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ORIGINAL PAPER



Why do firms fail? A new view on bankruptcy from the angle of top management team heterogeneity

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Abstract

Avoiding bankruptcy is a crucial task for any firm's top management team (TMT), and reasons for the failure to accomplish it have long been studied. While financial metrics can predict near-term bankruptcy, governance characteristics increase precision in the long term. With TMT heterogeneity, we introduce a powerful predictor for the critical time frame in between. Grounded in upper echelons theory, we argue that TMT age heterogeneity increases while heterogeneity in TMT pay and TMT functional backgrounds decreases the bankruptcy probability. We test our hypotheses using a unique dataset of large, public U.S. firms, about half of which filed for bankruptcy between 2001 and 2020. Our results support our research model and show how TMT heterogeneity significantly predicts bankruptcy. We contribute to both bankruptcy and strategic management research by underscoring the importance of TMT heterogeneity as a level of analysis when predicting bankruptcy and add to the ongoing discussion on the impact of TMT pay differences on firm performance. Additionally, we offer valuable insights to practitioners navigating their firms in times of crisis and to regulators shaping the insolvency statutes of the future.

Keywords Top management team (TMT) \cdot Heterogeneity \cdot Corporate governance \cdot Bankruptcy \cdot Firm survival

JEL Classification $~G33\cdot M14\cdot G34\cdot M12$

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1 Introduction

Firm bankruptcy not only directly and severely affects all stakeholders of the failing firm, but, as Bernstein et al. (2019, p. 5) emphasize, has "important implications for productivity and the speed of recovery" of the entire economy (Pajunen 2006). It is thus crucial for scholars and researchers alike to predict firm bankruptcies accurately (Merton 1974). Accordingly, researchers have "shown renewed interest" (Bharath and Shumway 2008, p. 1339) in the topic—particularly in times of global economic downturns, such as during the 2008/09 financial crisis (Bharath and Shumway 2008) and the recent global COVID-19 pandemic (Mirza et al. 2020). Over the years, a "voluminous stream of research into organizational failure, embedded in organizational ecology theory" (Kücher et al. 2020, p. 634). Bankruptcy describes the ultimate failure of strategic management, and studying its antecedents is key to understanding how management teams can steer a firm in a more successful manner (Daily and Dalton 1994). In a first effort to derive specific predictors of bankruptcy, Merton (1974) introduced a metric from his option pricing model: distance-to-default indicates how 'close' a firm is to bankruptcy from a purely financial standpoint. Such metrics have since been refined, often growing in statistical complexity but not necessarily in predictive or explanatory power (McKee and Lensberg 2002; Traczynski 2017).

However, no matter how sophisticated these financial predictors became, they failed to cover important drivers of distress situations, causing research attention to shift towards studying so-called governance factors (Hambrick and D'Aveni 1988). Grounded in upper echelons theory (Hambrick and Mason 1984), this research stream analyses the impact that characteristics on the level of CEO, board, and top management team (TMT) have on bankruptcy (Daily and Dalton 1994). Scholars devote special attention to the TMT as a level of analysis, as avoiding bankruptcy in a distress situation requires effective cooperation and information sharing between all firm departments (Dahya et al. 2002). In the TMT, defined as the CEO and those individuals "reporting directly to the CEO" (Guadalupe et al. 2014, p. 824), all departments convene to make decisions on strategy and execution as well as on current projects and budgets (Talke et al. 2010). Thus, the TMT is a crucial level of analysis in bankruptcy research: TMT members drive the decisions that determine whether a firm will have to file for bankruptcy over the medium-term time horizon studied in this work. Measures to predict bankruptcy in the long and short term (e.g., 5 years prior to bankruptcy for Daily and Dalton 1994; one year or less for most financial predictors as in Traczynski 2017) have been in use for some time. However, the medium-term outlook-2 years-that our research addresses has received little prior attention. This work connects the discussion of bankruptcy with current TMT research and thereby enters a promising avenue of inquiry.

To estimate TMT impact on distressed firms and to derive insightful predictions of firm-level outcomes, research should consider the TMT as a group rather than as the sum of all individuals (Hambrick 2007). While it can be argued that certain TMT members, like the CEO or the CFO, play a pivotal role in avoiding bankruptcy, the entire management team has to cooperate effectively to steer a firm in times of

crisis (Buchalik and Haarmeyer 2015). Given the growing complexity of the business environment in developed markets such as the United States, recent research shows that the relative influence of TMTs on firm-level outcomes, in general, has even increased over the past decades (Neely et al. 2020). Therefore, measures capturing the composition of the entire TMT-like those related to its heterogeneityappear appropriate for bankruptcy prediction as they indicate how team members work together (Dahya et al. 2002). In this context, information processing theory argues that group dynamics, which depend on the types of heterogeneity and thus the composition of TMTs, can affect information processing and exchange; this may relate to a firm's distress situation (De Dreu and Weingart 2003). Established research reveals that TMTs differ in their ability to process information in their strategic decision-making and that intrateam dynamics can potentially impede or foster the effective information processing required for sound decision-making (Hambrick 2007). Since TMTs need their full information processing capacity to assess potential risks and ensure their companies' long-term successful existence (Dahya et al. 2002), we theorize that TMT heterogeneity holds explanatory power and can serve as a governance-based predictor of firms' bankruptcy probabilities.

Prior research finds that some TMT compositions are more likely than others to hinder or promote information processing in TMTs (e.g., Bunderson and van der Vegt 2018). We aim to shed light on three specific heterogeneity indicators that research considers essential, as Bunderson and van der Vegt (2018) underscore in their comprehensive review. First, studying TMT heterogeneity in age provides us with an easily observable characteristic to which the underlying assumptions of social categorization theory apply (Ashford and Mael 1989; Hogg and Terry 2000). Intergroup conflict within a given TMT resulting from social categorization can negatively affect firm-level outcomes and may lead to, for example, distress situations. Second, we conceptually follow Bunderson and van der Vegt (2018, p. 47), who state that "the effects of diversity can depend critically on the degree of inequality within a team," which, in turn, results from pay imbalances and affects team members' struggle for influence over key business decisions. Pay imbalances are the most common operationalization of vertical TMT heterogeneity (Bunderson and van der Vegt 2018). Some power and pay structures within TMTs foster knowledge exchange, while others impede it (Carpenter and Sanders 2004; Haleblian and Finkelstein 1993). Against this backdrop, we explore how pay heterogeneity within a TMT relates to the probability that a firm files for bankruptcy. Third, cognitive conflicts caused by task-related heterogeneity due to TMT members' functional backgrounds can enhance strategic decision-making, which might counteract distress situations (Amason and Sapienza 1997; van Knippenberg et al. 2004).

In sum, we propose a research model studying three key TMT heterogeneity indicators that affect the probability of a firm filing for bankruptcy—or not doing so—in a given period. In detail, we explore how (1) TMT age, (2) TMT pay, and (3) TMT functional background heterogeneity relate to this probability. We test our hypotheses with a unique set of secondary data composed of almost 1,300 large, public U.S. companies, of which about 50 percent filed for bankruptcy under Chapter 11 between 2001 and 2020. The empirical findings largely support our hypotheses with high statistical significance.

This work makes at least three valuable contributions to academia and existing research on bankruptcy and the TMT literature. First, we address the puzzle as to why some companies are more likely to file for bankruptcy than others. Firm-level, mostly financial, predictors certainly play a crucial role-yet, importantly, they do not to cover all key facets of why the probability of filing for bankruptcy is higher for some firms than others (Traczynski 2017). Hambrick and D'Aveni (1988, 1992) or Daily and Dalton (1994) have convincingly argued in their studies that governance factors helped explain parts of those bankruptcies that financial ratios failed to predict accurately-yet again, several cases remain unexplained. Aiming to bridge this knowledge gap, we follow the argument of Neely et al. (2020), who emphasize that TMT influence on firm-level outcomes has increased in recent decades and that the TMT plays a central role in saving distressed firms from default (Dahya et al. 2002). Focusing on the TMT thus represents a purposeful and appropriate level of analysis, and the results will help further unravel the factors influencing firms' probability of bankruptcy. Second, we address the question of when different bankruptcy predictors are most effective, which refers to the time lag between the observation of a predictor (e.g., a financial ratio or TMT characteristic) and the potential bankruptcy filing. Established research has mostly focused on firm default in the near or the immediate future (<1 year; Merton 1974) or on time horizons of five or more years (Daily and Dalton 1994). However, research has yet to pinpoint clear and suitable predictors for the medium-term time spans in-between (e.g., two years). Daily and Dalton (1994, p. 1613) concluded early on that it "would be fascinating to determine at what [time] point governance structures no longer have some predictive ability concerning future bankruptcy"-but surprisingly, academia has hardly responded to their call for research. Third, we add to upper echelons research by revealing in our in-depth analysis that the three indicators of TMT heterogeneity under consideration have contradictory impacts on the same firm-level outcome—bankruptcy in our study. Accordingly, we call for a nuanced discussion of heterogeneity variables.

In addition to advancing the academic discussion, our research presents actionable insights to practitioners. We offer a differentiated perspective on how TMT heterogeneity might affect the probability of a firm going bankrupt. Our insights can assist investors, policymakers, and the general public in creating corporate governance rules that promote sustainable and lasting success for companies. For instance, we reveal positive effects of TMT pay and TMT functional background heterogeneity on distressed firms, and this finding should encourage board members and CEOs to reconsider incentive structures and onboard functionally diverse management teams when preparing for crisis.

