



Radboud Universiteit Nijmegen

Master Thesis

**Dissimilarities and Turnover:
Examining CDO Turnover in Response to
CDO-CEO Demographic Dissimilarities in
S&P 1500 Firms**

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PREFACE

In front of you, you can find my Master Thesis '*Dissimilarities and Turnover: Examining CDO Turnover in response to CDO-CEO demographic dissimilarities in S&P 1500 firms*'. I have written and conducted this research over the past six months to finalize the study business administration - strategic management at the Radboud University. Prior to this master's program, I completed the HBO International hospitality Management and the prerequisite pre-master's business administration. I can now look back on this educational journey with pride, in which I grew both professionally and personally, absorbing a wide range of academic skills and deepening my understanding of strategic management. With this thesis, I hope to fill a gap in the body of strategic management literature and contribute to the existing knowledge on TMT turnover.

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I am proud to present you my Master Thesis. I hope you will enjoy reading it!

Veerle Rengelink

Nijmegen, June 2024.

ABSTRACT

The current study examines demographic dissimilarities between Chief Digital Officers and Chief Executive Officers. Based on relational demography theory (Tsui et al., 1992), it is hypothesized that individual-level demographic dissimilarity between the CDO and CEO are positively related to CDO turnover. This dissimilarity is examined based on differences in age, gender, functional background, and educational level. A binary logistic regression on secondary panel data has been performed, based on BoardEx, LSEG Workspace and Orbis databases. Results indicated that no statistically significant influence of individual demographic dissimilarity between the CDO and CEO on CDO turnover can be found. Though, a statistically negative influence of overall demographic dissimilarity on CDO turnover has been found, implying that as CDOs and CEOs are demographically dissimilar on more traits, CDO turnover is reduced.

Keywords: Chief Digital Officer, CDO turnover, relational demography theory, demographic dissimilarity, CDO-CEO vertical dyad, S&P 1500

Contents

Ch.1 Introduction	8
Ch.2 Theoretical Background	10
2.1 Literature review	10
2.2 Theory and Hypotheses	11
2.2.1 Relational Demography Theory.....	11
2.2.2 Demographic dissimilarities	12
2.3 Conceptual Model	18
Ch.3 Methods	19
3.1 Data Sample.....	19
3.2 Operationalization	20
3.2.1 Dependent Variable.....	20
3.2.2 Independent Variables	20
3.2.3 Control Variables	22
3.3 Method of Analysis	24
3.4 Validity & Reliability	24
3.5 Ethics	25
Ch.4 Results	26
4.1 Data Analysis	26
4.2 Result Estimation	26
4.2.1 Descriptive statistics and Correlations.....	26
4.2.2 Hypothesis Testing.....	28
4.3 Supplementary Analysis	32
Ch.5 Discussion	37
5.1 Demographic Dissimilarity Effect.....	37
5.2 Theoretical Contributions	40
5.3 Practical Implications	42
5.4 Limitations & Future Research	42
Conclusion	44

Reference List	45
Appendices	53
Appendix I – Data Coding Scheme.....	53
Appendix II – Missing Value Analysis	68
Appendix III – Assumption Testing.....	68
Appendix IV – Case Summary & Variable Coding.....	70
Appendix V – Binary Logistic Regression Analysis.....	71
Logistic Regression model 0 – Constant.....	71
Logistic Regression model 1 – Constant with Control Variables	72
Logistic Regression Model 2 – Constant, Control Variables and Age Dissimilarity.....	74
Logistic Regression model 3 – Constant, Control Variables and Gender Dissimilarity	76
Logistic Regression model 4 – Constant, Control Variables and Functional Background Dissimilarity	79
Logistic Regression model 5 – Constant, Control Variables and Educational Level Dissimilarity	81
Logistic Regression model 6 – Constant, Control Variables and Demographic Dissimilarity....	83
Appendix VI – Supplementary Analysis.....	86
Logistic Regression model 7 – Constant, Control Variables and Demographic Dissimilarity Composite.....	87

Table of Figures

Figure 1. Conceptual Model	18
Figure 2. Conceptual Model (results).....	32

List of Tables

Table 1. Overview Variables	21
Table 2. Overview Control Variables.....	23
Table 3. Descriptive Statistics.....	27
Table 4. Correlations	28
Table 5. Regression Analysis.....	29
Table 6. Descriptive Statistics (composite).....	33

