussman 2005). Consistent with our expectations, we find that the positive association between CEO overconfidence and the probability of bankruptcy is mainly driven by our subsample of low financial distress firms when CEOs are not under the scrutiny of their creditors. To analyse the effect of institutional holdings we compare firms with low and high institutional ownership.

Since the investors can recognise managerial forecasts issued by overconfident managers (Hilary and Hsu 2011), we argue that even with passive attitude, the UK institutional investors may be effective in monitoring the biased decisions. In line with our expectations, we find that CEO overconfidence affects the probability of bankruptcy significantly only in firms with low institutional ownership.

Next, we conduct additional tests to check the robustness of our findings. First, we employ alternative measures of CEO overconfidence, which determine overconfidence internally (via shares and options trading by CEOs), as well as externally (via press-coverage). Second, we use propensity score matching technique and find that our findings remain robust. We also consider that the impact of the CEO overconfidence may not be strong enough during the first year of their tenure, and the effect can be driven more by the turnover than the overconfidence (Kim et al. 2016). We confirm that our results are not sensitive to the first year of CEOs tenure. Lastly, we consider whether the impact of overconfidence on corporate failure can change with CEOs' skills sets. To do so, we consider CEOs with generalised and specialist skills sets of Custódio et al. (2013, 2019) and find that generalist CEOs enhance the effect of the overconfidence on the probability of failure. This finding possibly suggests that generalist CEOs have more outside options in the labour market and are therefore more confident in their decision-making.

To the best of our knowledge, this paper is the first to explore the relationship between CEO overconfidence and the probability of corporate bankruptcy. We make important contributions to several strands in the literature. First, we add to the strand of the literature exploring the relevance of behavioural biases in affecting corporate policies and outcomes (see e.g. Hsu et al. [2017]; Kolasinski and Li [2013]; Kim et al. [2016]; Malmendier and Tate [2015]). We show that overconfident CEOs can influence the probability of corporate failure. Second, we add to the strand of research on the determinants of the probability of bankruptcy (see e.g. Campbell et al. [2008]; Chava and Jarrow [2004]; Shumway [2001]; Reisz and Perlich [2007]). We provide evidence that CEO overconfidence plays a significant role in the prediction of failure. Third, this paper adds to the emerging strand of the literature considering the effectiveness of corporate governance mechanisms in terms of restraining negative behavioural biases (see e.g. Ataullah et al. [2017]; Banerjee et al. [2020]; Banerjee et al. [2015]; Li and Tang [2010]; Chen et al. [2019]). Our results show that external and internal monitoring can moderate the behaviour of overconfident CEOs. Specifically, we find that bank monitoring can be effective in constraining the impact of CEO overconfidence on the probability of bankruptcy. However, smaller, less independent and non-diverse boards seem to be ineffective in constraining overconfident CEOs.

The remainder of the paper proceeds as follows. Section two presents the relevant literature and empirical predictions. Section three explains the data and methodology used in the study. Section four discusses the main results. Section five tests further explanations and shows robustness tests. Section six concludes the paper.

2. Related Literature and Main Empirical Predictions

The literature on corporate bankruptcy prediction dates back to Beaver (1966) and is dominated by contributions focusing on the empirical models as techniques that help to predict the event (see for e.g. Campbell et al. [2008]; Jones [2017]; Shumway [2001]). Majority of the models rely on the publicly available accounting and market data with an assumption that managers are perfect agents of shareholders. However, managers can maximise their own interests at the expense of shareholders' interests, creating agency costs. Even though managers' interests can be partly aligned with those of shareholders via corporate governance mechanisms, managers' perception may be biased, which might have important implications for managerial decision making. For instance, their decisions may be irrational, fundamentally different from agency problems which can arise in a rational setting and corporate governance systems are designed to correct them (Kim et al. 2016). Irrational CEOs can believe that they act in the best interest of shareholders, However, their biased perception may lead to sub-optimal decisions. In this study, we investigate whether managerial overconfidence, which can systematically bias managerial decisions, can impact the probability of bankruptcy.

Overconfident CEOs can overestimate future cash flows and underestimate risks that drive some suboptimal decisions. For example, Malmendier and Tate (2005) show that overconfident CEOs tend to overinvest when they have excessive internal funds and curtail investment when external financing is required. In a similar vein, Ben-David et al. (2013) find that overconfident managers underestimate the level of risk in appraising investment opportunities and hence invest more than optimal by incorporating lower discount rates to value future expected cash flows. Furthermore, prior work finds that overconfident managers not only underestimate the risk, but also overestimate the profitability, future growth prospects, and expected returns of firms. Additionally, they tend to favour higher than optimal leverage (Hackbarth 2008; Malmendier et al. 2011), as well as riskier short-term debt (Huang et al. 2016), and engage in value-destroying M&As (Malmendier and Tate 2008).

Additionally, Ho et al. (2016) find that CEO overconfidence can be directly associated with a greater probability of bankruptcy of banks for a sample of Russian banks. Their results show that during the economic upswing overconfident CEOs, driven by their tendency to underestimate downside risk and overestimate returns, could relax lending standards, and hence make the banks more vulnerable to external shocks. Consequently, banks with overconfident CEOs had a greater risk of default in the periods of the global financial crisis.

Kim et al (2016) show that overconfident CEOs tend to engage in value-destroying investments for too long, which causes poor performance and increases the probability of stock price crashes. Overconfident CEOs must have strong self-belief to neglect the surrounding warnings of approaching failure or unintentionally negate the existence of negative news. We note that UK CEOs may have additional incentives to reject privately received negative feedback for a longer period. Chen et al. (2018) present that in the UK setting, banks have the rights and incentives to exert greater control over firms facing financial difficulties. This has important implications since UK firms raise debt financing predominantly from banks (e.g., Marshall et al. [2016]), who therefore can be perceived as the main corporate creditors. This regulatory framework differentiates the UK banks from those in the USA, whose incentives to monitor financially distressed firms are limited by the lender's liability principle.[ii] The UK CEOs may, therefore, hold on to the negative feedback for longer knowing that creditors would impose greater vigilance in financial distress. The delayed reaction can in turn result in a greater probability of corporate bankruptcy. Thus, we offer the following hypothesis:

Hypothesis 1a: *CEO overconfidence is positively associated with the probability of bankruptcy*.

Prior studies also highlight the bright side of the overconfidence by showing that overconfident CEOs are better leaders and are therefore desired on the boards of directors. Specifically, the recent literature shows that overconfidence can be desired among leaders since it promotes value creation via innovation (Galasso and Simcoe 2011; Hirshleifer et al. 2012) and enhances personal motivation (Taylor and Brown 1988, B´enabou and Tirole 2002). Furthermore, Phua et al. (2018) show that the leadership style of overconfident CEOs who exhibit a strong belief in their firm’s prospects attracts more suppliers and induces stronger labour commitments (Phua et al. 2018), which leads to better firm performance.

Based on the prior literature, we have the following hypothesis:

Hypothesis 1b: *CEO overconfidence is negatively associated with the probability of bankruptcy*.

3. Research Sample and Design

3.1. Sample Selection and Data Sources

For our sample selection, we begin with a list of all live and dead UK firms listed on the London Stock Exchange at any time between 1999 and 2017. Second, we exclude all financial firms using the Industry Classification Benchmark (ICB). Using ISIN codes, we confirm the solvency status using FAME[iii] database and obtain the insolvency dates for firms that failed during the sample period. Following Charitou et al. (2004) and Ozkan et al. (2017), we define corporate failure by observing any one of the following events in the data: administration, liquidation, receivership, or dissolution. For all firms on our list, we obtain the accounting and market data needed for the bankruptcy model from Thomson Reuters Datastream, bank debt data from Capital IQ, managerial share options data from BoardEX, insider trading and shareholdings data from Thomson Reuters EIKON, and news information from Factiva. We combine all data types into one database using ISIN numbers, names of the directors, and years of annual reports.

To ensure that outliers do not bias our results, we replace all firm-year observations which are higher (smaller) than the 99th (1st) percentile of each variable with the value of the 99th (1st) percentile.

Our sample is constructed as the time-to-event data (also known as duration data), where the event is a corporate failure. The duration for each firm is measured discretely by the time spent as solvent using the registered date[iv]. A duration begins with the initial public offering (IPO) and ends with the filing for insolvency. The censoring occurs if a firm is delisted for a different reason other than failure. We censor the data by coding the bankruptcy indicator to zero in the final year of the duration. Due to the requirements of the hazard models, we ensure that the observations we include in each of the models are consecutive. Accordingly, for each model separately, we remove all firm-year observations if they are followed by any time gaps before the next available observation. We repeat the last step for each model specification, due to a various number of variables employed.

The sample analysed in our study is described in Table 1. We observe 1,891 firms in total. During the sample period from 1999 to 2017, we observe 235 cases of failures. Table 1 also reports the distribution of failures over time, during which the average failure rate is 1.69%.