2 Theoretical background

2.1 Bankruptcy

Bankruptcy is defined as a state in which a firm presently or in the near future is or will be unable to meet its contractual financial obligations as they come due (Merton 1974). In the United States, bankruptcy is governed, for the most part, by Title 11

of the United States Code, which provides debtors and creditors with the option to file for bankruptcy, either to liquidate (Chapter 7) or to reorganize (Chapter 11) a firm (United States Code, 1978). The academic discussion of bankruptcy focuses on determining when and why firms file for bankruptcy and identifying potential stakeholder implications. Literature on bankruptcy prediction mostly follows one of two distinct approaches, as Traczynski (2017) shows: Either researchers use theory to derive variables that serve as bankruptcy predictors and test them in empirical samples (like Merton 1974, see below), or they collect as "many different variables" (Traczynski 2017, p. 1211) as possible to determine those that optimally predict bankruptcy using statistical models (like Bharath and Shumway 2008, see below).

As one of the first widely cited researchers in the field, Merton (1974) derived his firm bankruptcy model purely from finance theory. Assuming efficient stock markets, he utilized stock price volatility, a firm's debt level compared to the value of its assets, and the risk-free rate to deduce what is, essentially, a market-implied default probability for a specific public firm. This value is then scaled into a generalized measure Merton called *distance-to-default*. While the theoretical validity of this approach is largely unquestioned, the degree to which it helps better predict bankruptcy in the real world is still controversial—Bharath and Shumway (2008, p. 1339), for example, find that the model's "functional form is useful for forecasting defaults" but emphasize that in their view it "does not produce a sufficient statistic for the probability of default."

Shumway (2001) had previously described an alternative bankruptcy prediction model that shares most input factors with Merton but estimates default probabilities with a different statistical approach. Under certain circumstances, this approach is empirically more powerful in accurately predicting firm bankruptcy; however, it lacks the stringent—and lauded—theoretical reasoning of Merton's model. Research has published a wide array of such "more atheoretical" (Traczynski 2017, p. 1212) empirical models over the decades, with varying results and impacts on the academic discussion (Chava and Jarrow 2004; Giordani et al. 2014). In summary, there is still no consensus on the optimal financial predictor(s) of bankruptcy and whether complex empirical models statistically significantly outperform indicators like Merton's distance-to-default or simple measures of indebtedness, liquidity, or profitability when tested out-of-sample (Cremers 2002; Campbell et al. 2008).

With the advent of upper echelons theory, a new set of potential predictors of bankruptcy entered the academic discourse (Hambrick and Mason 1984; Hambrick and D'Aveni 1988, 1992; McKinley 1993). Researchers have since argued convincingly that a set of governance indicators like board structure (e.g., CEO/Chairman duality, board member independence) or TMT characteristics (e.g., TMT turnover rates) are associated with bankruptcy over an extended observation period (Daily and Dalton 1994). Daily and Dalton (1994), for example, analyzed a matched sample of 57 pairs of one bankrupt and one nonbankrupt firm and found that the bankrupt firm was more likely to exhibit CEO/Chairman duality and a lower share of independent directors. This result corresponds to the work of Hambrick and D'Aveni (1992), who revealed that dominant CEOs are associated with a higher bankruptcy probability.

Dowell et al. (2011) argued that such findings presented substantial evidence supporting the link between governance factors and firm-level outcomes concerning companies in financial distress. However, since then, research has garnered few additional empirical insights into new governance-based predictors of bankruptcy. For complex firms, Darrat et al. (2014, p. 1) established decreasing bankruptcy probabilities with increasing board sizes; they add that "explanatory power from corporate governance variables becomes stronger as the time to bankruptcy is increased"—emphasizing the need to study which metrics optimally predict bankruptcy over varying time horizons. Recent studies on the relationship between bankruptcy and the COVID-19 pandemic have yet to include governance variables (e.g., Mirza et al. 2020).

Reinvigorating this crucial academic discussion is of particularly interest in times of crisis and the ongoing discourse on corporate governance reform. Adding significant predictors relating to TMT heterogeneity to bankruptcy studies provides researchers with a powerful tool to optimize bankruptcy prediction and practitioners with a firm characteristic they can easily observe and effectively adjust through corporate governance regulations. At the same time, bankruptcy is a crucial and distinct firm-level outcome that offers upper echelons researchers ample opportunity to test the implications of their models.

2.2 TMT heterogeneity

TMT heterogeneity research is grounded in upper echelons theory, which argues that top management executives are confronted with a lot of information in their complex work environment and, therefore, cannot process all available data simultaneously and always derive rational conclusions (Hambrick and Mason 1984). Top management executives' information processing can be described by the concept of bounded rationality, according to which managers take cognitive shortcuts to arrive at actionable decisions—and the nature of these shortcuts, in turn, is influenced by the characteristics of the individual executive or the relevant team of decision-makers (Cyert and March 1963). With this rationale, Hambrick and Mason (1984) were the first to argue credibly how cognitions, emotions, and other observable characteristics of executives and TMTs translate into organizational outcomes, thereby opening a broad avenue for further research.

While several individual top management roles, most notably the CEO (Chatterjee and Hambrick 2007), have since received substantial academic attention, upper echelons research has increasingly gravitated towards scrutinizing the TMT regarding its composition and, more specifically, its heterogeneity features (Bunderson and van der Vegt 2018). TMT heterogeneity was at first viewed as the variety of demographic factors within a firm's TMT, with increased heterogeneity mainly being associated with positive effects on firm-level outcomes—despite initially inconclusive empirical evidence (Bantel 1993; Nielsen 2010). Typical demographic TMT heterogeneity indicators include age, nationality, ethnicity/race, and gender, with a comprehensive meta study of 53 empirical articles revealing age as the most often studied demographic factor in the literature (11 articles), followed by nationality (3 articles) (Bunderson and van der Vegt 2018). Age is thus not only the most frequently used demographic factor in the literature, but also one that strongly affects the views and cognitions of a person while being easily observable by all team members (Bunderson and van der Vegt 2018).

Advances in social categorization and conflict theory have changed how researchers evaluate the impact of a team's demographic heterogeneity. Studies show that more demographically homogeneous teams outperform heterogeneous ones in some job-related tasks (Jehn et al. 1999; Simons et al. 1999). To explain this phenomenon, Amason and Sapienza (1997) draw on social identity theory (Ashford and Mael 1989), purporting that affective conflict might induce socially diverse groups' potential lack of inner cohesion, which, in turn, reduces the efficiency of information sharing and group-level outcomes.

TMT heterogeneity research moved beyond demographic factors to study other types of heterogeneity in management teams, which, as Nielson (2010) emphasized, should be evaluated in detail regarding their impact on firms. Extending upper echelons theory, Hambrick (2007) indicates another crucial category of heterogeneity: intra-TMT power distribution. In line with Finkelstein (1992), Hambrick (2007) argues that the impact of TMT variables can only be tangible if all TMT members carry some clout within the organization. If, for example, a powerful CEO dominates all decision processes within a firm and the influence of the overall management team on decision-making is low, the team's level of heterogeneity can hardly be an accurate predictor of firm-level outcomes. Earlier research, however, shows that in situations where intense collaboration is required, greater power imbalances may induce constructive competition between TMT members, ultimately improving firm-level outcomes (Ridge et al. 2015). Against this backdrop, we evaluate the influence of intra-TMT power distribution as a separate variable, operationalizing it as TMT pay heterogeneity (Greve and Mitsuhashi 2007; Steinbach et al. 2017).

Lastly, we need to consider a third distinction in TMTs: task-related heterogeneity, which refers to TMT members' varying educational, functional, and industry backgrounds and tenures (Bunderson and van der Vegt 2018). Functional background heterogeneity is the diversity indicator studied most frequently, with 27 out of the 53 articles surveyed by Bunderson and van der Vegt (2018) addressing it; it is followed by tenure, used in 24 studies, and educational background, used in 16 studies. Note that the same studies may use multiple diversity indicators.

Differences in task-related factors are expected to challenge team members' cognitive abilities to share information as efficiently as possible, thereby combining their unique, task-related backgrounds (Bunderson 2003). Neely et al. (2020) show that taskrelated heterogeneity affects managers' cognitions more directly than demographic factors do—and it ultimately has a positive impact on several firm-level outcomes, such as innovation and overall performance (Talke et al. 2011; Sperber and Linder 2018; Schubert and Tavassoli 2020; Zhou et al. 2022). For our study, we selected TMT members' functional backgrounds to represent task-related TMT heterogeneity because the functional experience managers accumulate during their careers is likely to have a strong influence on their approach to business challenges such as imminent bankruptcy. Prior literature has also predominantly explored this metric (Bunderson and van der Vegt 2018).

3 Hypotheses

3.1 TMT age heterogeneity and bankruptcy

Social identity theory suggests that individuals categorize themselves into groups and adjust their actions based on subsequent group identity (Tajfel 1972). Social categorization is contingent on the individuals recognizing potential differences between themselves and other group members, and this effect is most notable when the shared characteristic is readily observable (Ashford and Mael 1989; Amason and Sapienza 1997; Hogg and Terry 2000). For age, research has long since established that it "is a visible demographic characteristic that, from the social categorization perspective, may easily affect group process" (Williams and O'Reilly 1998, p. 102).

As van Knippenberg et al. (2004) argue, a group of people falling into similar categories acts as a homogeneous group trying to optimize overall (i.e., group-level) outcomes. If categories differ, there is a likelihood that the group breaks up into subgroups working against each other or at least not coordinating and communicating efficiently (Messick and Mackie 1989). Applied to management teams, this can mean that homogeneous TMTs readily share information and knowledge among all members as soon as it becomes available—potentially enabling more efficient decision-making (Hogg and Terry 2000). However, if the TMT is more demographically heterogeneous, different subgroups may form along these characteristics that are reluctant to cooperate and delay or deny mutual information sharing (Olson et al. 2006).