Table 7. Correlations (composite).....	33
Table 8. Regression Analysis (composite).....	35
Table 9. Univariate Statistics	68
Table 10. Multi-collinearity Diagnostics	69
Table 11. Case Processing Summary	70
Table 12. Dependent Variable Coding	70
Table 13. Categorical Variable(s) Coding.....	70
Table 14. Iteration History - Model 0.....	71
Table 15. Classification Table - Model 0.....	72
Table 16. Variables in the Equation - Model 0	72
Table 17. Iteration History - Model 1.....	73
Table 18. Hosmer and Lemeshow Test - Model 1	73
Table 19. Omnibus Test - Model 1.....	74
Table 20. Model Summary - Model 1	74
Table 21. Variables in the Equation - Model 1	74
Table 22. Iteration History - Model 2.....	75
Table 23. Hosmer and Lemeshow Test – Model 2.....	75
Table 24. Omnibus Test – Model 2	76
Table 25. Model Summary - Model 2	76
Table 26. Variables in the Equation - Model 2	76
Table 27. Iteration History - Model 3.....	77
Table 28. Hosmer and Lemeshow Test - Model 3	78
Table 29. Omnibus Test - Model 3.....	78
Table 30. Model Summary – Model 3.....	78
Table 31. Variables in the Equation - Model 3	78
Table 32. Iteration History - Model 4.....	80
Table 33. Hosmer and Lemeshow Test - Model 4	80
Table 34. Omnibus Test - Model 4.....	80
Table 35. Model Summary - Model 4	80
Table 36 Variables in the Equation - Model 4.....	81
Table 37. Iteration History - Model 5.....	82
Table 38. Hosmer and Lemeshow Test - Model 5	82
Table 39. Omnibus Test - Model 5.....	82
Table 40. Model Summary - Model 5	83
Table 41. Variables in the Equation - Model 5	83
Table 42. Iteration History - Model 6.....	85
Table 43. Hosmer and Lemeshow Test - Model 6	85

Table 44. Omnibus Test - Model 6.....	85
Table 45. Model Summary - Model 6	85
Table 46. Variables in the Equation - Model 6	86
Table 47. Collinearity Diagnostics.....	86
Table 48. Multi-collinearity Analysis.....	87
Table 49. Iteration History – Model 7	88
Table 50. Hosmer and Lemeshow Test – Model 7.....	88
Table 51. Omnibus Test – Model 7.....	88
Table 52. Model Summary – Model 7.....	89
Table 53. Variables in the Equation – Model 7.....	89

Ch.1 Introduction

Understanding turnover within the Top Management Team (TMT) is paramount for grasping organizational performance dynamics, strategic direction, and firm success (Messersmith et al., 2014). While extensive TMT research has focused on the turnover of Chief Executive Officers (CEOs) (e.g., Berns & Klarner, 2017; Busenbark et al., 2016; Zhu & Shen, 2016), the departure of other non-CEO executives remains understudied. This lack of understanding is particularly significant for Chief Digital Officers (CDOs) who play a critical role in strategic digital transformations and exhibit high turnover rates (Wade & Obwegeser, 2019). Although current research has focused on the drivers of CDO presence (e.g., Christofi 2024), little to no attention has been directed to understanding their turnover dynamics. Without understanding on this, firms' risk to disrupt organisational continuity and operational inefficiencies, causing strategic drift (Furtado & Karan, 1990; Shen & Cannella, 2002).

Although researchers have argued that findings on individual-level drivers of CEO turnover simply apply to other non-CEO executives, and thus CDOs, other scholars have countered this, asserting that they leave firms for varied reasons (Andrus et al., 2019; Nath & Mahajan, 2017). For instance, research showed that CEOs are more likely to depart during large mergers or ownership changes, while non-CEOs are more likely to depart because of joint ventures or spin-offs (Fee & Hadlock, 2004). Besides, while turnover among CEOs appears to be predominantly firm induced, as they are held accountable for firm performance (Fee & Hadlock, 2004), non-CEOs are held less accountable for firm performance, yet more likely to leave due to social interactions (Buyl et al., 2015). Therefore, as research indicates that the patterns of CEO turnover differ from those of non-CEOs, individual-level CEO turnover drivers cannot be generalized to CDOs. This necessitates insights into their turnover drivers as this will allow strategic leadership research to have a better understanding of individual-level CDO turnover causes (e.g., Godthelp & Glunk, 2003).

Within turnover research, it is demonstrated that demographic (dis)similarities among TMT members are key predictors of both CEO and non-CEO turnover (Godthelp & Glunk, 2003). Most of these studies have drawn from relational demography (Tsui et al., 1992) which asserts that demographic dissimilarities (e.g., in age, education, gender) between individuals lead to turnover because a lack of shared demographic traits emphasizes negative differences, which reduces social attraction and integration (Tsui et al., 2002; Westphal & Zajac, 1995). Especially within superior-subordinate dyads in which demographic dissimilarities influences the

individual behaviour of a subordinate by the perception of dissimilarity with the superior, resulting in turnover of the subordinate (Tsui et al., 1992).