[TABLE 1 NEAR HERE]

3.2. Model

Since the seminal paper of Beaver (1966), the research on bankruptcy prediction has been extensive. Notable contributions in the literature include the static approach for the identification of financial distress of Altman (1968) and Ohlson (1980); the hazard model of Shumway (2001); the contingent claims model of Black and Scholes (1973) and Merton (1974); and the emerging "new age" classification models such as AdaBoost, generalised boosting and random forests adopted from Hastie et al. (2009), and Schapire and Freund (2012) by Jones et al. (2015).

The investigation of the impact of CEO hubris on the probability of corporate failure requires a parametric approach. This eliminates the use of the "new age" models for the analysis in this paper. The proxy we use for the CEO confidence levels used in empirical specifications is semi-permanent. It is therefore crucial that the methodology employed in the analysis allows us to exploit the dynamic nature of the data. In this respect, the contingent-claims and hazard models are suitable for this research as they allow for the incorporation of time-varying explanatory variables within the matrix of predictors, which is not possible in traditional static bankruptcy prediction models. Finally, the selection between these two approaches is driven by their forecast accuracy. Drawing from the empirical evidence conducted by Campbell et al.

(2008), and Bauer and Agarwal (2014) who found hazard models to be superior in terms of out-of-sample prediction, we employ the hazard model in our analysis.

The most general form of the discrete-time hazard model is presented in equation (1) below.

$$\ln\left(\frac{h_j(t)}{1-h_j(t)}\right) = \alpha(t) + BX_j(t) \tag{1}$$

In equation (1), $h_j(t)$ represents the hazard (probability of bankruptcy) at duration time t for company j, which is conditional on survival up to time t; $\alpha(t)$ is the baseline hazard; B is the vector of coefficients, and $X_j(t)$ is a matrix of bankruptcy predictors including industry fixed effects. Hence the model predicts a single event of a corporate failure as a function of time and other explanatory variables.

As shown in Shumway (2001), the likelihood function of the hazard model is identical to the function of the multiple logit model. Hence, we estimate the hazard model using a logistic regression function, and specify the probability of bankruptcy at time t in the following way

$$P_{j,t}\left(Y_{j,t+1} = 1\right) = \frac{1}{1+e^{-\alpha(t)-BX_{j,t}}} \tag{2}$$

where $Y_{j,t}$ is an insolvency indicator; $\alpha(t)$ is the baseline hazard; B is the vector of coefficients, and $X_{j,t}$ is a matrix of bankruptcy predictors.

3.3. Variables

3.3.1. Bankruptcy Indicator

The dependent variable in our hazard model is an indicator of bankruptcy, i.e. a binary outcome variable equals one if a firm fails in a particular year, and zero otherwise. If the company fails, we code the dependent variable to one only in the final year of the duration. Following Charitou et al. (2004) and Ozkan et al. (2017), we define corporate failure by observing any one of the following events in the data: administration, dissolution, liquidation, or receivership.[v]

3.3.2. Measures of Overconfidence

The main explanatory variables of interest in our analysis proxy for managerial overconfidence. To assure robustness of the results we employ a broad range of established in the literature measures.

The first measure, *OVERCONFIDENCE (purchases)*[vi], is constructed by following Kolasinski and Li (2013). The measure is based on CEO insider purchase transactions and their returns. We classify CEO as overconfident when they purchase their stocks and ex-post earn a negative abnormal return over the next 180 calendar days, as measured by buy-and-hold abnormal returns[vii]. This measure acknowledges that the CEO mistakenly perceives her stock as undervalued, and hence via trading exhibits her overconfident perception. To adjust the measure to the hazard analysis we employ in this study, we allow CEOs to carry forward the classification even if in a particular year they do not trade. Due to smaller restrictions imposed by the availability of data in comparison to *OVERCONFIDENCE (options)*, using *OVERCONFIDENCE (purchases)* measure we can conduct more robust results.

To construct the second measure, *OVERCONFIDENCE (options)*, we adopt the construct of *Holder67* by Malmendier and Tate (2005, 2008) to the UK environment. *Holder67* is the popular measure of overconfidence in the US literature based on managerial options, however, it limits the sample of analysis significantly. The limitation is rooted in the differences between US and UK managerial compensation structure. Specifically, The Greenbury Report released in 1995 suggests that share options granted in the United Kingdom typically vest not solely based on vesting period as it is in the US, but also upon attainment of some performance criteria, although these are seldom binding (for further discussion see Conyon and Murphy [2000];

Goergen and Renneboog [2011]). Since we are unable to identify the dates from which the performance criteria are met we can not consider options that are based on the additional criteria apart from vesting period in the reported measures, which limits the number of option packages we can consider.

An executive is classified as overconfident *OVERCONFIDENCE (options)* if she refrains from exercising the option at the earliest opportunity at least twice during the tenure, despite the significant moneyness. Malmendier and Tate (2005) argue that rational managers would at least partially exercise the options, which are more than 67% in-the-money at their first opportunity[viii]. They define as the first opportunity as the year of vesting or earlier. In this paper, we define the earliest opportunity as the year of vesting or a year after to adjust the measure to the UK environment. Specifically, differently from Malmendier and Tate (2005), we do not consider the year before vesting since the managers in the UK are not allowed to exercise options before the vesting date. However, we consider a year after the vesting period, since present in the UK blackout periods restrict managerial trading around the earnings announcement dates, and hence limit the time for immediate exercise.

The *OVERCONFIDENCE (options)* measure is calculated using Boardex UK data. The significant advantage of BoardEx dataset, in comparison to Compustat used in the recent literature exploring US firms (see e.g., Hirshleifer et al. [2012]; Campbell et al. [2011]; Malmendier and Tate [2015]), is that BoardEX provides information on the individual option packages as opposed to Compustat's annual averages. In particular, the information on the vesting and expiry dates are provided, together with their exercise price and value. In constructing the measures we begin with Accumulated Wealth - Options panel on BoardEx dataset. Using the dataset we calculate percentage moneyness of options i.e. how much the stock price (*BoardEX item: stockprice*) exceeds the exercise price (*BoardEX item: exerciseprice*), by dividing the difference by the exercise price of individual option[ix]. In the next step we trace the options using individual vesting and expiry dates to check if these are reported as expired in the next years' annual statement. If the option does not appear as expired, we assume it was exercised.[x] We classify the CEO as overconfident if although her options are at least 67% in-the-money, she does not exercise them during the year of vesting, or a year after, and this event occurs at least twice during her tenure[xi]. The CEO is classified as overconfident on the first occasion the behaviour is exhibited (provided there is a second event recorded at a later stage).

In addition to the mentioned above *OVERCONFIDENCE (purchases)* and *OVERCONFIDENCE (options)* measures, which are internally determined, as they are determined by the CEO's account or firm's decision making, we also construct another measure of CEO overconfidence that relies on the media portrayal of the CEOs and is, therefore, externally determined. [xii]Specifically, we follow earlier literature including Malmendier and Tate (2005, 2008) and Hirschleifer et al. (2012) we construct a press-based measure of overconfidence, *OVERCONFIDENCE (press).* Specifically, we search FACTIVA for press-articles referring to the CEO in sources including The New York Times, BusinessWeek, Financial Times, The Wall Street Journal, The Economist, Fortune, and Forbes. For each firm and year, we retrieve the number of articles using the company name in three steps. First, we search the keyword "CEO" and record the total number of articles that mentioned the CEO and record it as *PRESS MENTIONS*. Second, we record the number of articles indicating overconfidence of the CEO using a keyword "CEO" in conjunction with any of the following words: confidence, confident, optimism, optimistic, overconfidence, overconfident, overoptimism, overoptimistic. Third, we record the number of articles indicating the opposite media portrayal, i.e. we record number using a keyword "CEO" in conjunction with any of the following words: cautious, conservative, frugal, gloomy, overpessimistic, pessimism, pessimistic, practical, reliable, steady.[xiii] We measure the CEO overconfidence for each firm and year, *CEO overconfidence (press),* by a dummy variable equal one if the number of articles indicating overconfidence exceeds the number of articles indicating the opposite media-portrayal, and zero otherwise. Following Hirschleifer et al (2012), our overconfidence (press) measure is lagged one year.[xiv]

3.3.3. Control Variables

For our empirical specification, we follow Shumway (2001), Campbell et al. (2008), and Charitou et al. (2004) and define our baseline hazard rate using a firm's survival time, proxied by the logarithm of its age, and include a set of accounting and market control variables. We control for profitability, leverage, size, market-to-book ratio and cash holdings, past stock returns and returns volatility. Additionally, we consider industry-specific factors, that can influence the probability of bankruptcy and therefore we include industry fixed effects, using Industry Classification Benchmark (ICB). The definitions of all the variables used in the analysis are given in Table 2.

[TABLE 2 NEAR HERE]

4. Main Empirical Results

4.1. Descriptive Statistics

Table 3 presents the descriptive statistics of the variables used in the hazard model for the period 1999-2017, for both solvent and insolvent firms. For the insolvent group, we present the descriptive statistics for the entire period of analysis and the final observed year[xv].