Based on this rationale, Talke et al. (2010) find negative impacts of TMT age heterogeneity on firm performance in general and innovativeness in particular. Williams and O'Reilly (1998, p. 102), in their comprehensive metastudy, conclude that "groups characterized by heterogeneity in age may find communication more difficult, [and] conflict more likely." The type of division potentially caused within TMTs by age heterogeneity is characterized as *affective conflict* (Amason and Sapienza 1997): Individuals who share few characteristics actively work against each other, which negatively affects various firm-level outcomes, for example, creativity (de Clercq et al. 2009) or strategic choices (Olson et al. 2006). However, previous research also identifies positive firm-level effects of demographic heterogeneity, as it enables management teams to make decisions based on more comprehensive knowledge. For example, Boone et al. (2018) show a positive change in corporate entrepreneurship and innovativeness as TMT nationality heterogeneity increases.

To determine the impact of TMT age heterogeneity on bankruptcy, which we explore in our study, we need to discuss the underlying reasons for and responses to firm decline. Literature on firm turnaround describes these factors conceptually. This research stream analyzes the causes behind firms' entry into downturn periods and the factors suitable to prevent them from defaulting (Pearce and Robbins 1993). The classical turnaround model (Pearce and Robbins 1993) describes the reasons for firm decline as the 'turnaround situation' which, according to the authors, has either internal or external causes. Pearce and Robbins (1993) propose that cost cuttings or other (internal) efficiency measures are likely the best response to internal causes, while external causes may require strategic repositioning (Pearce and Robbins 1993). Independent of the cause, the TMT nearly always influences the turnaround situation and is tasked with devising an appropriate strategy with measures leading the firm out of turmoil (Trahms et al. 2013). Such a response requires concerted management action—effective collaboration and information sharing within the TMT are crucial to prevent adverse outcomes such as bankruptcy (Buchalik and Haarmeyer 2015).

We have to acknowledge that the potential impeding effect of age heterogeneity on effective TMT collaboration and information sharing is not a direct one but is subject to mediating mechanisms (Talke et al. 2010). Previous research considers these by including in their models, for example, interpersonal relations and information elaboration (Samba et al. 2018). In our work, we follow Nielsen and Nielsen (2013) and hypothesize on how age heterogeneity directly affects firm-level outcomes. In line with their suggestion, we consider the specifics of the factor of age above and control for a set of firm-level variables in our model, which are specified in this manuscript's section on control variables (Nielsen and Nielsen 2013). In summary, we assume that TMT age heterogeneity impedes effective intra-TMT communication when it is urgently needed, such as during the crisis of a firm, and induce affective conflict in situations requiring bold, concerted action to avoid bankruptcy. Therefore, we hypothesize:

H1 TMT age heterogeneity exhibits a positive relationship with the probability of a firm filing for bankruptcy.

3.2 TMT pay heterogeneity and bankruptcy

When estimating the impact of heterogeneity in demographic factors like age and gender on firm-level outcomes, the prevailing implicit assumption is often that each TMT member contributes similarly to the considered result. However, as Finkelstein and Boyd (1998) point out, different members of the TMT—in their research, the CEO—influence the enterprise to a varying degree. Bunderson and van der Vegt (2018), therefore, refer to heterogeneity indicators such as age and gender as horizontal metrics of difference. To account for such intra-TMT power differences, upper echelons researchers began to study the impact of vertical heterogeneity characteristics, in addition to the horizontal characteristics like age and functional background (Bunderson and van der Vegt 2018).

Finkelstein (1992), Hambrick (2007) note that individual TMT members draw on different sources of power—for example, their compensation, stock ownership, titles, expertise, or prestige in the organization. To consider diverse power sources is highly significant in heterogeneity research because substantial power imbalances might exist within a TMT that—unlike a power balance—potentially entail negative group dynamics (Hambrick 2007). Extant research most commonly operationalizes TMT power differences as pay inequality among management team members (Bunderson and van der Vegt 2018). In their 2018 literature review, Bunderson and van der Vegt find that all but one of the studies surveyed in their work used this characteristic to account for vertical TMT heterogeneity, if this factor was considered at all. In line with Smith et al. (1994), we consider the coefficient of variation for the compensation of TMT members in the given year to arrive at a functioning metric. Power concentration in TMTs has been shown to affect an array of firm-level outcomes, such as strategic decision making (Greve and Mitsuhashi 2007; Steinbach et al. 2017).

Still, the study of TMT pay heterogeneity and its impact on the firm is less developed compared to 'classical', i.e., horizontal diversity indicators. Bunderson and van der Vegt (2018) show, that only about 11% of studies in the field even consider pay heterogeneity as a factor in their hypotheses, with researchers arguing into diverging direction regarding its impact on the firm. A relevant part of the literature views pay as a quite visible characteristic (as e.g., in the US, major public enterprises have to disclose their TMT's earnings), differences in which are said to induce the formation of sub-groups, hinder effective collaboration and thereby negatively impact key firm-level metrics—similar to the case of TMT age heterogeneity discussed in detail before (e.g., Carpenter and Sanders 2004; Fredrickson et al. 2010; Patel and Cooper 2014).

However, in the situation of distressed enterprises threatened by bankruptcy, close collaboration between all stakeholders, particularly in top management, is required to ensure firm survival (Buchalik and Haarmeyer 2015). In the context of publicly listed firms in the tourism and leisure sector, current research already reveals that firms with higher compensation packages for TMTs have an increased survival likelihood (Trinh and Seetaram 2022). In particular, compensation schemes inducing tournament-style competition between managers, and thereby most often leading to higher pay inequity, have been shown to improve team outcomes in such settings, and therefore are preferrable for distressed firms (Frick et al. 2003; Halevy et al. 2011; Ridge et al. 2015). Indeed, a larger pay gap in the TMT motivates managers and discourages shirking, as argued by Henderson and Fredrickson (2001). Following tournament theory, a higher TMT pay heterogeneity is especially "appropriate when employee contributions are critical and affect firm performance more directly" (Sanchez-Marin and Baixauli-Soler 2015, p. 438). Sanchez-Marin and Baixauli-Soler (2015) were among the first to empirically illustrate that in owner-controlled firms, increased TMT pay dispersion positively relates to better firm performance. Therefore, we hypothesize:

H2 TMT pay heterogeneity exhibits a negative relationship with the probability of filing for bankruptcy.

3.3 TMT heterogeneity in functional background and bankruptcy

Already in 1958, Dearborn and Simon described how that a manager's functional background defines how this individual will approach business problems, regardless of whether the individual has experience in those issues. In recent years, effectively managing a company has become more complex, leading to the need for and creation of additional functional roles with expertise in several functional areas (Menz 2012). This need becomes particularly apparent when a firm faces a crisis requiring decisive action based on functional expertise (Buchalik and Haarmeyer 2015). When functionally diverse management teams collaborate to avoid bankruptcy, the ultimate negative outcome of a crisis, they are less likely to split into subgroups and therefore maintain their effective cooperation—unlike TMTs heterogeneous in age (Hogg and Terry 2000). The reason for this is that the functional background of managers is not a readily apparent trait, which helps eliminate issues related to social categorization (Hogg and Terry 2000).

Smith et al. (1994) showed how managers' cognitive frames, which draw on measurable characteristics like functional or educational backgrounds, shape their decisionmaking. An additional and different view on the challenges a firm faces may stimulate constructive, cognitive conflict (Amason and Sapienza 1997): team members reflect on issues based on their knowledge background and try to contribute to the group-level outcome in a positive way, as they do not resent the other group members but view their input as potentially beneficial for themselves and the overall goal. Such a group setting can motivate members to even go beyond what they initially wanted to contribute and further elevate firm-level outcomes, as Yang and Wang (2014) have shown for strategic orientation and Hambrick et al. (1996) for competition behavior.

Yet, regarding functional background heterogeneity, we must also acknowledge that mediating factors, such as interpersonal relations and information elaboration, exist (e.g., Samba et al. 2018). However, functional experience is more closely related to individual cognitions than to demographic factors, and we thus expect the impact of these mediators to be more limited for functional background heterogeneity than for age heterogeneity (Talke et al. 2010).

Consequently, we argue that for management teams heterogeneous in age, the negative implications of such heterogeneity dominate (H1) because the induced affective conflict makes TMT members work against each other and reduces effective information sharing. Functionally heterogeneous TMTs, in contrast, are more likely to experience constructive cognitive conflict, as team members differ in their job-related experience; conflicts, therefore, revolve around questions of managerial decision-making rather than personal attributes. As a result, functionally diverse management teams are able to leverage experience from diverse backgrounds and cooperate efficiently to avoid bankruptcy in times of crises. Therefore, we hypothesize:

H3 TMT heterogeneity in functional backgrounds exhibits a negative relationship with the probability of a firm filing for bankruptcy.

4 Method and measures

4.1 Data collection

To test our hypotheses, we constructed an extensive sample consisting of 1290 observations of large, public US companies, about half of which (610 specifically) filed for bankruptcy under US Chapter 11 between 2001 and 2020. All observations—except those for the dummy variable indicating whether the firm filed for bankruptcy or not—were lagged by two years to enable us to assess firms' TMT composition in the medium term prior to a bankruptcy event; this allowed us to observe a time frame that lies between those selected in established research (see, e.g., Merton 1974; Daily and Dalton 1994). Including only large, public U.S. firms ensures a high availability of secondary data and a comparable, strictly enforced legal disclosure framework and bankruptcy filing requirements that were largely invariant over the observation period.