Within the TMT, CDOs report directly to the CEO (Bilgili et al., 2017). Therefore, the relationship between a CEO and CDO is a typical example of a vertical dyad (Zhang et al., 2011). Tsui and O'Reilly (1989) concluded that demographic dissimilarities within such a dyad result in the turnover of the subordinate. Nevertheless, although this effect has been found within the vertical dyad of a CEO with other TMT members (Godthelp & Glunk, 2003; Wiersema & Bird, 1993), there is no evidence that demographic dissimilarities within this dyad results in CDO turnover. This reinforces the inference whether studies on CEO turnover can simply be applied to another TMT member, such as CDOs. Therefore, scholars stress the importance of focusing on demographical dissimilarities to understand their turnover dynamics within such vertical dyads (e.g. Godthelp & Glunk, 2003; Harrison et al., 1998).

Therefore, the objective of the current study is to create a better understanding of the CDO turnover phenomenon. The research question is as follows: *To what degree do individual demographic dissimilarities between CDOs and CEOs influence CDO turnover, and what particular types of dissimilarities significantly influence their departure within S&P 1500 firms?* Based on this, the research aims to contribute to strategic leadership research on turnover by establishing a better understanding of CDO turnover as part of non-CEO turnover research. The study intends to contribute to this by examining individual demographic dissimilarities which may influence CDO turnover. Hence, the research broadens the understanding of CDO turnover by looking into what specific demographic dissimilarities significantly influence CDO turnover. Furthermore, the study extends on relational demography by investigating the influence of demographic dissimilarity on CDO turnover, within the CDO-CEO vertical dyad.

Ch.2 Theoretical Background

2.1 Literature review

Although researchers have shown that the predictors of non-CEO turnover (e.g., poor firm performance, lack of insider-ness) seem to correspond with the predictors of CEO turnover (e.g., poor firm performance, politics), other studies have demonstrated that non-CEO turnover occurs along different patterns (Finkelstein et al., 2009; Nath & Mahajan, 2017; Shen & Canella, 2002). For example, it was discovered that turnover behaviour in relation to performance declines follows distinct patterns for non-CEOs in comparison to CEOs (Mian, 2001). Especially because organisational performance is frequently more directly related to the individual performance of a CEO in comparison to a non-CEO (Buyl et al., 2015). Besides, non-CEOs are held less accountable for overall firm performance yet being more closely tied to the turnover of a CEO due to performance decline (Buyl et al., 2015; Chen et al., 2012).

Similarly, it has been discovered that CEO and non-CEO turnover in relation to the turnover of other TMT members follows distinct patterns (Fee & Hadlock, 2004; Nath & Mahajan, 2017). It was demonstrated that the departure of CEOs influenced turnover of other non-CEOs (Fee & Hadlock, 2004). This is mostly due to the impact that CEO turnover has on team composition and interrelationships with other members. If this CEO is replaced by someone outside the team, this will increase the likelihood of non-CEO turnover due to lack of attraction (Fee & Hadlock, 2004). Therefore, CEO turnover is related to non-CEO turnover. However, in the opposite direction this relationship is not explicitly present, meaning that non-CEO turnover will not directly result in CEO turnover.

Apart from the differences, there also exists parallels between the turnover patterns. It has been demonstrated that turnover behaviour for both CEOs and non-CEOs are directly correlated with social dynamics, with individual dissimilarities serving as primary theme. These studies found that the more dissimilar group members are, the more likely they are to leave due to a lack of integration and cohesion (Finkelstein et al., 2009; Jackson et al., 1991). Consequently, this suggests that the more dissimilar a TMT member, such as a CEO, is to others in the group, the greater the risk of turnover. Especially as these differences between executives are associated with weaker social ties, fewer communication, and less cohesion, leading to an increased turnover (Finkelstein et al., 2009).

Besides, turnover owing to dissimilarity is related to superior-subordinate power dynamics within TMTs (Tsui & O'Reilly, 1989). Since it is proposed that lower levels of cohesiveness and integration are generated by a subordinate's perceived demographic dissimilarity to the

superior, which may influence executive turnover since they have fewer comparable experiences, attitudes, and beliefs, resulting in lower levels of attraction (Tsui et al., 1992; Wagner et al., 1984). On the contrary, the more demographically similar the superior and subordinate are, the better integration and communication will be, lowering turnover rates (O'Reilly et al., 1989; Wagner et al., 1984). As a result, this highlights the significance of power dynamics and demographic dissimilarities among TMT members influencing both CEO- and non-CEO turnover.

Although CEO and non-CEO studies have shown that demographic dissimilarities influence turnover, there is limited research on this relationship among some non-CEOs. Specifically, its influence on CDO turnover remains unexplored, despite evidence suggesting that their turnover rates are comparable to, if not higher than, those of CEOs (Dikolli et al., 2014; Wade & Obwegeser, 2019). Besides, because this role is part of the superior-subordinate relationship with the CEO and is occupied by individuals holding varying demographic traits (Christofi, 2024; Péladeau & Acker, 2019), the relationship between CDOs' and CEOs' demographic dissimilarity may influence CDO turnover. Therefore, understanding this relationship on CDO turnover dynamics is essential, especially due to their responsibility in driving a firm's digital transformation through a digital strategy (Firk et al., 2021).