First, we report the statistics for measures of overconfidence. All of the measures are binary variables, hence the mean values represent the proportion of firm-year observations classified in a particular sub-sample. Over the sample period, the mean ratio of overconfident managers classified on the basis of the option exercises and share purchases in the solvent firms is significantly lower than those in the insolvent firms. Interestingly the level of overconfidence a year prior to failure increases even further. In other words, the proportion of firms led by the overconfident CEOs is greater in insolvent firms and escalates further in the year before insolvency. Given the way we estimate overconfidence using the insider trading measure (i.e. OVERCONFIDENCE (purchases)), these statistics suggest that the average CEO in the insolvent subgroup of firms is more likely to increase her holdings in the company before the insolvency occurs. This is surprising but consistent with the recent findings of the analysis of UK insolvencies and the trading behaviour of managers before insolvency Ozkan et al. (2017). Overall, initial analysis reveals that the CEOs of the firms approaching insolvency are more likely to be overconfident in comparison to the average degree of confidence exposed during the lifetime of failed firms.

The statistics describing the third measure, OVERCONFIDENCE (press) do not reveal a consistent story. The proportion of overconfident CEOs is significantly lower in the sample of insolvent firms, in comparison to those remaining solvent throughout our analysis. Hirshleifer et al. (2012) suggest, that the press may be biased towards positive stories. Hence, it may not be capturing the story of insolvent firms. To control for the bias in regression models, following Hirshleifer et al (2012) we include an additional variable counting the number of times a CEO's name appeared in the media outlets, PRESS MENTIONS.

The statistics reported for financial controls are in line with the previous UK studies (Agarwal and Taffler, 2008; Bauer and Agarwal, 2014; Chava and Jarrow, 2004). In line with expectations, firms that file for insolvency are smaller (10.118 vs. 11.518), have higher leverage (0.210 vs. 0.186), and are less profitable (-0.151 vs. -0.001) than the average solvent firm in the sample. In the last observed year prior to insolvency, the average size further decreases to 9.719. Other notable changes in this period relate to leverage and profitability, which change to 27.3% and -28.2%, respectively.

[TABLE 3 NEAR HERE]

Similarly, the market variables reveal poor performance and greater risk for insolvent firms, as evidenced by an average excess return of -36.2% (in comparison to -7.2% for the average solvent firm in the sample), and sigma equals to 0.138 (in comparison to 0.096 for the average firm). Both measures capture further distress in the last year prior to insolvency, with the average excess return dropping to -64.8% and sigma rising to 0.171.

In terms of the variables used for further analysis and identification of channels via which CEO overconfidence affects the probability of bankruptcy, we note that firms in insolvent subsample have significantly higher R&D ratios (1.379 vs. 0.435). However, we do not observe significant differences in terms of the accounting conservatism.

Interesting insights are provided by the mean (median) bank debt ratio, which shows that on average 73.8% (95.8%) of debt for the solvent firms originates from banks. The figures for the insolvent firms in the sample are even higher, i.e. 77.5% for the total period and 78.5% for the final year prior to the year of failure. The statistics, therefore, indicate that UK firms generally rely on bank debt financing, which is different from what is observed in the USA where debt markets are dispersed (for more details see Chen et al. [2016] and Marshall et al. [2016]).

Finally, we report the descriptive statistics for the corporate governance characteristics incorporated in the analysis. The average solvent (insolvent) company in our sample is managed by about 7 (about 6) directors. The mean board independence in the solvent sub-sample is 55% whereas for the insolvent firms it is only about 49%. Overall, the results show that insolvent firms have smaller and less independent boards. However, it is important to note that the boards of the insolvent firms may get smaller as directors may choose to depart before the insolvency occurs. This is evidenced by the statistics reported in the last column. The average board size drops to about 5.25 in the last year. Lastly, we observe significant differences in terms of board diversity, with boards of solvent firms being more gender diverse than the boards of insolvent firms (0.4 vs. 0.234), as well as significant differences in terms of institutional holdings, with the average of 47% (35%) in the solvent (insolvent) firms.

4.2. Hazard Models

Table 4 presents the results of various specifications of the hazard model, focusing on the main aim of the paper, which is to test if the likelihood of insolvency is impacted the CEO overconfidence bias.

In the first model of Table 4, we present our baseline hazard model. The set of variables used in the model follows prior literature. Specifically, we select accounting and market variables following Shumway (2001); Zmijewski (1984); and Campbell et al. (2008), control for industry effects using the Industry Classification Benchmark (ICB), and set the baseline as a natural logarithm of firms age[xvi]. In line with earlier studies, the estimated coefficients, except for CASH, are significant and have the expected signs. Specifically, the reported coefficients imply that smaller firms and firms with higher leverage, lower profitability and past returns, and higher return volatility are associated with a greater risk of bankruptcy. On the other hand, firms with greater growth opportunities exhibit a lower probability of bankruptcy.

Building on the baseline model (1) we add various measures of overconfidence discussed earlier. Specifically, in model (2), we start with the main measure used in our analysis, OVERCONFIDENCE (purchases) employing 9,061 observations. Next, in model (3), we incorporate the measure of overconfidence based on delayed execution of stock options of Malmendier and Tate (2005), which is the most common in the literature examining the overconfidence of CEOs in the US firms. We note that adding the OVERCONFIDENCE (options) measure significantly reduces the number of observations (from 15,521 in model (1) to 1,771 in model (3)), due to smaller popularity of stock options in the UK compensation packages. Lastly, in model (4), we consider the measure OVERCONFIDENCE (press) of Hirshleifer et al. (2012), which incorporates the external view of the CEO in our analysis. While we consider the externally determined media-based measure of overconfidence we additionally control for the number of times a CEO was mentioned in media outlets, by including the variable PRESS MENTIONS in the analysis. Overall, the reported coefficients of OVERCONFIDENCE suggest that the direction of the association between the probability of bankruptcy and CEO overconfidence is positive. The result is robust to the measure of employed proxy for OVERCONFIDENCE, i.e. it is consistent across overconfidence measures based on stock purchases, options execution, and media portrayal. This positive association indicates that 'suboptimal decision-making' dominates the 'effective leadership' of overconfident CEOs in the context of the probability of bankruptcy.

[TABLE 4 NEAR HERE]

5. Further analysis

5.1. Channel analysis

In this section, we further investigate the mechanisms that drive the significant association between CEO overconfidence and the probability of bankruptcy. In this regard, we explore two potential mechanisms, namely the investment environment and accounting conservatism. We report the empirical results in Table 5.

We expect the association between CEO overconfidence and the probability of corporate failure to be more pronounced in firms operating in innovative environments. We identify the potential for innovation at two levels, industry (in Panel A) and firm (in Panel B). We then test if it affects the association of CEO overconfidence with the probability of bankruptcy by running logistic regressions for each sub-sample of firms in models (1) and (2).

Additionally, we repeat the analysis by focusing on the propensity score matched samples in models (3) and (4).

In Panel A we define an industry as innovative following Hirshleifer et al. (2012), who build their classification on the sum of the adjusted patent citations across all patents applied for during each firm year. Specifically, we map their frequency of innovativeness (i.e. the frequency with which each two-digit SIC industry in their sample is classified as innovative) to each two-digit SIC code present in our sample and consider the top quartile of our distribution as innovative and the bottom quartile as non-innovative industries. [xvii] To name a few, innovative industries in our sample include petroleum and natural gas, commercial machinery and computer hardware, and electric and electronic equipment. Non-innovative industries include agricultural services, retail' food and drink products, and transit and passenger transportation. In Panel B, we define subsamples of high (low) R&D if their R&D is greater (lower) than the sample median.

In line with our expectations, we find that the association between CEO overconfidence and the probability of failure is more pronounced for the firms operating in innovative industries and the sub-sample of more innovative firms, defined by R&D spending. Specifically, in model (2) of Panel A and Panel B, the estimated coefficients are positive and statistically significant (Panel A: *coeff* =0.762, t-stat=2.59; Panel B: *coeff* =1.587, t-stat=2.44), while the coefficients in model (1) of Panel A and Panel B are positive and insignificant (Panel A: *coeff* =0.816, t-stat=1.64; Panel B: *coeff* =0.418, t-stat=0.73). The results presented in models (3) and (4) of both panels conducted on the propensity score matched samples are quantitatively similar.

The findings possibly suggest that the presence of overconfident CEOs is more desired in innovative environments (for evidence on the desirability of overconfident CEOs see e.g., Galasso and Simcoe [2011]; Taylor and Brown [1988], B´enabou and Tirole [2002]). Therefore, in an innovative environment, overconfident CEOs are able to take more risky decisions not only due to their capability and lower risk aversion, but also due to allowed greater discretion in the decision-making.

The second channel we consider is the degree of accounting conservatism. We expect that overconfident CEOs create more risks in firms with less conservative accounting. To test the channel, we split the sample into subsamples with strong and weak accounting conservatism based on the value of C-SCORE as defined by Khan and Whatts (2009). In particular, firms are classified as high (low) C-SCORE if their C-SCORE is greater (lower) than the sample median.