The list of bankrupt firms was compiled using the LoPucki Bankruptcy Research Database with data from the beginning of 2001 to the end of 2020; the authors acquired access to the database for the purpose of this study (LoPucki 2020). This database lists all insolvencies of public firms with assets of at least USD 100 million (inflation-adjusted to the value of USD 1 in 1980 when data collection for the LoPucki set began); the listing is based on bankruptcy filings with the U.S. Securities and Exchange Commission (SEC) (LoPucki 2020). The LoPucki database includes a total of 1,208 insolvencies between 1980 and 2020, each of which represents a single bankruptcy filing. 1180 of these firms filed for Chapter 11 of the bankruptcy code; the remainder (28 cases under Chapter 7) were excluded to ensure that the legal framework under which all cases for this study are filed is consistent. Since online filing with the SEC has only been available from 2000 onward, we had to exclude 435 filings submitted before 2000 as the data was not accessible to us; therefore, we decided to limit our observations to the period between 2001 and 2020. We omitted an additional 135 filings for which we could not obtain sufficient TMT data, resulting in a final count of 610 observations of bankruptcy cases to include in our overall sample.

We established the list of nonbankrupt firms as follows. First, we selected firms from the Standard and Poor's (SandP) 500 index that were part of this index at any point between 2005 and 2018, resulting in an initial list of 690 firms. We excluded 10 firms that filed for bankruptcy during the observation period and are thus part of the dataset of bankrupt firms (e.g., Lehman Brothers filed for Chapter 11 bankruptcy in 2008). Second, for the remaining 680 firms, we manually collected information on their respective TMT members from multiple sources. We applied the same data collection method for both bankrupt and nonbankrupt firms. Merging the lists of bankrupt firms (610 firms) and nonbankrupt firms (680 firms) leads to a final sample of 1,290 firms.

For our entire sample, we followed previous upper echelons research and collected data on the TMT of each firm. The TMT is thus defined as consisting of those members listed in the mandatory annual SEC filings, specifically the forms DEF-14A and 10-K; by means of this procedure we excluded members with only regional or supervisory responsibilities (e.g., a head of European operations would not be considered a TMT member in a global firm) (Garms and Engelen 2019). Beyond the information on TMT members that was readily available in these filings (e.g., in the Summary Compensation Table, executive officers' short biographies, etc.) and the LoPucki database, we complemented the data with information we gleaned from company websites and professional profiles we found online. We compiled company-level controls for financial or size-related data using Compustat.

Our final sample is diverse across industries. As Fig. 1 shows, the industry split of the two subsamples (bankrupt and nonbankrupt firms) is comparable.

4.2 Dependent variable

Our primary research objective is to study how TMT heterogeneity affects the probability of a firm filing for bankruptcy. Consequently, our dependent variable *bankruptcy* describes whether a firm has filed for bankruptcy in a given period. In line with the literature, the variable is coded as a dummy variable taking the value 1 if the firm filed for bankruptcy and the value 0 if it did not (e.g., Traczynski 2017). As a result of the sample composition—610 bankrupt and 680 nonbankrupt firms—the mean of the dependent variable is 0.47; its standard deviation is 0.50.

4.3 Independent variables

The independent variables used in this study are all centered on TMT heterogeneity; each variable is lagged by 2 years compared to the dependent variable to study the likelihood of bankruptcy over the medium term.

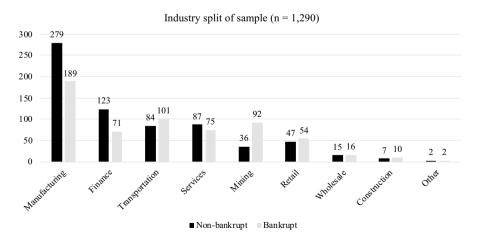


Fig. 1 Sample description. Source Own illustration

To represent *TMT age heterogeneity*, we calculated the coefficient of variation (i.e., the standard deviation scaled by the mean) of the age of each TMT member of a firm in a given year, which is a common approach to estimating heterogeneity for continuous variables (Smith et al. 1994). As some TMTs of the firms in our sample consisted of TMT members of the same age, the minimum of this independent variable is 0, and the maximum is 0.42; the mean is 0.11. The standard deviation is 0.06.

To measure *TMT pay heterogeneity*, we followed Smith et al. (1994) and determined TMT pay heterogeneity as the coefficient of variation of each TMT member's compensation in a given year. Importantly, we use total compensation as indicated in the Summary Compensation Table of each firm's mandatory annual SEC filing, as this provides a figure comparable within and across the TMTs in our sample; this would not be the case when selecting, for example, the base salary or cash compensation (Lee et al. 2018). With a minimum slightly above 0 and a maximum of 2.20, the mean of TMT pay heterogeneity is 0.65; the standard deviation is 0.29. On average, a CEO in our sample received a total compensation of about USD 7.56 million annually, compared to a non-CEO TMT member with annual average earnings of USD 2.53 million. Interestingly, the factor by which a CEO earns more than a non-CEO TMT member is about 3 and is almost identical for firms that filed for bankruptcy and firms that did not.

Literature presents different definitions for *TMT heterogeneity in functional backgrounds*. Earlier sources mostly focused on the so-called dominant function—the functional area in which an individual TMT member has been the most active—and established a measure that indicates intra-TMT heterogeneity regarding dominant functions across the team (Bantel 1993; Hambrick et al. 1996). Similarly, though less prominent, research has drawn on the so-called current function to develop an intra-TMT measure comparable to the above that considers each manager's current functional position, thereby essentially creating an indicator measuring how many functional areas a firm's current TMT members cover (Simons et al. 1999). In this study, we combine both measures into the so-called total functional background heterogeneity, which considers all functional areas in which managers have worked during their earlier careers up to and including their current position. While acknowledging the distinct advantages of each approach (Bunderson and Sutcliffe 2002), we consider the total functional background as the most complete measure currently available.

TMT members' functional areas of expertise typically are accounting or finance, law or a legal department, management or general administration, marketing or sales, human resources or labor relations, production or operations, research or development, or engineering or technology (Cannella et al. 2008). TMT members in our sample on average have 1.96 functional areas of expertise, with those in firms that went bankrupt covering fewer areas (1.47 for TMT members in bankrupt firms compared to 2.43 for those in reference firms). The most frequent functional areas of expertise across all TMT members are management or general administration, followed by accounting and finance as well as production and operations. In line with prior upper echelons research (e.g., Knight et al. 1999), we determined functional background heterogeneity using the Blau (1977) heterogeneity index, estimating the share of individuals with a background in each of the eight areas outlined above and subtracting the sum of squared shares for all eight areas from 1. With a minimum of 0.32 and a maximum of 0.88, the mean of this independent variable is 0.74; the standard deviation is 0.08.

4.4 Control variables

Following extant research on governance-based bankruptcy prediction, we control for a set of firm- and TMT-level variables that might significantly influence the relationship between dependent and independent variables (e.g., Traczynski 2017; Daily and Dalton 1994). It is especially important to control for financial default predictors, as firms that already face financial distress at a certain point in time have a higher probability of default two years later. Accordingly, we control for Merton's (1974) well-established *distance-to-default*, as it integrates several key firm-level metrics into one meaningful variable. Distance-to-default accounts for the current value of a firm's assets (A), which is a size indicator derived by adding total debt to year-end market capitalization. Furthermore, the variable considers the face value of a firm's total debt (D), its stock price volatility (V), and the market risk-free rate (R) (Kato and Hagendorff 2010):

distance - to - default =
$$\frac{\ln\left(\frac{A}{D}\right) + R + 0.5*V^2}{V}$$

As outlined in the introduction section, we are familiar with the criticism towards the Merton model (e.g., Bharath and Shumway 2008) and the alternative models proposed (e.g., Shumway 2001). However, we find no clear consensus on which of these models is to be preferred and consider the Merton model, with its clear theoretical foundation, a suitable control metric for our study (Traczynski 2017). In our sample, the values for this control variable range from 0.22 to 17.31, with a mean of 2.46 and a standard deviation of 2.29.

As the overview of input variables above shows, distance-to-default accounts for two of the three typical financial controls-indebtedness and returns-but does not include liquidity (Cremers 2002; Campbell et al. 2008). Hence, we separately add *liquidity* as a firm-level control that is estimated by subtracting current liabilities from current assets, the so-called current ratio (Mishina et al. 2004). In our sample, this control variable ranges from 0.08 to 18.85, with a mean of 3.25 and a standard deviation of 3.40. On the firm level, we additionally control for firm age, using the proxy of the firm IPO date, and for risk, measured by stock price volatility, both available in Compustat (Keil et al. 2008). We also contemplated controlling for firm size by number of employees but ultimately refrained from doing so, as the nonbankrupt SandP 500 firms, on average, have more employees than the insolvent firms in the sample. This is clearly due to our overall sample composition and does not have a causal link to the bankruptcy event. We do not view this as a problem for our study and argue in line with Altman and Hotchkiss (2006, p. 4): "Even adjusting for inflation, it is clear that size is no longer a proxy for corporate health, and there is little evidence, except in very rare circumstances, of the old adage 'too big to fail'.".

Further, we use different control variables at the level of the CEO. We controlled for *CEO age* and *CEO gender*, whereas CEO age is a continuous variable and CEO gender a binary variable coded with the value 0 for "Female" and 1 for "Male." We also used *CEO educational degree* as a categorical variable with four characteristics (i.e., none, bachelor, master, MBA/PhD, Professor). We followed Daily and Dalton (1994) and controlled for *CEO/Chairman duality*, which we coded as a dummy variable that takes the value 1 if CEO and board chairman were the same individual at the time of observation and 0 if otherwise.

In line with current upper echelons research, we additionally controlled for *TMT size* (Bunderson and van der Vegt 2018). We also include *TMT gender heterogeneity* as a control variable in our analysis using the Herfindahl–Hirschman index (HHI) following (Blau 1977; Cannella et al. 2008; Tihanyi et al. 2000).

We also used dummy variables for the *industry category* based on the one-digit SIC industry level and for the *firm age* and included the individual data in our analysis. The dummy variables are analyzed but not shown in the results table to conserve space.