2.2 Theory and Hypotheses

2.2.1 Relational Demography Theory

Relational demography provides an underlying theoretical framework for investigating the effect of demographic dissimilarity on CDO turnover. This theory assesses individual-level demographic differences, with demography serving as a social connection (Tsui et al., 1992; Tsui et al., 2002). Its fundamental principle is that demographic similarity influences attraction between individuals since it enhances each other's positive traits and develops a social identity (Tsui et al., 2002; Westphal & Zajac, 1995). Hence, demographic traits influence individuals' attitudes and behaviours in which similarities between two individuals may result in positive outcomes (e.g., higher job satisfaction) (Schieman & McMullen, 2008; Tsui et al., 1992). However, this also suggests that dissimilar individuals view each other less favourable which could result in negative outcomes, such as reduced effective communication and increased cognitive conflicts (Duffy & Ferrier, 2003). Therefore, the degree to which individuals within a social unit are demographically dissimilar affects both individual and group outcomes (Schieman & McMullen, 2008).

Social identity (Tajfel & Turner, 1979), similarity-attraction paradigm (Byrne, 1971), and self-categorization theory (Turner et al., 1987) are serving as the foundation for relational demography. These theories suggest that individuals categorise themselves and others in a group based on demographic traits in which similarity stimulates mutual attraction because of resemblances in values, attitudes, and experiences (Cunningham, 2007; Ibarra, 1992; Linnehan et al., 2006). This positively supports social interaction as similarities will enhance communication between individuals (Ibarra, 1992). Therefore, individuals sharing demographic traits will recognize themselves in the social identity, resulting in increased job satisfaction, and lower turnover rates (Cunningham, 2007; O'Reilly et al., 1989).

Demographic dissimilarity refers to the demographic trait differences between two individuals. These traits can be classified into two categories: visible and informational, both of which generate various behaviours and attitudes (Tsui et al., 1992). Informational traits refer to the demographic differences in terms of education level, work experience, and tenure whereas the visible traits refer to age, gender, and race. It has been demonstrated that visible trait dissimilarities between individuals have a negative effect on relationships due to a lack of attraction, and commonly shared values, which increases relational conflicts (Jehn et al., 1997). In contrast, informational differences will strengthen task-related conflicts, since they represent, frequently opposing, mindsets and behaviours that characterise these individuals' working approaches (Jehn et al., 1997).

Within relational demography, most research has focused on both demographic dissimilarities within superior-subordinate relationships by comparing individual's demographic traits (Tsui & O'Reilly, 1989). These dyads represent vertical relationships in which demographic similarity influences attraction between the subordinate and superior. The extent to which they share demographic traits influences behaviours that may affect work outcomes since a lack of similarity may lower attraction, decreasing frequency of interaction, trust, and social integration (Tsui et al., 1992; Tsui & O'Reilly, 1989). Eventually, this influences individual-level outcomes, such as higher turnover rates among subordinates (Tsui et al., 1992; Godthelp & Glunk, 2003).

2.2.2 Demographic dissimilarities

Most firms adopt the CDO role within the TMT to implement and achieve a strategic digital transformation (Firk et al., 2021). These CDOs are responsible for accelerating digital innovation and stimulating collaboration with the purpose of developing a unified strategic alignment throughout the entire firm (Kunisch et al., 2022; Singh & Hess, 2017). Hence, these

CDOs complement the existing TMT by taking on the responsibility of reshaping the firm's strategic agenda towards a digital organisational transformation (Singh et al., 2020).

Nevertheless, CDOs may encounter certain challenges in the implementation of digital transformation, as it frequently necessitates to change the status quo. This requires CDOs to collaborate closely with other executives, to collectively shape and implement the required strategical change (Rickards et al., 2015). Especially the relationship with the CEO is crucial for advancing this new strategic agenda given their authority and resources to bring about a change (Ng et al., 2021). Within this relationship, CDOs frequently report directly to the CEO (Bilgili et al., 2017). Therefore, they form a vertical dyad, characterized by frequent interaction to achieve the digital transformation. It would be beneficial within this dyad for CDOs and CEOs to share certain similarities by having comparable demographic traits, since this could reinforce trust, attraction, and cohesion (Tsui & O'Reilly, 1989). However, this also emphasizes the possible consequences (e.g., turnover) when individuals in these two roles are more dissimilar. Especially subordinates are more likely to depart if they have a greater demographic dissimilarity with the CEO (Finkelstein et al., 2009), given that this dissimilarity leads to lower social integration, cohesion, and attraction, which reduces job satisfaction of the subordinate (e.g., Godthelp & Glunk, 2003; Jackson et al., 1991).