In Panel C of Table 5 we show that the degree of accounting conservatism can help explain the significant association between CEO overconfidence and the probability of failure. In model (2), the estimated coefficient of OVECONFIDENCE is positive and statistically significant (*coeff.* = 1.587, t-test=2.44), while in model (1) the coefficient is positive but insignificant (*coeff.* = 0.418, t-test=0.73). The results for the matched samples reported in models (3) and (4) show quantitatively consistent results.

Overall, Panel C shows that firms with low accounting conservatism are exposed to the greater influence of CEO overconfidence than firms with high accounting conservatism. The weak regime might not constrain overconfident CEO's tendency to delay their reaction to negative news and feedback, which may result in an increased risk of failure.

[TABLE 5 NEAR HERE]

5.2. Corporate Governance Analysis

In the next step of our analysis, we explore potential corporate governance mechanisms, which may have the capacity to moderate the detrimental impact of CEO overconfidence on the probability of bankruptcy.

5.2.1. The Effect of Internal Monitoring

While Banerjee et al. (2015, 2020) document that improvement to broadly defined corporate governance marked by the implementation of Sarbanes-Oxley Act (SOX) lead to a decrease in the impact of CEO overconfidence on decision making, the literature on effectiveness of specific board characteristics in terms of moderating CEO overconfidence is fairly limited. Among few contributions, Malmendier and Tate (2008) and Li and Tang (2010) suggest that the board of directors is likely to be effective in challenging the biased executive and limiting its risky decisions if it is dominated by independent directors. Coles et al. (2008), Graham et al. (2011), and Nakano and Nguyen (2012) add that boards with a sufficient variety of director expertise will be more effective. Furthermore, Chen et al. (2019) find that female directors to attenuate the CEO's overconfident views about the firm. This is because female directors enrich boards with more divergent and independent thinking (Adams and Ferreira, 2009; Chen et al. 2005; Miller and Triana, 2009; Gul et al. 2011) and hence, CEOs are less likely to focus on information confirming their thinking. Hence, we expect that it is more likely that larger, more independent, and gender-diverse boards would be more effective in weighing the impact of overconfident CEO on the probability of corporate bankruptcy.

To test our prediction we split the sample using the three board characteristics, and separately test the association between CEO overconfidence and the probability of bankruptcy in well-governed and poorly governed firms. We show the empirical results in Table 6. In models (1) and (3), we report results on subsamples with more effective board characteristics, while in models (2) and (3) we report more results on subsamples with less effective board characteristics. Specifically, in Panel A, firms are classified in the subsample of large (small) board if the number of their boards of directors is greater (smaller) than the sample median. In Panel B, firms are classified in the subsample of more (less) independent board if the proportion of independent directors on the board of directors is greater (smaller) than the sample median. In Panel C, firms are classified in the subsample of gender-diverse board if there is at least one female director on the board. Similarly, to the structure of analysis presented in Section 5, the analysis is performed on a full set of observations (models (1) and (2)) and matched samples (models (3) and (4)).

In Panel A of Table 6 we show that the impact of CEO overconfidence on the probability of bankruptcy is only significant in a subsample of firms managed by smaller boards of directors (*coeff.* 0.909***). This suggests that overconfident CEOs can dominate smaller boards, and therefore make their decision making more impactful. Next, in Panel B, we show that the studied association is significantly pronounced only in a subsample of firms managed by less independent boards (*coeff.* 0.606**), which confirms our expectation that less independent boards are less effective in challenging the decisions of overconfident CEOs. Further in Panel C, we report that the association between CEO overconfidence and the probability of bankruptcy is only significantly pronounced on male-only boards (*coeff.* 0.669***), characterised by less-diverse and less-independent thinking. The results for matched-sample analysis confirm these trends.

Overall, our findings suggest that larger, more independent, and gender diverse boards are more effective in moderating the impact of the dark side of overconfident CEOs.

[TABLE 6 NEAR HERE]

5.2.2. The Effect of External Monitoring

Kahnem and Lovalo (1993) and Hedon (2002) argue that optimistic decisions can be best alleviated by external monitoring. In this section, we study the effect of monitoring by banks and institutional investors. The UK banks may have incentives to intervene when firms are at a stage of financial distress, and therefore can reduce the impact of CEO overconfidence on the probability of bankruptcy, by the use of control rights and/or ensuring that CEOs will not select value-destroying projects. We, therefore, expect the banks to limit the negative association between CEO overconfidence and the probability of bankruptcy when firms experience signs of financial distress. We argue that when firms face financial distress, they are likely to be subject to greater bank monitoring. First, we consider the state of financial distress using *z-score*[xviii] of Altman (1968, 2013), where values lower than 1.81 indicate the state of financial distress. Second, we conduct a stronger test by repeating the analysis with the *z-score* but consider only a sub-sample of firms which rely on bank debt financing in at least 50% of their debt financing. The second test could be viewed as a robustness test to the first one since in this sub-sample banks will have stronger incentives to monitor the firm. [xix] We examine whether the monitoring moderates the association between CEO overconfidence and the probability of bankruptcy by dividing our sample into two subsamples based on the financial distress identified using *z-score.*

We present the results of the analysis in Table 7. In Panel A models (1) and (3) the reported coefficients are 1.070 and 1.383 are significant at 1% level indicating the positive association of CEO overconfidence and the probability of corporate failure in healthy firms. The coefficients reported for the distressed subsample are also positive but statistically insignificant. In Panel B we focus on the subsample of firms which source their debt from banks in at least 50%. In models (1) and (3) the reported coefficients are higher than in the corresponding models of Panel A. Specifically, the coefficients are 1.844 and 2.161 and are also significant at 1% level, while the reported coefficients for models (2) and (4) are insignificant.

The results are in line with our expectations. In the state of financial distress when the monitoring of UK banks is stronger, the impact of the bias is not significant. Therefore, banks can be perceived as effective monitors of CEO overconfidence, since they seem to be able to moderate the negative effect of CEO overconfidence and the probability of bankruptcy. Furthermore, the negative association between the probability of bankruptcy and CEO overconfidence seems to be driven by the decisions made when the firm is perceived as healthy.

[TABLE 7 NEAR HERE]

The predictions regarding the effectiveness of institutional investors are not clear-cut. While in the UK the institutional investors are viewed as passive monitors allowing greater managerial discretion (Franks et al. 2001; Cosh Hughers 1997), they might still have incentives to prevent firms from being mishandled and abused (Croci et al. 2012). Even if they have a lower tendency to participate in shareholders' meetings than those institutional investors in the US firms (Mallin 1996, 2001; PIRC 1998), their threat of exit (i.e. selling shares) may be very powerful governance tool, since they represent largest owners of equity in the UK (Aguilera 2005). Additionally, Hilary and Hsu (2011) show that investors can recognise the earnings forecast issued by overconfident managers. To this end, we expect institutional investors to mitigate the negative effect of overconfident CEOs on the probability of corporate failure.

To analyse the effect of institutional ownership we classify firms in the subsample of high (low) institutional ownership considering the median value for institutional ownership. In Table 8 we report the results of the logistic regression. In line with our expectations, we find that the association between CEO overconfidence is positive and statistically significant only in the subsample of firms with low institutional ownership. This result suggests that the impact of overconfident CEOs on the probability of bankruptcy can be moderated by institutional shareholders with large share ownership.

[TABLE 8 NEAR HERE]

5.3. The Effect of CEO Experience

In this section, we examine if the CEO experience influences the association between CEO overconfidence and the probability of corporate failure. We consider two elements of experience that may be important, tenure and skills set.

CEOs with more generalist skills set (i.e. generalist CEOs) have been increasingly more desired on the market and therefore better paid than their specialist counterparts (Custodio et al. 2013, 2019; Murphy and Zabojnik 2004, 2007). [xx] Our empirical prediction is that generalist CEOs may have more outside options in the labour market and are, hence, more confident in their decision-making than CEOs with specialized skill sets (i.e., specialist CEOs). As a result generalist skillset, therefore, can amplify the effect of the overconfidence on the probability of failure.

To capture generality of CEO's human capital we follow Custódio et al. (2013, 2019) and create a General Ability Index (GAI) based on the human capital based on lifetime work experience a CEO gained before the current post. We consider the following five factors, i.e. a number of different positions that CEO has had during his career (No_positions); a number of firms for which a CEO worked (No_firms); a number of different industries in which a CEO worked (No_industries); if a CEO held a position of the CEO at another firm (Previous_CEO); and if a CEO had an experience of working in a conglomerate (Conglomerate). We source No_positions, No_industries, and Previous_CEO from BoardEx database, and Conglomerate from Datastream. [xxi] The GAI is generated using Principal Component Analysis. Similar to Custódio et al. (2013, 2019) we obtain only one component, with eigen value higher than one (eigen value of 3.09026) which successfully compresses all five considered components with positive loadings. Therefore, higher levels of GAI indicate a higher degree of human capital associated with a CEO. The GAI is calculated by applying PCA scores to the standardised general ability components in the as presented in equation (3) and standardised to have a mean of zero and standard deviation of one.

$$GAI_{i,t} = 0.4301 \times \text{No\_positions}_{i,t} + 0.5350 \times \text{No\_firms}_{i,t} + 0.2132 \times \text{Previous\_CEO}_{i,t} + 0.4502 \times \text{Conglomerate}_{i,t} \qquad (3)$$

Using the GAI we classify CEOs with an index above the yearly median as *generalist* and CEOs with the index below the yearly median as a specialist. We report the results of our analysis in the models (2) and (3) of Table 8. Specifically, we run logistic regression using sub-sample of generalist CEOs in model (2) and sub-sample of specialist CEOs in model (3).