4.5 Model specification

Given the binary nature of our dependent variable *bankruptcy*, we applied a logistic regression analysis to test our hypotheses. Literature on bankruptcy has commonly used this approach (Daily and Dalton 1994; Traczynski 2017). Table 1 shows the descriptive statistics and the correlation matrix for all variables used. We checked the pairwise correlations for the independent variables following Kalnins (2018). Table 1 shows that risk displays a correlation of -0.39 with distance-to-default, TMT gender heterogeneity a correlation of -0.33 with CEO gender, and TMT heterogeneity in functional backgrounds a correlation of 0.37 with TMT size. These correlations exceed the threshold of 0.30 for pairwise correlations as proposed by Kalnins (2018). Therefore, we checked the coefficients of the variables in the regression results (Kalnins 2018). As shown in Table 1, risk and distance-to-default display coefficients of opposite signs (risk, log coef. = 0.05; distance-to-default, log coef. = -0.87). TMT gender heterogeneity and CEO gender also show coefficients of opposite signs (TMT gender heterogeneity, log coef. = -0.12; CEO gender, log coef. = 0.04). As these pairs of variables are correlated negatively and display coefficients of opposite signs, we conclude that these correlations might not be problematic (Kalnins 2018). However, TMT heterogeneity in functional backgrounds and TMT size are correlated positively and display coefficients of opposite signs (TMT heterogeneity in functional backgrounds, log coef. = -0.71; TMT size, log coef. = 0.67), which indicates a threat of multicollinearity to our analysis (Kalnins 2018). Consequently, we conducted a separate regression excluding TMT size. As shown in Table 2, the signs and magnitudes of all hypothesized associations remain robust. Thus, we infer that multicollinearity is unlikely to be a threat to our analysis (Cohen et al. 2003; Kalnins 2018).

Table 1(Correlat	tions and	Table 1 Correlations and descriptive statistics	ve statis	tics													
	Mean	Std. Dev	Min	Max	(1) (1	(2) ((3)	(4)	(5)) (9)	(7)	(8)	(6)	(10)	(11) (1	(12)	(13) (14)	_ ⊕
Bank- ruptcy	0.473	0.499	0.000	1.000	1.000													
Distance- to- default	2.457	2.457 2.292	0.215	17.311	17.311 -0.565***	1.000												
Liquidity	3.252	3.252 3.403	0.080	18.851	0.032	-0.074^{**}	1.000											
Firm age	11.564	11.564 11.490	1.000	121	-0.385^{***}	0.269^{***}	- 0.023	1.000										
Risk	41.465	41.465 18.239	7.050	201.15	0.415*** -	-0.385***	-0.070^{*}	-0.153^{***}	1.000									
CEO age	55.857	7.225	33.000	86.000	-0.127^{***}	0.011	0.005	0.105^{***}	-0.096^{***}	1.000								
CEO gender	0.953	0.211	0.000	1.000	0.047	- 0.004	0.008	-0.053	0.033	-0.006	1.000							
CEO edu- cational degree	1.998	1.009	0.000	4.000	-0.082^{**}	0.031	0.028	0.083**	-0.080^{**}	0.020	0.007	1.000						
CEO/ Chair- man duality		0.471 0.499	0.000	1.000	-0.022	0.026	0.013	-0.047	-0.089**	0.280**** 0.031	0.031	-0.002	1.000					
TMT size	3.799	0.852	2.000	7.000	0.200***	-0.137^{***}	-0.067^{*}	-0.070^{*}	0.131***	-0.028	-0.056^{*}	0.030	0.023 1.000	1.000				
TMT gender heteroge- neity	0.133	0.192	0.000	0.500	-0.085**	0.041	0.024	0.048	-0.068*	0.038	-0.325***	-0.009 -0.009		0.101***	1.000			
TMT age heteroge- neity	0.108	0.055	0.000	0.424	0.143*** -	- 0.112 ^{***}	0.067*	-0.059^{*}	0.055*	$0.255^{***} - 0.004$	- 0.004	-0.025	0.053 (0.012	0.003	1.000		
TMT pay heteroge- neity		0.650 0.286	0.004	2.195	-0.177***	0.079**	- 0.044	0.060*	-0.058*	0.038	-0.051	0.082**	0.082** 0.104***0.069*		0.060*	0.019	1.000	

(6) (7) (8) (9) (10) (11) (12) (13) (14) 19 -0.062^* -0.042 0.056^* -0.069^* 0.367^{***} 0.112^{***} -0.121^{***} 0.087^{**} 1.000 lays the pairwise correlation coefficients; statistics reported for unstandardized verexceeding the threshold > 0.3 following Kalmins (2018)	(5) (6) (7) (8) (9) (10) (11) (12) (13) 0.019 -0.062^* -0.042 0.056^* -0.069^* 0.367^{***} 0.112^{***} -0.121^{***} 0.08 ble displays the pairwise correlation coefficients; statistics reported for unstandar ariables exceeding the threshold > 0.3 following Kalmins (2018)	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	x (1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11) (12) (13) 5 -0.141^{***} 0.108^{***} -0.050 0.019 -0.062^{*} -0.069^{*} 0.367^{***} 0.112^{***} -0.121^{***} 0.08 5 -0.141^{***} 0.108^{***} 0.050 0.019 -0.062^{*} -0.069^{*} 0.367^{***} 0.112^{***} -0.121^{***} 0.08 at * < 0.05, ** < 0.01, *** < 0.001. The table displays the pairwise correlation coefficients; statistics reported for unstandar at * < 0.05, ** < 0.01, *** < 0.001. The table displays the pairwise correlation coefficients; statistics reported for unstandar	Max (1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11) (12) (13) 20 0.875 -0.141^{***} 0.108^{***} -0.198^{***} 0.050 0.019 -0.062^* -0.069^* 0.367^{***} 0.112^{***} -0.121^{***} 0.08 20 0.875 -0.141^{***} 0.108^{***} -0.050 0.012^* -0.042 0.056^* -0.121^{***} 0.08 20 0.875 -0.141^{***} 0.108^{***} 0.050 0.019 -0.062^* -0.069^* 0.367^{***} 0.112^{***} 0.08 30 0.875 -0.141^{***} 0.050 0.019 -0.062^* -0.069^* 0.367^{***} 0.112^{***} 0.08 30 0.367^{***} 0.050 0.019 -0.062^* 0.056^* 0.056^* 0.012^{****} 0.012^{****}	Max (1) (2) (3) (4) (5) (6) (7) (3) 20 0.875 -0.141^{4**} 0.108^{***} -0.198^{***} 0.050 0.019 -0.062^{*} -0.042 splayed at *<0.05 -0.001 The table displays the pairwise correlations of independent variables exceeding the threshold	(14)	37** 1.000
(6) (7) (8) (9) (10) (11) (12) 19 -0.062* -0.042 0.056* -0.069* 0.367 *** 0.112*** -0.12 lays the pairwise correlation coefficients; statistics reported for un exceeding the threshold > 0.3 following Kalmins (2018)	(5) (6) (7) (8) (9) (10) (11) (12) 0 0.019 -0.062^* -0.042 0.056^* -0.069^* 0.367^{***} 0.112^{***} -0.12 ble displays the pairwise correlation coefficients; statistics reported for un ariables exceeding the threshold > 0.3 following Kalmins (2018)	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	κ (1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11) (12) 5 -0.141^{***} 0.108^{***} -0.050 0.050 -0.042 0.056^* -0.069^* 0.367^{***} 0.112^{***} -0.12 5 -0.141^{***} 0.108^{***} -0.030 0.019 -0.062^* -0.069^* 0.367^{***} 0.112^{***} -0.12 4 $*<0.05$, $**<<0.01$, $****<<0.001$. The table displays the pairwise correlation coefficients; statistics reported for un ate pairwise correlations of independent variables exceeding the threshold > 0.3 following Kalmins (2018)	Max (1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11) (12) 20 0.875 -0.141 ^{***} 0.108 ^{***} -0.198 ^{***} 0.050 0.019 -0.062 [*] -0.042 0.056 [*] -0.169 ^{***} 0.112 ^{***} -0.12 20 0.875 -0.141 ^{***} 0.108 ^{***} -0.198 ^{***} 0.050 0.019 -0.062 [*] -0.042 0.056 [*] -0.069 [*] 0.367 ^{***} 0.112 ^{***} -0.12 20 0.875 -0.042 0.056 [*] -0.069 [*] 0.367 ^{***} 0.112 ^{***} -0.12 splayed at * <0.05, ** <0.01, ***	ev Min Max (1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11) (12) 0 0.320 0.875 -0.141*** 0.108*** -0.198*** 0.050 0.019 -0.062* -0.042 0.056* -0.069* 0.367*** 0.112*** -0.12 0 0.320 0.875 -0.141*** 0.108*** -0.050 0.050* 0.367** 0.112*** -0.12 state 0.320 0.875 -0.042 0.056* -0.069* 0.367*** 0.112*** -0.12 state displayed at * <0.05, ***<0.01, ***<<0.01. The table displays the pairwise correlation coefficients; statistics reported for un es in bold indicate pairwise correlations of independent variables exceeding the threshold > 0.3 following Kalmins (2018)	(13)	1*** 0.05
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$(6) (7)$ $(19 - 0.062^{*} - 1)$ $(19 + 0.062^{*} - 1)$ $(19 + 0.062^{*} + 1)$	$\begin{array}{c cccc} (5) & (6) & (7) \\ \hline 0 & 0.019 & -0.062^{*} & -1 \\ \hline \text{ble displays the pairwise} \\ \text{ariables exceeding the tt} \\ \end{array}$	$\begin{array}{c ccccc} (4) & (5) & (6) & (7) \\ \hline & 0.050 & 0.019 & -0.062^{*} & -1 \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & &$	(3) (4) (5) (6) (7) -0.198^{***} 0.050 0.019 -0.062^{*} $-1000000000000000000000000000000000000$	$\begin{array}{c ccccc} (3) & (4) & (5) & (6) & (7) \\ \hline 0.108^{***} & -0.198^{***} & 0.050 & 0.019 & -0.062^{*} & -1 \\ \hline 0.01, *** < 0.001. The table displays the pairwise elations of independent variables exceeding the the table exceeding the the table exceeding the the table element of the table exceeding the table table table table table table exceeding the table tabl$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	κ (1) (2) (3) (4) (5) (6) (7) r_5 -0.141^{***} 0.108^{***} -0.198^{***} 0.050 0.019 -0.062^{*} -1.062^{*} r_5 -0.141^{***} 0.108^{***} -0.198^{***} 0.050 0.019 -0.062^{*} -1.062^{*} r_8	Max (1) (2) (3) (4) (5) (6) (7) 20 0.875 -0.141^{***} 0.108^{***} -0.198^{***} 0.050 0.019 -0.062^{*} -1.062^{*} 20 0.875 -0.141^{***} 0.108^{***} -0.198^{***} 0.050 0.019 -0.062^{*} -1.062^{*} 21 aparticle aparticle -0.065 $*.88^{*}$ 0.001 The table displays the pairwise aplayed at * <0.05, ** <0.01, *** <0.001. The table displays the pairwise	ev Min Max (1) (2) (3) (4) (5) (6) (7) $0.320 0.875 -0.141^{***} 0.108^{***} -0.198^{***} 0.050 0.019 -0.062^{*} -1$ are displayed at * < 0.05, ** < 0.01, *** < 0.001. The table displays the pairwise es in bold indicate pairwise correlations of independent variables exceeding the th		0.042
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to address potential multicollinearity