Demographic dissimilarities are thus associated with differences in values, attitudes, and beliefs, resulting in individuals holding diverse sets of experiences and ways of thinking. Different outcomes are caused by these differences, such as cognitive conflicts, because these may heighten differences in opinions and behaviours, leading to, for example, less effective communication and increased complexity of decision-making (Jackson et al., 1991). Besides, demographically dissimilar individuals will encounter challenges integrating into the socially formed identity of a group (Cunningham, 2007; Westphal & Zajac, 1995). As a result, individuals who feel less attracted to others, will have fewer interactions and more disagreement with others, which increases conflicts (Cunningham, 2007; Jehn et al., 1997), making them more likely to leave the firm (Perry et al., 1999).

It has been shown that CDOs hold diverse backgrounds (e.g., marketing, technology, sales) as well as often differ in demographic traits (Christofi, 2024; Péladeau & Acker, 2019). Given their diversified backgrounds, it is reasonable to assume that this role is not occupied by a single type of person. As a result, the high turnover rate among CDOs may indicate a lack of similarity with other TMT executives. Furthermore, considering the transformative approach

throughout the entire firm, this role necessitates cross-functional interaction and cooperation (Péladeau & Acker, 2019). Consequently, it may be impossible to ensure similarities, with for instance the CEO, as this role must engage with multiple actors. Therefore, these CDOs may perceive more dissimilarities with the CEO, which could result in lower levels of attraction, social integration, and thus higher turnover rates among CDOs (e.g., Tsui et al., 1992). When further evaluating demographic dissimilarities between CDOs and CEOs, certain traits stand out.

2.2.2.1 Age

Age as visible trait is an indicator for understanding individual's behaviour as it reflects work attitude and performance (Cleveland & Shore, 1992; Wiersema & Bird, 1993). For instance, it was discovered that age is related to work attitudes (e.g., risk-taking behaviour) as well as decision-making style (Westphal & Zajac, 1995). Besides, research has shown that an individual's age influences commitment towards an organisation (Tsui et al., 1992). As a result, age differences among executives are believed to reflect variances in beliefs and attitudes towards TMT level responsibilities, such as determining a firm's strategic direction (Westphal & Zajac, 1995).

Given that age is a predictor of behaviour and attitudes, (dis)similarities in age tends to induce different work-related outcomes. For instance, age similarity is thought to be associated with similarity in attitudes as individuals experience similar work-related and non-work-related occurrences at the same time in their lives (Wagner et al., 1984; Westphal & Zajac, 1995). Therefore, these individuals tend to share the same social values, attitudes, and believes structures. Besides, similarity in age between individuals positively contributes to self-categorization within a social unit which reduces uncertainty about perceptions on attitudes and behaviours, making individuals more likely to stay (Chattopadhyay et al., 2004).

However, age dissimilarities negatively influences cohesion among individuals as this result in a diverse set of beliefs and value, which can occasionally result in mismatches, power struggles, and turnover (Wiersema & Bird, 1993; Zhang et al., 2011). For instance, if the subordinate is older than the superior, the superior will show less support and consideration for the subordinate which negatively influences their relationship and induces turnover (Perry et al., 1999). Besides, it is expected that if age dissimilarity exists, there will be less attraction between the superior and subordinate given that this often violates age norms, such as that it is expected that supervisors supervise younger rather than older subordinates. Therefore, age dissimilarities within vertical dyads could result in greater cognitive conflicts due to

mismatches in views and attitudes, leading to lower levels of social integration and cohesion, inducing higher rates of turnover (e.g., O'Reilly et al., 1989; Wagner et al., 1984).

Therefore, within the vertical dyad between the CDO and CEO, age similarity is considered to reduce turnover as similarity will enhance attraction, cohesion, and shared trust (Tsui et al., 1992). However, as the CDO role is filled by a variety of individuals, CDOs and CEOs are more likely to be dissimilar in terms of age, which is expected to influence CDO turnover.

Hypothesis 1: Age dissimilarity between a CDO and the existing CEO will be positively associated with CDO turnover.

2.2.2.2 Gender

Gender as visible demographic trait is an indicator explaining differences in individual's behaviours, such as work-, leadership- and decision-making styles (Fenwick & Neal, 2001; Goergen et al., 2015). For instance, female workstyles are characterized as co-operative, holding a negotiating communication style compared to male workstyles characterized as more forceful and traditional with a conveying communicating style in which status is important (Fenwick & Neal, 2001). Therefore, these work- and communication styles influence work behaviour of executives who are responsible for strategic decision-making (Ling et al., 2015).