We report the results in Table 9 Panel A. The coefficient for the Generalist subsample is positive (coeff. 0.802) and significant at 5% level in model (1), while it is positive (0.478) and insignificant n model (2). The results for the matched sample show quantitatively similar results. Overall, the reported coefficients indicate that the relationship between CEO overconfidence and the probability of failure is more pronounced among firms run by the generalist CEOs, which is in line with our expectations.

The second aspect of CEO experience we examine is her tenure. A newly appointed CEO may not be able to influence the decision making to the same extent as later during his tenure, hence his overconfidence may not affect his decision making to the same extent in the first year of the tenure. To verify, if the early years of overconfident CEO's tenure do not bias our results, we impose an additional restriction and include the observations of the CEOS only from the second year of their tenure onwards. We report the results in Table 8 Panel B. The reported coefficients for both full and matched samples are positive and statistically significant confirming the positive association between CEO overconfidence and probability of failure.

[TABLE 9 NEAR HERE]

5.4. *Propensity Score Matching*

To reduce the problem of endogeneity in our analysis, we balance our covariates using propensity score matching (PSM). We generate the sample with most comparable treated (overconfident) and controlled (non-overconfident) CEOs. Due to a limited number of observations of overconfident directors under measures of overconfidence employing options and media portrayal, we only conduct the PSM robustness check using the OVERCONFIDENCE (purchases) measure.

Table 10 compares the probability of bankruptcy for firms with overconfident CEOs that were matched via propensity score matching with the firms run by non-overconfident CEOs. The propensity score is the predicted value from a logit regression using the same controls as those included in the main model capturing the relation between the probability of bankruptcy and overconfidence, presented in Table 4. The logit regression results are reported in the first column of Panel A in Table 10. The dependent variable is CEO OVERCONFIDENCE. We find that cash holdings, leverage, profitability, excess returns and their volatility are negatively associated with the presence of overconfident CEOs, while size and market to book ratios are positively associated with the presence of the biased CEOs. In the next step, we adopt the nearest neighbour approach to ensure that firms with overconfident CEOs are sufficiently similar to the matched firms with non-overconfident CEOs. In doing so we match the treatment and control observations with the closest propensity score as proposed by Smith and Todd (2005) and allow observation to enter the control group only once (no replacement). To make sure that our sub-samples, i.e. treatment and control group, are sufficiently similar in terms of observable characteristics we conduct univariate analysis and also re-estimate the logit model used for PSM for the post-match sample. All the coefficients presented in the second model of Panel A are consistently insignificant, suggesting that the firms in the sample are similar in terms of observable characteristics, other than if they are run by the overconfident CEO. This is further confirmed by a drop in pseudo R square, from 0.030 in model (1) to 0.001 in model (2).

Panel B reports the mean comparisons between the treatment and control group. The differences between the groups are tested using t-statistics. The results show that the firms in the two-sub groups do not show significant differences in terms of observable characteristics.

Finally, Panel C of the table reports the coefficients of the logistic regression where the dependent variable is the probability of bankruptcy using matched samples. The reported results on the reduced sample confirm our main prediction, i.e. CEO overconfidence is significantly and positively associated with the probability of corporate bankruptcy.

[TABLE 10 NEAR HERE]

5.5. Forecast accuracy

We examine if the inclusion of CEO overconfidence in the probability of bankruptcy specification increases the prediction accuracy. To do so, we divide our sample into two periods, i.e. 1999-2008, and 2009-2017. We then estimate the hazard models in the first period and, using the estimated coefficients we predict the bankruptcies that occurred in the out-of-sample sub-period 2009-2017. In Table 11, we report the comparisons of the out-of-sample accuracy of the models that contain various sets of predictors. Similar to the approach taken for the earlier hazard models in the study, we begin with the baseline model (i.e. the one which contains a market, accounting, and governance variables) and then proceed by adding the main overconfidence proxy, i.e. OVERCONFIDENCE (purchases). We do not conduct tests for the accuracy of the forecast with the OVERCONFIDENCE (options) and OVERCONFIDENCE (press) measures due to the insufficient number of observations in the sub-periods. The results reveal that the model which includes the overconfidence measure is more accurate than the baseline model. Specifically, the second model classifies 48.214% of bankrupt firms accurately in the highest bankruptcy decile, in comparison to 44.643% in the baseline model. Therefore, we confirm that introducing managerial bias into the bankruptcy prediction model increases predictive accuracy.

[TABLE 11 NEAR HERE]

6. Concluding Remarks

This study provides the first attempt in the literature to analyse the relationship between CEO overconfidence and the likelihood of corporate bankruptcy. Using a large sample of UK companies, we find that CEO overconfidence is associated with a greater probability of corporate failure. Our results are robust to the choice of overconfidence proxy we employ and potential endogeneity concerns.

Our analysis indicates that there are two main channels through which overconfident CEOs affect the probability of bankruptcy. First, we provide evidence that the impact of CEO overconfidence on corporate failures is more pronounced in firms that operate in innovative sectors or have higher R&D spending. This finding suggests that overconfident CEOs tend to make riskier decisions in innovative environments. Second, we show that the association between overconfidence and bankruptcy risk is more pronounced in firms with weak accounting conservativism, which implies that overconfident CEOs increase the likelihood of bankruptcy by delaying the reaction to bad news. Furthermore, our analysis shows that the impact of overconfidence on bankruptcy risk is moderated by external and internal corporate governance mechanisms. Specifically, the results reveal that the association is less pronounced when firms are not under closer scrutiny of banks. Banks, as major creditors, seem to play an important role in constraining CEO overconfidence and hence reducing the likelihood of bankruptcy. We also find that the overconfidence bias is moderated by larger, independent and gender diverse boards of directors. Finally, we show that the association between CEO overconfidence and the probability of bankruptcy is affected by the skills set of the CEO. In particular, the impact of overconfidence on the probability of bankruptcy is stronger for generalist than specialist CEOs.

Overall, two important conclusions can be drawn from the analysis in this paper. First, it is important to incorporate personal managerial attributes and biases in corporate failure prediction models. Our research provides the first attempt in that direction by incorporating CEO overconfidence in the bankruptcy prediction analysis. However, we acknowledge that it is also important to consider other executive directors, in particular, Chief Finance Officers, and other institutional contexts. As for the latter, it would be interesting to explore the association between overconfidence and bankruptcy risk in the context of US and consider if the differences between the UK and US insolvency procedures change the interplay between overconfidence and bankruptcy risk.

Further research is needed to explore the impact of their behavioural traits on the probability of bankruptcy. Second, the findings of our research suggest that stricter monitoring of creditors and the characteristics boards of directors play an important role in restraining the adverse effects of CEO overconfidence. While this is a step forward in our understanding of the effectiveness of corporate governance in restraining behavioural biases, further research is needed to shed further light into the relationship between the behavioural characteristics of directors and the likelihood of failure of the companies they manage.

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Tables

Table 1: Corporate Failures across Years

Year	Number of observations	Number of failures	Failure rate (%)
1999	619	0	0
2000	663	0	0
2001	768	0	0
2002	849	0	0
2003	904	4	0.44
2004	905	5	0.55
2005	962	9	0.94
2006	1,003	20	1.99
2007	1,021	53	5.19
2008	957	34	3.55
2009	888	23	2.59
2010	846	12	1.42
2011	806	18	2.23
2012	787	10	1.27
2013	755	16	2.12
2014	732	14	1.91
2015	701	8	1.14
2016	688	3	0.44
2017	667	6	0.90
Total	15,521	235	1.51

This table reports the annual distribution of observations and insolvencies observed during the period of analysis from 1999 until 2017. The total number of firms used in the study is 1,891 inclusive of 235 that failed during the period. The failure rate is the ratio of the number of failures to the total number of observations.