Dependent variable: bankruptcy*	Model (0)	Model (1)	Model (2)
Controls			
Distance-to-default	-0.892	-0.904	-0.905
	(0.086)	(0.086)	(0.087)
	0.000	0.000	0.000
Liquidity	0.160	0.167	0.166
	(0.048)	(0.049)	(0.049)
	0.001	0.001	0.001
Firm age	-0.091	-0.087	-0.088
	(0.014)	(0.014)	(0.014)
	0.000	0.000	0.000
Risk	0.049	0.046	0.049
	(0.008)	(0.008)	(0.009)
	0.000	0.000	0.000
CEO age	-0.009	-0.023	-0.025
	(0.015)	(0.016)	(0.016)
	0.531	0.149	0.118
CEO gender	-0.130	-0.143	-0.223
	(0.469)	(0.462)	(0.470)
	0.782	0.757	0.635
CEO educational degree	-0.036	0.002	0.008
	(0.099)	(0.101)	(0.102)
	0.718	0.985	0.934
CEO/Chairman duality	-0.470	-0.388	-0.428
	(0.215)	(0.219)	(0.223)
	0.029	0.077	0.055
TMT gender heterogeneity	-0.092	-0.069	-0.049
	(0.105)	(0.106)	(0.107)
	0.378	0.515	0.648
Direct effects			
(H1) TMT age heterogeneity		0.278	0.284
		(0.104)	(0.107)
		0.008	0.008
(H2) TMT pay heterogeneity		-0.323	-0.310
		(0.098)	(0.099)
		0.001	0.002
(H3) TMT heterogeneity in functional backgrounds			-0.466
			(0.135)
			0.001
Nonlinear effect			
TMT heterogeneity in functional backgrounds squared			-0.145
			(0.061)
			0.017

Table 2 (continued)			
Dependent variable: bankruptcy*	Model (0)	Model (1)	Model (2)
Constant	484.259	478.557	467.934
Prob>chi2	0.000	0.000	0.000
LR chi2	1091	1109	1121
Pseudo R2	0.612	0.621	0.628

N=1290 firms; standard errors in parentheses; *p* values listed below standard errors; *The dependent variable bankruptcy reflects whether the firm filed for bankruptcy. The variable is coded as a dummy variable assuming the value 1 if the firm filed for bankruptcy and 0 if it did not. Control variables for industry categories (one-digit SIC industry level) and firm year are included but not displayed

5 Results

To test our hypotheses, we used the standardized values of all independent TMT heterogeneity variables, including the moderating variable, to reduce multicollinearity and facilitate interpretation (Aiken and West 1991; Dawson 2014). Table 3 shows the results of the logistic regression. The baseline model (Model 0) shows a regression with controls only; Models 1 and 2 test the corresponding hypotheses.

Our first hypothesis (H1) predicts a positive relationship between TMT age heterogeneity and firm bankruptcy. The significant effect combined with the positive logistic regression coefficient (log coef. = 0.294; p = 0.005) in Model 1 shows empirical support for H1. In our second hypothesis (H2), we purport a negative relationship between TMT pay heterogeneity and firm bankruptcy. Again, the highly significant effect combined with the negative coefficient (log coef. = -0.337; p = 0.001) in Model 1 indicates support for H2. Our hypothesis H3 assumes a negative association of TMT heterogeneity in functional backgrounds with the probability of a firm filing for bankruptcy. Model 2 shows a negative, significant association (log coef. = -0.713; p = 0.000). We also tested whether the linear associations of the independent variables might be misinterpreted due to potential nonlinear associations. While neither TMT age heterogeneity nor TMT pay heterogeneity reveal such a nonlinear association (cf. robustness and bias testing), TMT heterogeneity in functional backgrounds shows an inverted U-shaped association with bankruptcy. To display the results, we added the squared term of TMT heterogeneity in functional backgrounds in Model 2 (Haans et al. 2016). The estimation shows that the logistic regression coefficient for TMT heterogeneity in functional backgrounds is negative and significant (loeg coef. = -0.713; p = 0.000), indicating a potential U-shaped association. Following Lind and Mehlum (2010) and using the Stata command "utest," we further considered the conditions of a U-shaped association. Therefore, following Haans et al. (2016), we used the unstandardized values of the variables to enhance interpretation. However, the results are also robust to using the standardized values of the variables. The estimates reveal a significant lower bound of t = 1.909 (p = 0.028) and a significant upper bound of t = -4.089 (p = 0.000).

Table 3	Coefficient estimates	from logistic regr	essions on the bankrup	otcy variable

Dependent variable: bankruptcy*	Model (0)	Model (1)	Model (2)
Controls			
Distance-to-default	-0.874	-0.886	-0.879
	(0.086)	(0.086)	(0.087)
	0.000	0.000	0.000
Liquidity	0.166	0.173	0.167
	(0.049)	(0.050)	(0.050)
	0.001	0.000	0.001
Firm age	-0.092	-0.088	-0.090
	(0.014)	(0.014)	(0.015)
	0.000	0.000	0.000
Risk	0.047	0.044	0.046
	(0.008)	(0.008)	(0.009)
	0.000	0.000	0.000
CEO age	-0.007	-0.022	-0.023
	(0.015)	(0.016)	(0.016)
	0.637	0.175	0.155
CEO gender	0.036	0.044	0.054
	(0.484)	(0.481)	(0.504)
	0.941	0.927	0.915
CEO educational degree	-0.049	-0.009	0.004
	(0.100)	(0.103)	(0.105)
	0.623	0.930	0.969
CEO/Chairman duality	-0.518	-0.438	-0.545
	(0.217)	(0.222)	(0.229)
	0.017	0.049	0.018
TMT size	0.401	0.437	0.673
	(0.120)	(0.123)	(0.138)
	0.001	0.000	0.000
TMT gender heterogeneity	-0.121	-0.099	-0.073
	(0.106)	(0.108)	(0.110)
	0.255	0.361	0.506
Direct effects			
(H1) TMT age heterogeneity		0.294	0.298
		(0.104)	(0.108)
		0.005	0.006
(H2) TMT pay heterogeneity		-0.337	-0.329
		(0.099)	(0.101)
		0.001	0.001
(H3) TMT heterogeneity in functional backgrounds			-0.713
-			(0.147)
			0.000

Dependent variable: bankruptcy*	Model (0)	Model (1)	Model (2)
Nonlinear effect			
TMT heterogeneity in functional backgrounds squared			-0.166
			(0.059)
			0.005
Constant	483.162	475.454	455.247
Prob>chi2	0.000	0.000	0.000
LR chi2	1103	1122	1147
Pseudo R2	0.618	0.629	0.643

N=1290 firms; standard errors in parentheses; *p*-values listed below standard errors; *The dependent variable bankruptcy reflects whether the firm filed for bankruptcy. The variable is coded as a dummy variable assuming the value 1 if the firm filed for bankruptcy and 0 if it did not. Control variables for industry categories (one-digit SIC industry level) and firm year are included but not displayed

The turning point, with a value of 0.567, is in the data range of the Fieller interval (0.320, 0.875; 95% confidence interval). These estimations confirm the presence of an inverted U-shaped association of TMT heterogeneity in functional backgrounds with bankruptcy, which leads us to reject a linear association. The

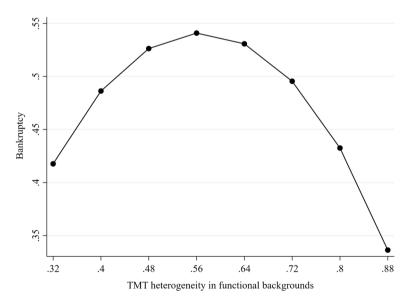


Fig. 2 Interpretation of inverted U-shaped association—TMT functional background heterogeneity. *Note* Bankruptcy reflects whether the firm filed for bankruptcy. The variable is coded as a dummy variable assuming the value 1 if the firm filed for bankruptcy and 0 if it did not. The plot is estimated with unstandardized values to enhance interpretation. 95% Filler confidence interval: lower bound 0.32, upper bound 0.88; Extreme point=0.57; Slope at TMT heterogeneity in functional backgrounds low=12.97, p=0.028; Slope at TMT heterogeneity in functional backgrounds high=-16.15, p=0.000. Overall test of the presence of an inverted U-shaped association p=0.028

likelihood of bankruptcy increases with higher levels of TMT heterogeneity in functional backgrounds; when heterogeneity in functional backgrounds exceeds the value of 0.57, however, the likelihood of bankruptcy decreases. Figure 2 shows the inverted U-shaped association of TMT heterogeneity in functional backgrounds with bankruptcy.