Within the literature, it has been shown that the gender ratio within teams is a key element for understanding the effects of dissimilarities. Especially, as gender ratios reflect these work styles, in which an unequal ratio may create a sense of dissimilarity in comparison to others in the TMT. Besides, the ratio influences individual's attraction and self-identity, which affect social integration and individual-level performance (Jansen et al., 2017). This gender ratio is also important in vertical dyads between executives as it was found that same-gender dyads result in better performance compared to mixed-gender dyads (Tsui & O'Reilly, 1989). Especially as similarity in gender between subordinates and superiors is associated with higher degrees of attraction and better informal connections, which positively increases the frequency of communication. This frequency and quality of communication promotes stronger integration and cohesion, reducing executive turnover (Tsui et al., 1992). Therefore, the gender ratio is a key predictor of individual-level executive turnover (Zhang & Qu, 2016).

Within the CDO literature, no empirical research has yet been performed to determine whether gender dissimilarity between a CDO and the CEO is a key influence of CDO turnover. However, based on the existing literature, the following hypothesis is proposed:

Hypothesis 2: Gender dissimilarity between a CDO and the existing CEO will be positively associated with CDO turnover.

2.2.2.3 Functional Background

Functional background, as an informational demographic trait, has been discovered to influence individuals' opinions and attitudes towards certain perceptions or decisions. Especially as experiences in specific functional areas lead to various viewpoints, which influences how they interpret opportunities and challenges, therefore shaping behaviour (Campbell et al., 2023; Westphal & Zajac, 1995). Besides, researchers found that executives were more sensitive and likely to act upon strategic issues if these were related to their own functional area (Westphal & Zajac, 1995). As a result, the functional background affects an executive's behaviour, perception and beliefs, primarily towards strategic decision-making.

Given its impact on the behaviour of an executive, it is also proven that similarity in a functional background will result in a commonly shared set of beliefs and attitudes among executives, through which they produce the same problem-solving solutions (Westphal & Zajac, 1995). However, if executives do not share functional background, these dissimilarities will result in diverse opinions on the best course of action. In addition, functional background dissimilarity within vertical dyads limits the extent to which opinions are shared which could constrain decision-making (Zhu & Westphal, 2014). For instance, if a subordinate and a superior do not share functional backgrounds, it may result in communication and power struggles, which could negatively affect relationships within vertical dyads, as well as firm outcomes (e.g., Tsui et al., 1992; Westphal & Zajac, 1995; Zhang et al., 2011). Hence, within the CDO-CEO dyad, dissimilarity in functional background may have a negative effect as it could limit the CDO's ability to implement a digital transformation, potentially leading to CDO turnover.

Research has demonstrated that CDOs come from a wide range of functional backgrounds (Kunisch et al., 2022). Given their responsibility on implementing a digital transformation, one might assume a digital or technological background to effectively coordinate and integrate transformation (Berbel-Vera et al., 2022). Especially, as the transformations requires to change systems and the implementation of innovative technologies (Péladeau & Acker, 2019). Additionally, as individuals in this function hold a new role within the TMT, it requires them to demonstrate expertise and the ability to ensure that the new role is of strategic significance. Though, it has also been argued that CDOs should have a background in business strategy, rather than just digital knowledge (Berman et al., 2020).

Given the ambiguity regarding the ‘standard’ functional background of CDOs, it is expected that CDOs hold diverse functional backgrounds. This diversity in functional backgrounds indicates a broader range of perspectives and expertise, which indirectly suggests functional background dissimilarity with others in the vertical dyad.

Hypothesis 3: Functional background dissimilarity between a CDO and the existing CEO will be positively associated with CDO turnover.

2.2.2.4 Educational Level

Educational level as informational demographic trait influences an individual’s behaviour as educational choices are associated with personality and attitudes (Jackson et al., 1991). Besides, higher levels of education are associated with better capabilities in information processing, receptivity to innovation, and complexity handling, which is found to influence decision-making capabilities (Westphal & Zajac, 1995) Furthermore, educational level is perceived to influence cognitive styles, which impacts their values and beliefs (Wiersema & Bantel, 1993). Therefore, given that it has a considerable influence on behaviours, dissimilarities on educational level will lead to differences in attitudes and beliefs, which may be reflected in willingness to change and decision-making.

Researchers have demonstrated that teams consisting of diverse educational levels perform better as they have more knowledge and experiences to draw upon (Bengtsson et al., 2020). Therefore, it is assumed that TMTs are frequently composed of a variety of educational levels to increase performance. Tsui et al. (1992) found evidence that, within these varying compositions, an executive’s educational dissimilarity in comparison to other TMT members is associated with the inclination to stay rather than depart. However, other researchers found that dissimilarity in educational levels could constrain decision making and individual performance due to diverse viewpoints and cognitive styles (Wiersema & Bantel, 1993). Hence, researchers found evidence that executives who are dissimilar in terms of educational level in comparison to other TMT members are more likely to leave (Jackson et al., 1991). Especially given that this dissimilarity results in cognitive differences constraining communication and cohesiveness among executives.