Table 2: Definitions of Variables

Variable name	Definition
	CEO characteristics
OVERCONFIDENCE (purchases)	A dummy variable equal one if the CEO insider purchases earned on average a negative abnormal return over a six-month horizon within the next two calendar years, and zero otherwise.
OVERCONFIDENCE (options)	A dummy variable equal one if the CEO does not exercise at least 67% in-the-money options at the earliest opportunity at least twice during the tenure, and zero otherwise.
OVERCONFIDENCE (press)	A dummy variable equal one if the number of press-articles within a year indicating overconfidence of the CEO exceeds the number of articles indicating the opposite media-portrayal, and zero otherwise.
PRESS MENTIONS	The number of times the CEO was mentioned in the press.
GENERALIST	A dummy variable equal one if the skills set of the CEO is more generalist, and zero if it is more specialist.
TENURE	The number of years the CEO spent in the role to date.
	Control variables
PROFIT	The ratio of EBIT to total assets.
LEVERAGE	The ratio of total debt to total assets.
SIZE	The logarithm of total assets in constant prices.
MTB	The ratio of total assets minus book value of equity then plus the market value of equity to total assets.
CASH	The ratio of cash and equivalent to total assets.
EX.RET	The return of the firm in year t minus the value-weighted FTSE index return in year t.
SIGMA	The standard deviation of residuals obtained by regressing each stock’s monthly returns in the previous year on the FTSE ALL SHARE index return for the same year.
R&D	The ratio of research and development to total sales.
C-SCORE	The score measures the degree of accounting conservatism in accordance with Khan and Watts (2009).
FINANCIAL DISTRESS	A dummy variable equal one if a firm is in financial distress, and zero otherwise. The state of financial distress is determined by the value of z-score of Altman (1968, 2013) lower than 1.81.
BANK DEBT	The ratio of total bank debt to total debt.
	Corporate governance characteristics
BOARD SIZE	The natural logarithm of the number of directors on the board.
BOARD INDEPENDENCE	The ratio of non-executive directors to the total number of directors on the board

BOARD DIVERSITY	A dummy variable equal one if there is at least one female director on the board of directors, and zero otherwise.
INSTITUTIONAL OWNERSHIP	The fraction of total company shares outstanding held by the institutions.

Table 3: Descriptive Statistics

	Solvent Sub-sample			*Insolvent Sub-sample*					
	Whole period			Whole period			Final year		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
OVERCONFIDENCE									
~(purchases)	0.32	0	9273	0.36†	0	669	0.46‡	0	109
~ (options)	0.11	0	1794	0.29†	0	91	0.36‡	0	14
~ (press)	0.26	0	1195	0.16†	0	49	0.6	1	5
PRESS MENTIONS	17	2	1195	4.43†	2	49	9.8	2	5
GENERALIST	0.45	0	6444	0.42	0	436	0.39	0	83
TENURE	4.27	3.74	12,453	3.42†	2.93	1,129	3.18‡	2.78	230
CASH	0.154	0.089	14,148	0.156	0.078	1,373	0.171	0.061	235
SIZE	11.518	11.308	14,148	10.118†	9.9	1,373	9.719‡	9.474	235
LEV	0.186	0.148	14,148	0.210†	0.155	1,373	0.273‡	0.188	235
MTB	1.967	1.42	14,148	1.967	1.256	1,373	2.251	1.207	235
PROFIT	-0.001	0.061	14,148	-0.151†	-0.019	1,373	-0.282‡	-0.117	235
EXC. RET	-0.07	-0.01	14,148	-0.362†	-0.257	1,373	-0.648‡	-0.558	235
SIGMA	0.096	0.079	14,148	0.138†	0.12	1,373	0.171‡	0.157	235
R&D	0.435	0.027	5,619	1.379†	0.046	369	2.275‡	0.06	69
C-SCORE	0.203	0.194	12,898	0.205	0.192	1,278	0.209	0.18	227
FINANCIAL DISTRESS	0.273	0.958	14,066	0.423†	0	1,365	0.631‡	1	233
BANK DEBT	0.738	0.958	8,737	0.775†	0.962	836	0.785‡	0.963	152
BOARD SIZE	1.881	1.946	12,453	1.706†	1.792	1,129	1.598‡	1.609	230
BOARD INDEPENDENCE	55%	57%	12,453	49%†	50%	1,129	51%‡	50%	230
BOARD DIVERSITY	0.400	0	12,453	0.234†	0	1,129	0.230‡	0	230
INSTITUTIONAL OWN.	47%	47%	13,038	35%†	29%	1,300	30%‡	21%	230

This table presents means, medians, and the number of observations of all variables used in the analysis, with a distinction for firms which remained solvent during the analysed period (solvent sub-sample) and which failed at any point during the analysed period (insolvent sub-sample). For insolvent sub-sample, we additionally present the statistics for the final year before the failure. The mean values are compared using t-tests (with unequal variances). † denotes the significance of the differences in means of the solvent and insolvent sub-sample at 10% significance level. ‡ denotes the significance of the differences in means of the solvent sub-sample and the final year before the failure in insolvent sub-sample at 10% significance level.

Table 4: CEO Overconfidence and Probability of Corporate Failure

Model	(1)	(2)	(3)	(4)
OVERCONFIDENCE				
(purchases)		0.629***		
		(0.205)		
(options)			1.136**	
			(0.558)	
(press)				2.341***
				(0.731)
PRESS MENTIONS				-0.001***
				(0.000)
CASH	-0.569	-0.767	2.481	-3.636
	(0.427)	(0.711)	(1.983)	(2.211)
SIZE	-0.352***	-0.319***	-0.353**	-0.092
	(0.044)	(0.061)	(0.163)	(0.380)
LEV	1.178***	1.643***	3.180***	-0.286
	(0.293)	(0.470)	(1.105)	(2.756)
MTB	-0.099**	-0.131*	-0.192	-0.416***
	(0.039)	(0.079)	(0.191)	(0.150)
PROFIT	-0.669***	-0.651*	0.387	-0.608
	(0.226)	(0.360)	(1.122)	(3.346)
EXC. RET	-0.557***	-0.353**	-1.163**	-0.213
	(0.108)	(0.165)	(0.512)	(0.730)
SIGMA	5.670***	7.009***	5.765	19.198*
	(0.912)	(1.374)	(4.079)	(11.089)
Constant	-2.108***	-3.254***	-2.847	-4.476
	(0.599)	(0.825)	(2.378)	(5.092)
Model fit	506.358	237.355	161.608	120.911
Pseudo R^2	0.165	0.157	0.272	0.382
# of firm/year observations	15,521	9,061	1,771	809
# of insolvencies	235	109	14	5
# of firms	1,891	1,359	303	325

This table reports the results from discrete-time hazard models. The dependent variable is insolvency indicator, equal 1(0) if the firm failed (survived) during the year. The baseline hazard rate is set using the natural logarithm of the firm's age. All models include industry controls in accordance to the industry classification benchmark (ICB). Model fit is the chi-square of the likelihood ratio. Robust standard errors are reported in parentheses. ***, **, * indicates that the estimated coefficient is significant at the 1%, 5%, and 10% levels respectively. The variables are defined in Table 2.

Table 5: Channel Analysis

Panel A: Industry investment environment: Innovative versus non-innovative industries

	Full sample		Matched sample	
	Non-innovative industries	Innovative industries	Non-innovative industries	Innovative industries
	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.816	0.762***	0.986	1.054***
	(0.499)	(0.294)	(0.608)	(0.386)
Constant	-3.894**	-6.337***	-2.167	-6.140***
	(1.799)	(1.442)	(1.803)	(1.563)
Model fit	84.628	110.079	138.580	86.428
Pseudo R^2	0.252	0.220	0.346	0.239
# firm/year obs.	2,534	5,195	1,673	3,370

Panel B: Firm investment environment

	Full sample		Matched sample	
	Low R&D	High R&D	Low R&D	High R&D
	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.418	1.587**	0.052	1.958*
	(0.570)	(0.651)	(0.653)	(1.114)
Constant	-1.436	-7.354*	-1.780	-8.207**
	(2.112)	(3.883)	(2.213)	(3.596)
Model fit	102.756	108.635	86.517	89.313
Pseudo R^2	0.251	0.398	0.300	0.465
# firm/year obs.	2,100	1,394	1,437	925

Panel C: Accounting conservatism

	Full sample		Matched sample	
	High C-SCORE	Low C-SCORE	High C-SCORE	Low C-SCORE
	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.158	1.110***	-0.019	1.477***
	(0.311)	(0.312)	(0.339)	(0.439)

Constant	-5.017***	-2.489*	-4.051***	-2.781*
	(1.463)	(1.399)	(1.485)	(1.575)
Model fit	175.675	168.440	157.698	165.051
Pseudo R^2	0.205	0.221	0.213	0.287
# firm/year obs.	3,850	3,616	2,587	2,341

The table presents the logistic regression results for the full sample in models (1) and (2) and the matched sample in models (3) and (4). The dependent variable is insolvency indicator, equal 1(0) if the firm failed (survived) during the year. The industry-level investment environment analysed in Subsamples in Panel A are defined in accordance with Hirshleifer's et al (2012) frequency of innovativeness. The industries from the top (bottom) decile of the sums of patent citations are classified as (non)innovative. In Panel B, firms are classified in the subsample of high (low) R&D if their R&D is is greater (lower) than the sample median. In Panel C, firms are classified in the subsample of high (low) C-SCORE if their C-SCORE is greater (lower) than the sample median. Overconfidence is proxied by OVERCONFIDENCE (purchases) measure. All models include year dummies as well as proxies for cash holdings, firms size, leverage, market-to-book, profitability, market returns and their volatility. Industry controls are included only in Panel B and Panel C. Robust standard errors are reported in parentheses. ***, **, * indicate that the estimated coefficient is significant at the 1%, 5%, and 10% levels respectively. Definitions of all variables are provided in Table 2.