5.1 Robustness and bias testing

To validate the outlined empirical findings further, we conducted several robustness checks with our sample data. First, in an effort to eliminate the potential effects of economic downturns or financial crises, we excluded all observations for the years of the financial crisis (2008 and 2009). After dropping a total of 88 observations, the results for our regression analyses remain robust regarding the signs of the logarithmic coefficients and their significance levels. Table 4 shows the estimated results.

Second, we tested whether the independent variables of TMT age heterogeneity and TMT pay heterogeneity might display (inverted) U-shaped associations with the dependent variable. We followed the procedure by Haans (2016) and used the squared term of the independent variables, respectively, in our logarithmic regression analysis. To confirm a nonlinear association, the estimation should reveal that the squared term is significant, that a steep slope exists at both ends of the variable, and that the turning point is in the data range. None of the conditions is met for neither variable, which leads us to reject the existence of a nonlinear association.

Third, we tested TMT heterogeneity in educational backgrounds—which is frequently cited in the literature—as a potential alternative for TMT heterogeneity in functional backgrounds (Bunderson and van der Vegt 2018). The results show a negative insignificant coefficient for the direct effect (log coef. = -0.323; p = 0.020), whereas the squared term in insignificant (log ceof. = -0.079; p = 0.298). The negative coefficient of the direct effect indicates an association with bankruptcy that is different to TMT heterogeneity in functional backgrounds, for which we found a U-shaped association. This result opens up an interesting avenue for potential further research in this area.

Fourth, we tested whether independent variables might interact with TMT gender heterogeneity. We estimated three models, each including the interaction term of the respective independent variable (TMT age heterogeneity; TMT pay heterogeneity; TMT heterogeneity in functional backgrounds) with TMT gender heterogeneity. None of the estimates display a significant interaction effect.

Additionally, we considered endogeneity and reverse or simultaneous causality, as these factors are common concerns in TMT publications (Hambrick 2007). Thus, we followed recent studies on TMT heterogeneity (e.g., Lee et al. 2018) and implemented the instrumental variables method in two-stage least squares (2SLS) regression. To identify and employ instrument variables, we considered that a potential instrument variable meets the relevance condition and the exclusion restriction (Chenhall and Moers 2007; Semadeni et al. 2014). As Germann et al. (2015), Ebbes et al. (2017) show, firms within the same industry sector tend to resemble one another. Thus, we established our instruments by estimating the average industry

Dependent variable: bankruptcy*	Model (0)	Model (1)	Model (2)
Controls	·		
Distance-to-default	-0.938	-0.951	-0.946
	(0.092)	(0.093)	(0.094)
	0.000	0.000	0.000
Liquidity	0.182	0.189	0.183
	(0.054)	(0.054)	(0.055)
	0.001	0.001	0.001
Firm age	-0.084	-0.081	-0.084
	(0.015)	(0.015)	(0.015)
	0.000	0.000	0.000
Risk	0.047	0.045	0.046
	(0.009)	(0.009)	(0.009)
	0.000	0.000	0.000
CEO age	-0.017	-0.031	-0.032
	(0.016)	(0.017)	(0.018)
	0.300	0.071	0.072
CEO gender	0.335	0.330	0.283
	(0.532)	(0.526)	(0.544)
	0.528	0.531	0.603
CEO educational degree	-0.050	-0.010	0.001
-	(0.110)	(0.113)	(0.115)
	0.651	0.932	0.995
CEO/Chairman duality	-0.463	-0.414	-0.511
	(0.238)	(0.243)	(0.250)
	0.052	0.088	0.040
TMT size	0.485	0.528	0.741
	(0.134)	(0.137)	(0.152)
	0.000	0.000	0.000
TMT gender heterogeneity	-0.037	-0.027	-0.012
	(0.116)	(0.118)	(0.120)
	0.750	0.821	0.918
Direct effects			
(H1) TMT age heterogeneity		0.313	0.310
		(0.113)	(0.116)
		0.006	0.007
(H2) TMT pay heterogeneity		-0.310	-0.310
		(0.110)	(0.113)
		0.005	0.006
(H3) TMT heterogeneity in functional backgrounds			-0.613
-			(0.155)
			0.000

 Table 4
 Robustness analysis excluding the years of the financial crisis (2008 and 2009)—coefficient estimates from logistic regressions on the bankruptcy variable

Table 4 (continued)			
Dependent variable: bankruptcy*	Model (0)	Model (1)	Model (2)
Nonlinear effect			
TMT heterogeneity in functional backgrounds squared			-0.118
			(0.063)
			0.060
Constant			
Prob>chi2	0.000	0.000	0.000
LR chi2	1084	1099	1116
Pseudo R2	0.652	0.661	0.671

N=1202 firms; standard errors in parentheses; *p*-values listed below standard errors; *The dependent variable bankruptcy reflects whether the firm filed for bankruptcy. The variable is coded as a dummy variable assuming the value 1 if the firm filed for bankruptcy and 0 if it did not. Control variables for industry categories (one-digit SIC industry level) and firm year are included but not displayed

levels of TMT age heterogeneity, TMT pay heterogeneity, and TMT heterogeneity in functional backgrounds (two-digit SIC level). The three instruments likely correlate with the respective TMT heterogeneity levels of the focal firm, but it is rather unlikely that the industry levels of TMT heterogeneity directly associate with a firm's filing for bankruptcy.

We used Stata's "ivreg2" command to estimate the 2SLS regression. Following Semadeni et al. (2014), we treated each independent variable as separate endogenous regressors. We used the three instruments as linear terms for hypotheses H1 and H2. For the nonlinear term of TMT heterogeneity in functional backgrounds, we implemented the squared term of the instrument variables. Table 5 shows the results of the 2SLS regression. The estimates for all models are consistent with those in our main analysis. The key statistics and the tests for strength and endogeneity indicate acceptable values; only the Cragg-Donald F-statistics for Model (H3) is lower than the commonly used threshold of 10 percent (Wooldrige 2002), which we accept as we use three instruments and their squared terms (Sanderson 2016).

6 Discussion

Our study explores how specific heterogeneity characteristics of TMTs affect the probability of a firm filing for bankruptcy. The outlined empirical analysis provides strong evidence for a link between the heterogeneity characteristics considered and the likelihood of a firm's bankruptcy. In line with our expectations, TMT age heterogeneity contributes to an overall higher probability of bankruptcy, as hypothesized in H1. Much to the contrary, TMT heterogeneity in pay and functional backgrounds partially reduces the bankruptcy probability (see H2 and H3). While TMT pay heterogeneity is negatively and linearly related to the probability of a firm filing for bankruptcy, it needs to be acknowledged that the likelihood of bankruptcy first increases with higher levels of TMT heterogeneity in functional backgrounds

Dependent variable: bankruptcy*	Model (H1)	Model (H2)	Model (H3)
Controls			
Distance-to-default	-0.067	-0.069	-0.062
	(0.007)	(0.007)	(0.008)
	0.000	0.000	0.000
Liquidity	0.011	0.013	0.014
	(0.004)	(0.004)	(0.005)
	0.006	0.000	0.001
Firm age	-0.005	-0.005	-0.004
	(0.001)	(0.001)	(0.001)
	0.000	0.000	0.001
Risk	0.004	0.005	0.005
	(0.001)	(0.001)	(0.001)
	0.000	0.000	0.000
CEO age	-0.005	-0.001	-0.004
	(0.002)	(0.001)	(0.002)
	0.029	0.299	0.056
CEO gender	0.008	-0.000	-0.012
-	(0.050)	(0.046)	(0.051)
	0.865	0.994	0.809
CEO educational degree	-0.009	-0.008	-0.003
-	(0.009)	(0.009)	(0.011)
	0.340	0.351	0.797
CEO/Chairman duality	-0.020	-0.021	-0.035
	(0.020)	(0.021)	(0.022)
	0.308	0.313	0.116
TMT size	0.050	0.052	0.093
	(0.011)	(0.011)	(0.019)
	0.000	0.000	0.000
TMT gender heterogeneity	-0.007	-0.005	-0.006
	(0.010)	(0.010)	(0.011)
	0.496	0.609	0.592
Direct effects			
(H1) TMT age heterogeneity	0.124	0.029	0.037
	(0.045)	(0.010)	(0.014)
	0.006	0.003	0.008
(H2) TMT pay heterogeneity	-0.047	-0.069	-0.027
	(0.010)	(0.034)	(0.014)
	0.000	0.044	0.053
(H3) TMT heterogeneity in functional backgrounds			-0.233
			(0.097)
			0.016
Nonlinear effect			

 Table 5
 2SLS estimation with instrument variables

Table 5 (continued)

Dependent variable: bankruptcy*	Model (H1)	Model (H2)	Model (H3)
TMT heterogeneity in functional backgrounds squared			-0.141
			(0.074)
			0.058
Constant			
R2	0.563	0.593	0.434
Key statistics for endogeneity tests			
First Stage F-Statistic	22.95	26.68	3.505
Second Stage F-Statistic	137.3	150.3	127.7
Testing strength of instruments			
Cragg-Donald F	18.38	29.67	1.517
Testing endogeneity of instruments			
Hansen J Statistic	0.882	5.809	2.378
Hansen J p value	0.644	0.059	0.304

N=1290 firms; standard errors in parentheses; *p*-values listed below standard errors; *The dependent variable bankruptcy reflects whether the firm filed for bankruptcy. The variable is coded as a dummy variable assuming the value 1 if the firm filed for bankruptcy and 0 if it did not. Control variables for industry categories (one-digit SIC industry level) and firm year are included but not displayed

and only decreases after the level of TMT heterogeneity in functional backgrounds exceeds a value of 0.57. By considering three different types of TMT heterogeneity, we provide strong evidence that the impact of the individual heterogeneity metrics on bankruptcy varies substantially regarding the direction, magnitude, and significance of their effect. Our findings have implications for theory and practice.