Therefore, the findings are ambiguous on whether dissimilarities in educational level has a favourable or negative impact on executive turnover because these studies’ findings are contradicting. Furthermore, within the CDO literature, no empirical research has yet determined whether educational level dissimilarity between CDOs and their superiors, CEOs,

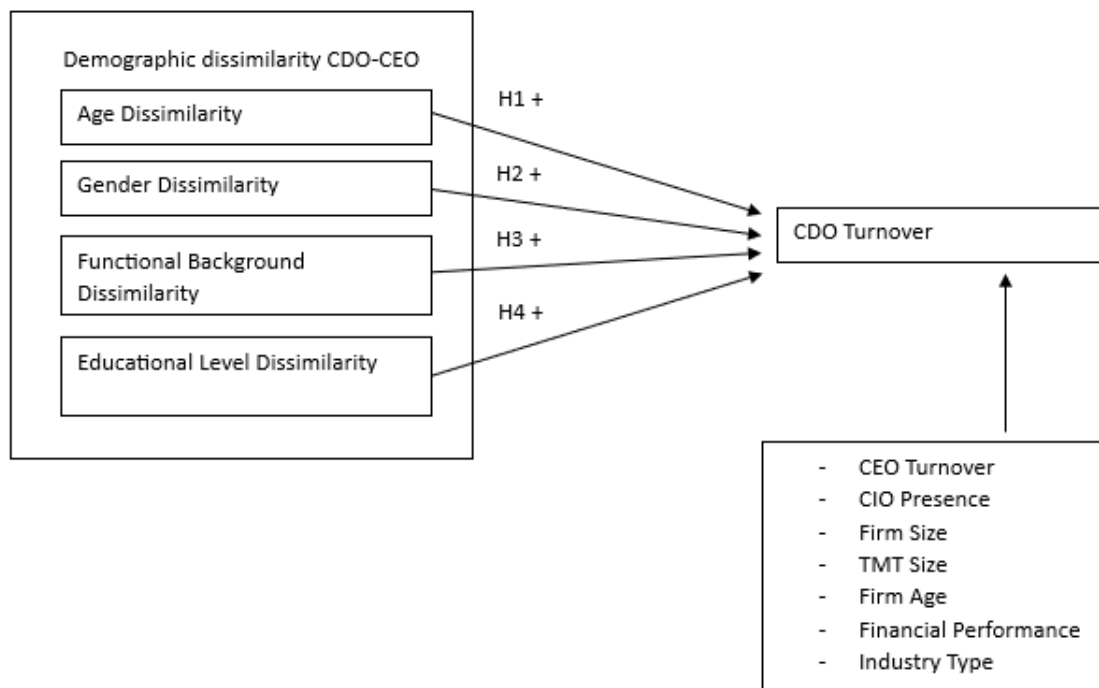
positively or negatively influences CDO turnover. Therefore, the following hypothesis is proposed.

Hypothesis 4: Educational level dissimilarity between a CDO and the existing CEO will be positively associated with CDO turnover.

2.3 Conceptual Model

Figure 1 displays the conceptual model which illustrates the hypothesized relationship between demographic dissimilarities and CDO turnover.

Figure 1. Conceptual Model



Ch.3 Methods

3.1 Data Sample

The data sample was constructed based on the BoardEx, LSEG Workspace, and Orbis databases. The BoardEx database contains information on all top executives and board members, based on personal profiles, education histories, employment histories, and other activities (Wharton University of Pennsylvania, n.d.), including those working in firms listed in the S&P 1500. The S&P 1500 composites three indices; S&P 500, S&P MiddleCap 400, and S&P SmallCap 600 (S&P Dow Jones Indices, 2024), which covers approximately 90% of the U.S. market capitalization. Within research, this composite has been used as a backbone to analyse CEO and non-CEO turnover within firms, historically or currently listed in the S&P 1500 (e.g., Gentry et al., 2021; Messersmith et al., 2014). Given that most studies employed the North American BoardEx database (e.g., Burns et al., 2023; Liu, 2014), and that only this database can be linked to the S&P 1500 composite, this database was used to draw the dataset. To incorporate the S&P 1500, a dataset was drawn from LSEG workspace for the period of 2005-2023, which was later merged with the dataset obtained from BoardEx and Orbis.