Table 6: The Effect of Boards of Directors

Panel A: Size of the board

	Full sample		Matched sample	
	Small board	Large board	Small board	Large board
	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.909***	0.364	0.841**	0.415
	-0.309	-0.3	-0.366	-0.338
Constant	-5.303***	-3.691***	-4.617***	-2.899**
	-1.697	-1.402	-1.746	-1.347
Model fit	141.357	192.667	148.815	211.464
Pseudo R^2	0.223	0.163	0.24	0.184
# firm/year obs.	2,189	6,113	1,322	4,111

Panel B: Board independence

	Full sample		Matched sample	
	Less independent board	More independent board	Less independent board	More independent board
	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.606**	0.518	0.431	0.760*
	-0.275	-0.359	-0.322	-0.423
Constant	-4.547***	-4.084**	-3.350***	-3.799**
	-1.368	-1.942	-1.163	-1.913
Model fit	150.296	227.28	123.34	172.821
Pseudo R^2	0.168	0.236	0.178	0.288
# firm/year obs.	4,120	3,492	2,440	2,490

Panel C: Board gender diversity

	Full sample		Matched sample	
	Male-only board	Gender-diverse board	Male-only board	Gender-diverse board
	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.669***	0.422	0.508*	0.505
	-0.245	-0.421	-0.288	-0.503
Constant	-5.452***	-4.637**	-4.229***	-6.514***

	-1.179	-1.932	-1.133	-1.924
Model fit	251.254	226.113	210.096	157.247
Pseudo R^2	0.229	0.2	0.24	0.22
# firm/year obs.	6,023	3,919	3,407	2,489

The table presents the logistic regression results for the full sample in models (1) and (2) and the matched sample in models (3) and (4). The dependent variable is insolvency indicator, equal 1(0) if the firm failed (survived) during the year. In Panel A, firms are classified in the subsample of large (small) board if the number of their boards of directors is greater (smaller) than the sample median. In Panel B, firms are classified in the subsample of more (less) independent board if the proportion of independent directors on the board of directors is greater (smaller) than the sample median. In Panel C, firms are classified in the subsample of gender-diverse board if there is at least one female director on the board. Firms are classified in the subsample of male-only board if their board contains only male directors. Overconfidence is proxied by OVERCONFIDENCE (purchases) measure. All models include year and industry dummies as well as proxies for cash holdings, firms size, leverage, market-to-book, profitability, market returns and their volatility. Robust standard errors are reported in parentheses. ***, **, * indicate that the estimated coefficient is significant at the 1%, 5%, and 10% levels respectively. Definitions of all variables are provided in Table 2.

Table 7: The Effect of Bank Monitoring

Panel A: Financial distress

Sample	Full sample		Matched sample	
	Healthy	Distressed	Healthy	Distressed
Model	(1)	(2)	(3)	(4)
OVERCONFIDENCE	1.070***	0.219	1.383***	0.066
	(0.321)	(0.283)	(0.489)	(0.307)
Constant	-5.701***	-2.792**	-4.577**	-3.132***
	(1.736)	(1.096)	(2.019)	(1.135)
Model fit	138.684	114.056	142.098	111.540
Pseudo R^2	0.169	0.166	0.229	0.172
# of firm/year obs.	4,884	2,067	3,071	1,474

Panel B: Financial distress in firms dependent on bank financing

Sample	Full sample		Matched sample	
	Healthy	Distressed	Healthy	Distressed
Model	(1)	(2)	(3)	(4)
OVERCONFIDENCE	1.844***	0.426	2.161***	0.252
	(0.510)	(0.387)	(0.785)	(0.419)
Constant	-2.013	-2.632**	-0.851	-2.238*
	(2.432)	(1.190)	(2.441)	(1.240)
Model fit	278.633	57.382	292.367	57.598
Pseudo R^2	0.269	0.168	0.329	0.166
# of firm/year obs.	2,660	1,017	1,683	700

The table presents the logistic regression results for the full sample in models (1) and (2) and the matched sample in models (3) and (4). The dependent variable is insolvency indicator, equal 1(0) if the firm failed (survived) during the year. In Panel A, firms are classified in the subsample of healthy (distressed) if *z-score* of Altman (1968, 2013) is higher (lower) than 1.81. All firms included in the analysis presented in Panel B have BANK DEBT higher than 50%. Overconfidence is proxied by OVERCONFIDENCE (purchases) measure. All models include year and industry dummies as well as proxies for cash holdings, firms size, leverage, market-to-book, profitability, market returns and their volatility. Robust standard errors are reported in parentheses. ***, **, * indicate that the estimated coefficient is significant at the 1%, 5%, and 10% levels respectively. Definitions of all variables are provided in Table 2.

Table 8: The Influence of Institutional Investors

	Full sample		Matched sample	
	Low institutional ownership	High institutional ownership	Low institutional ownership	High institutional ownership
	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.888***	0.131	0.892***	0.141
	-0.27	-0.372	-0.333	-0.414
Constant	-4.210***	-1.884	-3.761***	-2.154
	-1.282	-1.637	-1.357	-1.656
Model fit	199.441	270.942	168.317	218.109
Pseudo R^2	0.187	0.197	0.201	0.258
# firm/year obs.	3,274	3,573	2,029	2,190

The table presents the logistic regression results for the full sample in models (1) and (2) and the matched sample in models (3) and (4). The dependent variable is insolvency indicator, equal 1(0) if the firm failed (survived) during the year. Firms are classified in the subsample of high (low) institutional ownership if the fraction of total company shares outstanding held by the institutions is higher (lower) than the sample median. Overconfidence is proxied by OVERCONFIDENCE (purchases) measure. All models include year and industry dummies as well as proxies for cash holdings, firms size, leverage, market-to-book, profitability, market returns and their volatility. Robust standard errors are reported in parentheses. ***, **, * indicate that the estimated coefficient is significant at the 1%, 5%, and 10% levels respectively. Definitions of all variables are provided in Table 2.

Table 9: The Effect of CEO Experience

Panel A: CEO Skills Set

Sample	Full sample		Matched sample	
	Generalist	Specialist	Generalist	Specialist
Model	(1)	(2)	(3)	(4)
OVERCONFIDENCE	0.802**	0.478	1.163**	0.189
	(0.392)	(0.311)	(0.522)	(0.337)
Constant	-3.472**	-18.773***	0.990	-4.247**
	(1.608)	(1.580)	(1.400)	(2.065)
Model fit	161.849	1629.935	141.339	122.730
Pseudo R^2	0.224	0.212	0.277	0.219
# of firm/year observations	3,111	3,769	1,700	2,107

Panel B: CEO Tenure longer than 1 year

Sample	Full sample	Matched sample
Model	(1)	(2)
OVERCONFIDENCE	0.510**	0.461*
	(0.221)	(0.259)
Constant	-4.181***	-4.700***
	(1.089)	(0.979)
Model fit	287.328	259.185
Pseudo R^2	0.200	0.217
# of firm/year observations	8,348	5,378

The table presents the results from logistic regressions for the full sample in models (1) and (2) and the matched sample in models (3) and (4). The dependent variable is insolvency indicator, equal 1(0) if the firm failed (survived) during the year. In Panel A, firms are classified in the subsample of Generalist (Specialist) if the skills set of the CEO is more generalist (specialist) in accordance with the definition of Custodio et al. (2013, 2019). All firms included in the Panel B have the CEOs running their firms for a period longer than one year. Overconfidence is proxied by OVERCONFIDENCE (purchases) measure. All models include year and time controls as well as proxies for cash holdings, firms size, leverage, market-to-book, profitability, market returns and their volatility. Robust standard errors are reported in parentheses. ***, **, * indicate that the estimated coefficient is significant at the 1%, 5%, and 10% levels respectively. Definitions of all variables are provided in Table 2.