6.1 Theoretical implications

We contribute threefold to the fields of bankruptcy and TMT research. For one, to the best of our knowledge, we are the first to establish a statistically significant link between TMT heterogeneity and bankruptcy based on extensive empirical evidence. In doing so, we provide further evidence that the field of bankruptcy prediction cannot rest fully in the realm of finance theory: governance factors, particularly on the TMT level, play a crucial role when assessing which firms might default. We are convince that reviving this somewhat nascent discussion (e.g., Hambrick and D'Aveni 1988) is important. Our contribution is not only of an empirical nature and limited to introducing two new strong predictors of bankruptcy; our findings also concern the discussion in theory regarding which level of analysis is appropriate when predicting bankruptcy using firm-related governance variables (Daily and Dalton 1994). Established turnaround research has shifted its focus towards the top management (e.g., Trahms et al. 2013), and we make a strong case that TMT-level variables deserve significant attention when predicting bankruptcy. From a theoretical viewpoint, we provide initial insights into the mechanisms at play in this relationship: Different types of heterogeneity cause the TMT to function more or less

effectively with regards to certain factors (e.g., collaboration and information sharing impacted by age heterogeneity); those factors, in turn, distinctly affect firms in financial distress, such that bankruptcy probabilities shift (Buchalik and Haarmeyer 2015).

Second, while long- and short-term predictions of bankruptcy have long existed (e.g., 5 years prior to bankruptcy, Daily and Dalton 1994; 1 year or less for most financial predictors, Traczynski 2017), the medium-term that is addressed in this work has received little attention. The TMT as a level of analysis and the mediumterm as a prediction horizon is a fruitful combination that complements existing research. Firm strategy is typically decided on the CEO- or board-level and is set for the long term (Finkelstein and Boyd 1998), which is why CEO- or board-level bankruptcy indicators are most impactful when applied to long-term prediction horizons (such as five years, Daily and Dalton 1994). In the short run, firm survival depends on the successful management of the cash balance and other current assets and liabilities—as financial short-term predictors reflect (Merton 1974). During the crucial medium-term, the TMT has to successfully execute the strategy set at higher levels and deliver against the derived targets. Our insights extend existing bankruptcy prediction research: We show that variables centering on the TMT as the decisive factor within this medium-term time frame can yield superior prediction results for this period.

Third, we hope to advance current upper echelons research. Since the first seminal publication in the field (Hambrick and Mason 1984), studies have yielded ambivalent findings as to how different types of heterogeneity affect firm-level outcomes (Bunderson and van der Vegt 2018). In our work, we thoroughly distinguish the different metrics and derive clear predictions for their individual impacts based on social categorization and conflict theory (Hogg and Terry 2000; Nadolska and Barkema 2014; Amason and Sapienza 1997), and our empirical analysis confirms these impacts. We thus help reconcile the findings of existing literature with the predictions of these theories: We show for age heterogeneity that negative impacts from social categorization and affective conflict reduce effective information sharing and negatively influence firm-level outcomes. For functionally heterogeneous teams, heterogeneity benefits outweigh these negative factors after exceeding a threshold. Moreover, teams with higher heterogeneity in pay increase the probability of a firm not filing for bankruptcy. We fully acknowledge the existing positive perspective on demographic diversity indicators like age heterogeneity that has been prominent in the literature for several years. Researcher underlining this perspective argue that diverse management teams can incorporate a broader range of information into their decision-making and, therefore, find more effective solutions to complex problems (Fredrickson 1984; Simons et al. 1999). However, we argue that this positive effect on information processing (Hambrick and Mason 1984) is more pronounced for task-oriented types of heterogeneity, such as TMT heterogeneity in functional backgrounds. Our findings indicate that the negative potential consequences of age heterogeneity dominate.

6.2 Practical implications

Our study entails several valuable practical implications. The public discourse on diversity underscores how important it is for academic research to explore management team heterogeneity. Global economic downturns, such as during the recent COVID-19 pandemic, further prove the need for firms to be resilient against bankruptcy. Combining these two aspects, we offer actionable insights into corporate governance—one of the most visible and immediately adjustable drivers of firm-level outcomes—and, specifically, into TMT composition. Our findings are valuable not only for the boards of major corporations and other firm stakeholders that determine TMT composition but also for policymakers and the general public when discussing and deciding on the political frameworks that guide and restrict management appointment decisions.

We add to current discussions in two ways. First, we emphasize the importance of functionally heterogeneous management teams. Including a set of managers with diverse functional experience is clearly beneficial to the firm, particularly in distress situations. Importantly, positive diversity effects are not limited to the heterogeneity of the dominant or current functional experience of TMT members but already exist if the individuals have had some experience in diverse functional areas at some point in their career. In very specific terms, board members and CEOs of distressed enterprises should actively search for new TMT members who add experience from other functional backgrounds to their teams and equip them with the decision power required to generate a positive impact for the firm. Policymakers should shape corporate governance recommendations and frameworks in such a way that they encourage increased functional diversity, particularly in crises. Shareholders should actively monitor the functional background diversity of the firms in their investment portfolio. Furthermore, our results yield actionable knowledge for managers responsible for devising compensation packages: We recommend introducing tournamentstyle competition between TMT members, which increases pay heterogeneity and lowers the bankruptcy risk.

Second, from an ethical standpoint, we explicitly applaud the overall push towards more demographically diverse management teams—in terms of gender, ethnicity, age, or other factors. However, we still need to emphasize that it should not be taken for granted that the firm-level effects of increased demographic TMT heterogeneity are always positive, as our research shows for the specific event of bankruptcy. In high-risk situations, such as when trying to avoid bankruptcy, age heterogeneity might affect firms negatively. This insight raises the question how firms can mitigate the negative impact of demographic heterogeneity in TMTs to enable diverse teams to steer firms optimally—especially during crises.

6.3 Limitations and future research

We are aware that our work has several limitations. As mentioned, the strongest methodological challenge to our approach lies in the indirect nature of the relationship between heterogeneity factors—especially demographic ones (see, e.g., Priem et al. 1999)—of the TMT and firm-level outcomes in general (Talke et al. 2010). While we believe that we were able to mitigate this challenge slightly by following a consistent rationale closely in line with established research (e.g., Nielsen and Nielsen 2013), the vast number of potential mediating effects between the variables we observe does leave room for alternate interpretations (Samba et al. 2018). For instance, we infer what types of conflict or communication failures are driven by TMT heterogeneity but we do not measure these conflicts—which provides ample opportunity for future research. Additional evidence on how team composition actually drives managers' cognitions, how these cognitions tangibly affect group performance, and how such group-level outcomes translate to the larger corporate context in terms of bankruptcy probabilities would be highly desirable.

Furthermore, the composition of our data and sample somewhat limits the implications we can derive from our study. All firms in our empirical sample were subject to the bankruptcy regime of Chapter 11 in the U.S. Still, findings can certainly be generalized to some degree to other common law jurisdictions such as the UK or Canada; they might also inform the discussion on the revised German insolvency code. The 2012 German bankruptcy law reform aimed to strengthen the opportunities for firms to restructure their businesses successfully under bankruptcy protection, thereby partially assimilating the code to the provisions of Chapter 11 (Buchalik and Haarmeyer 2015). Conducting comparative studies in different countries that explore how the legal frameworks mediate the relationship between TMT variables, such as heterogeneity, and bankruptcy is certainly an insightful endeavor.

In addition, in our analysis and robustness checks, we only tested a limited number of specific heterogeneity indicators of the TMT. It would be highly interesting to see the impacts of other common metrics such as TMT gender or firm tenure heterogeneity. Beyond the development of new strong predictors, such studies could further improve our understanding of how demographic and taskrelated heterogeneity drive the specific firm-level outcome of bankruptcy.

Finally, there are interesting variations possible with respect to the dependent variable of our research. One might reasonably argue that our work prematurely stops at the question of whether or not a firm has filed for bankruptcy in a given time period. Filing for bankruptcy today, however, does not necessarily mean that a firm must completely cease to exist (Buchalik and Haarmeyer 2015). Researchers should, therefore, analyze what happens to companies during and after their bankruptcy and whether TMT characteristics can be helpful in predicting bankruptcy proceeding outcomes. After all, when faced with financial distress, a TMT may intentionally decide to utilize the protections of the bankruptcy code to restructure the business.

6.4 Concluding remarks

Summarizing, we find that studying the connection between governance factors of firms and bankruptcy is a highly insightful and important topic for both academic

and practical discussions. We are delighted to have found additional notable relationships between the two and introduce TMT heterogeneity characteristics to bankruptcy prediction literature. Following the outlined paths for further research will hopefully allow scholars to develop a more nuanced understanding of how TMTs influence crucial organizational outcomes and offer valuable advice to practitioners—ultimately enabling them to steer their companies successfully through inevitable crises.

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Data availability Underlying data for our research cannot be provided to third parties as per the copyright conditions of the UCLA LoPucki Bankruptcy Research data base. Please reach out in case access is required for any review processes and we will do our best to accommodate your request in cooperation with UCLA.

Declarations

Conflict of interest The authors have no relevant financial or nonfinancial interests to disclose.

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