Table 10: Probability of Bankruptcy Using Propensity Score Matched Samples

Panel A: Pre-match propensity score regression and post-match diagnostic regression

Model	(1)		(2)	
Dependent variable	OVERCONFIDENCE		OVERCONFIDENCE	
CASH	-0.340**	(0.159)	-0.020	(0.185)
SIZE	0.159***	(0.015)	-0.010	(0.017)
LEV	-0.033	(0.136)	0.002	(0.157)
MTB	0.050***	(0.014)	-0.007	(0.016)
PROFIT	-0.305**	(0.123)	0.106	(0.139)
EXC. RET	-0.239***	(0.050)	-0.044	(0.056)
SIGMA	-0.138	(0.476)	-0.304	(0.549)
Constant	-3.176***	(0.285)	0.169	(0.339)
Industry effects	*Yes*		*Yes*	
Year effects	*Yes*		*Yes*	
Model fit	356.043		7.614	
Pseudo R^2	0.030		0.001	
# of firm/year obs.	9,942		6,490	

Panel B: Differences in means

Sample	Treatment	Control	t	p>|t|
CASH	0.139	0.141	-0.800	-0.310
SIZE	10.031	10.041	-0.500	-0.180
LEV	0.193	0.194	-0.400	-0.160
MTB	1.912	1.938	-1.600	-0.630
PROFIT	0.000	-0.004	1.900	0.770
EXC. RET	-0.104	-0.101	-0.600	-0.230
SIGMA	0.091	0.092	-2.000	-0.810

Panel C: Logistic regression using Propensity Score Matched sample

Dependent variable	Insolvency indicator	
CASH	-1.310	(0.860)
SIZE	-0.360***	(0.078)
LEV	1.772***	(0.519)
MTB	-0.125	(0.077)
PROFIT	-0.795*	(0.420)
EXC. RET	-0.309	(0.204)
SIGMA	7.770***	(1.637)
OVERCONFIDENCE	0.549**	(0.248)
Constant	-3.975***	(0.851)
Industry effects	*Yes*	
Year effects	*Yes*	
Model fit	263.564	
Pseudo R2	0.224	
# of firm/year obs.	6,490	

Model fit is the chi-square of the likelihood ratio. Robust standard errors are reported in parentheses. ***, **, * indicate that the estimated coefficient is significant at the 1%, 5%, 10% level, respectively. The definitions of all variables are reported in Table 2. Panel A reports pre-match propensity score regression in model (1) and post-match diagnostic regression results in model (2). Panel B reports differences in means between Treatment (3,245 firm-year obs. with overconfident CEOs) and Control (3,245 firm-year obs. with non-overconfident CEO) groups. Panel C reports results of the logistic regression using propensity score matched sample.

Table 11: Forecast accuracy

Decile	(1)	(2)
1	44.643	48.214
2	19.643	14.286
3	12.500	16.071
4	8.929	3.571
5	5.357	5.357
6-10	8.929	12.500
	100.000	100.000

This table reports forecast accuracy of two specifications of the hazard model. Column (1) reports forecast accuracy of the baseline model. Column (2) reports the accuracy of hazard model with OVERCONFIDENCE (purchases) measure.

[i] In this paper, we use interchangeably the terms bankruptcy, insolvency, and failure to mean the same thing.

[ii] The principle of lender liability holds that banks may face a penalty if it is judged to have taken actions that improve their position at the expense of other owners (for e.g. shareholders). This principle discourages US creditors from active monitoring when a firm faces financial distress.

[iii] FAME, Financial Analysis Made Easy, is a database of public and private companies, administered by Bureau Van Dijk.

[iv] We use Thomson Reuters Datastream item: *BDATE* to mark the start of the duration.

[v] Following Charitou et al. (2004) and Ozkan et al. (2017), we define corporate failure by observing any one of the following events in the data: administration, liquidation, receivership and dissolution. Administration is a formal rescue procedure, involving to appoint an insolvency practitioner as administrator to salvage the company in financial distress. During the period of administration, the debt repayments are suspended and creditors' rights freeze. Liquidation is a procedure whereby a liquidator is appointed to sell the assets of the firms and distribute the proceeds to debtholders. The liquidation procedure can be initiated either by the company through a 'voluntary liquidation' or by the creditors through a 'compulsory liquidation'. Receivership takes place only when one or more of a firm's creditors (lenders) have a particular right to the firm's assets. The creditor has a right to appoint an administrative receiver, who then 'receives' any of the assets of the company that it can liquidate in order to pay back the lender. Dissolution involves voluntarily striking the company off the register at Companies House and thereby terminating its existence. For details on the legal qualities of the insolvency procedures and dissolution see Insolvency Act of 1986 and Companies Act 2006.

[vi] Our overconfidence measures are based on insider dealings which regulated by the Companies Act 2006, and Model Code on directors' dealings, set out in Chapter 9 of the Listing Rules (LR9 Annex 1). For a discussion on the UK regulatory framework of the insider trading activity see Ozkan et al. (2017).

[vii] The construction of buy-and-hold abnormal returns is described in detail in Ozkan and Trzeciakiewicz (2014).

[viii] Following Campbell et al. (2011) and Kim et al. (2016) we additionally construct the overconfidence measure requiring that the CEO does not exercise (at least twice) his options that are more than 100 percent in the money. We further test the stricter measure in the hazard model (as in Table 4) and find that the association between CEO overconfidence and the probability of corporate failure remains positive and significant.

[ix] For a number of option packages BoardEX does not provide the stock price, but the elements from which the stock price can be derived. Specifically the items that can be used are *Exintval*, which is the intrinsic value of exercisable options, that is defined as a gap between stock price and the exercise price multiplied by the volume of exercisable shares, and is reported in '000s, and *Exvol*, which is the volume of exercisable shares. Hence we calculate the missing stock prices as *exintval*1000/exvol + exercise price.*

[x] We have also tested an alternative methodology and matched the names of individual directors with the Thomson Reuters EIKON database that contains the information on insider dealings. Out of all types of transactions we considered only the ones that are labelled as "exercise of options". We have not been able to identify a sufficient number of trades to perform the classification.

[xi] Malmendier and Tate (2005) suggest that to guarantee that every CEO in the sample had an opportunity to be classified as Holder67, one should restrict the sample to CEOs who a least twice held options, which were valued above the threshold during the year of vesting, and hence limit the degree of unobserved bias in the control group. Due to a limited number of observations we also include in our control group those CEOs who who a least once held options, which were valued above the threshold during the year of vesting.

[xii] We are grateful to the anonymous referee for suggesting this extension to the analysis.

[xiii] In this process, we limit our search to English language and drop identical duplicates.

[xiv] In untabulated results, for robustness purposes, we also include the firm/year observations where Factiva reports zero articles on the CEO and generally obtain similar results.

[xv] We observe that there are firms which stop producing financial statements well ahead of recording failure. In our sample 71% of failed firms produce financial statement until the year of filing, 27% produce the statements between three to one year prior to the year of filing and 2% stop earlier than 3 years. The main results of our study are not sensitive to the exclusion of the firms with the gap longer than 1 year.

[xvi] In untabulated results we further the analysis by including the year dummies to our hazard models. The inclusion of the main results does not affect our main results.

[xvii] The innovative industries include all those which have 100% innovative years, i.e. petroleum and natural gas (sic 13); household and office furniture (sic 25); commercial machinery and computer hardware (sic 35); electric equipment and electronic equipment (sic 36); measuring & control equipment, medical equipment (sic 38); consumer goods (sic 39); communications (sic 48); business services (sic 73, 87). The non-innovative industries include all those which have less than 30 % of innovative years, i.e. agricultural services (sic 7); coal mining & coal mining services (sic 12), heavy construction – not building contractors (sic 16); food and drink products (sic 20); tobacco products (sic 21);transit and passenger transportation (sic 41); retail (sic 52, 54, 55, 58); metal mining and metal mining services (sic 10), apparel and other finished products (sic 23); wholesale (sic 50); construction (sic 17); primary metal (sic 33); water transportation (sic 44); transportation services (sic 47); services (sic 82); build construction (sic 15); textiles (sic 22). The full classification is provided in Table IA.II of online appendix to Hirshleifer et al. (2012).

[xviii] We calculate *z-score* using the following formula and Datastream items, *z-score*=1.2*(WorkingCapital/Total Assets)+1.4*(Retained Earnings/Total Assets)+3.3*(EBIT/Total Assets)+0.6*(Market Capitalization/ Total Liabilities)+0.999*(Net Sales or Revenue/Total Assets).

[xix] In unatbulated results we also consider the financial crisis as a period during which banks behaved more vigilantly and raised monitoring of the corporations. We define the period of the financial crisis from 2008 to 2013, as the time when economic conditions are adverse (Salachas et al 2017). We find that the association between CEO overconfidence and the probability of corporate failure is more pronounced in the period outside financial crisis, when the monitoring of corporations by banks was weaker.

[xx] This could be the effect of a rapidly changing business environment, which creates a risk for the specialist's skills to get quickly outdated and therefore a risk for specialist CEOs to be less demanded on the job market. Changes in the business environment are driven by, among others, advancements in technology (Garicano and Rossi-Hansberg 2006), product market changes due to industry deregulation (Cunat and Guadalupe 2009a), or foreign competition (Cunat and Guadalupe 2009b).

[xxi] We source our data on conglomerates from Datastream. Following Custodio et al. (2013) we a firm as a conglomerate if operates across at least two different segments and use dummy variable to flag if

a firms is a conglomerate. To verify operations across two sectors we consider if a firm reports total sales (Datastream items: WC19501, WC19511, WC19521, WC19531, WC19541, WC19551, WC19561, WC19571, WC19581, WC19591) as well as total assets (Datastream items: WC19503, WC19513, WC19523, WC19533, WC19543, WC19553, WC19563, WC19573, WC19583, WC19593) for least two different product segments.