Within the current study, the following data filtering techniques were used to identify the CDO executives to ensure an adequate sample, representative of the CDO position. First, a search algorithm including the term ‘Chief Digital Officer,’ ‘digital,’ and ‘executive’ was run within the merged dataset. Second, if a CDO position was identified, an additional search was done to verify the CDOs’ responsibilities, to ensure the position is in correspondence with the role description (e.g., through LinkedIn profiles). Thirdly, given that the CDO role varies per company, various synonyms for the CDO position were included and accounted for (e.g., Chief Digital Innovation Officer, Chief Digital Strategy Officer, Chief Transformation and Digital Officer). However, in line with the findings of Gupta et al. (2021), and Kesner and Dalton (1994), only digital positions of ‘Vice President’ and above were included. Lastly, an extra search was conducted to check unclear CDO title synonyms to determine if the responsibilities of the role aligned with the CDO role (e.g., Firk et al., 2021).

For the entire data sample, a timeframe of 2005 until 2023 was adopted. Research showed that most perceive the appointment of the CDO of Capital One, in 2002, to be the first (Wallace, 2018). However, research also shows that it was only after 2005 that the number of CDOs implemented within TMTs began to increase (Singh et al., 2020). Besides, considering that this role was newly introduced to the TMT, it could have taken some time for the role to be shaped and adopted by more firms. Therefore, 2005 was taken as starting point for data collection. As

a result, 19 years of panel data has been collected on ISIN-year observations. The final sample included 1334 observations with 224 observed CDO turnovers.

3.2 Operationalization

3.2.1 Dependent Variable

CDO Turnover. Executive turnover is typically defined by an individual leaving its position within the TMT (e.g., Gentry et al., 2021). Within the current study, *CDO turnover* refers to an individual leaving its CDO position, which was measured based on end-of-role data. To operationalize it, a binary dependent variable was constructed, coded as 0 if there was no CDO turnover and 1 in the presence of CDO turnover.

3.2.2 Independent Variables

Demographic Dissimilarities. Dissimilarity is a relational concept that is measured by comparing the characteristics of two individuals. The current study measures *demographic dissimilarity* in terms of age, gender, educational level, and functional background. First, *age dissimilarity* was included as dissimilarities between the CDO and CEO might indicate differences in experience, values, and attitudes, which could potentially harm communication and cohesiveness between the two, leading to CDO turnover (e.g., Tsui et al., 1992). To operationalize *age dissimilarity*, the difference between year of birth was measured (e.g., Wagner et al., 1984). A binary variable was created in which *age dissimilarity* was coded 1 if one standard deviation difference was observed and 0 if they differed by less than (e.g., Westphal & Zajac, 1995).

Secondly, *gender dissimilarity* was included as this is an important variable for understanding power- and turnover dynamics within vertical dyads, as dissimilarity between the CDO and CEO might induce different behaviour. Besides, the gender ratio between the CDO and CEO is of importance to understand individual-level executive turnover (e.g., Tsui & O'Reilly, 1989). Therefore, *gender dissimilarity* was examined by comparing the CDO- and CEO gender, for which a binary variable was generated, coded as 1 if a difference was observed and 0 otherwise (e.g., Lyness & Judiesch, 2001).

Thirdly, *functional background dissimilarity* was included. It was argued that there is a lack of understanding to what extent the functional background of CDOs influences their turnover patterns. Especially considering the discussion whether CDOs should hold specific digital- or technological backgrounds (e.g., Berbel-Vera et al., 2022). Besides, it is argued that if a CDO and a CEO differ in functional backgrounds, this could lead to conflicts (e.g., Zhu & Westphal, 2014). Therefore, the current study classified *CDO-* and *CEO functional background* into the

categories ‘tech functional background’ and ‘non-tech functional background’. The first group consists of those who have experiences in digitalization and technological functions (e.g., ‘Electronic & Electrical Equipment’, ‘Information Technology Hardware’, ‘Software & Computer Services’, and other functions identifying ‘Digital’), while those in the latter consists of others who have dominant experiences in other dimensions (e.g., marketing, finance) (e.g., Zhang & Rajagopalan, 2010). Therefore, a dummy variable has been created in which at tech functional background gets assigned a value of 1, and 0 otherwise. Based on this coding, the *functional background dissimilarity* variable was generated, coded as 1 if a difference was observed, and 0 otherwise.

Lastly, *educational level dissimilarity* was included. Although there is ambiguity as to whether educational level dissimilarity influences CDO turnover, it was expected that CDOs who are dissimilar in terms of educational level in comparison to the CEO, will be more likely to leave. Therefore, *educational level dissimilarity* was operationalized by CDO and CEO educational levels. A binary variable has been created in which a difference was coded as 1, and 0 otherwise (e.g., Zhang & Rajagopalan, 2010).

Table 1. Overview Variables

Variable	Type	Value	Description
CDO Turnover	Dependent Variable	0 – No CDO turnover 1 – CDO Turnover	Indicates whether there has been a change in the CDO
Age Dissimilarity	Independent Variable	0 – Age similarity 1 – Age dissimilarity	Indicates whether a CDO is dissimilar in age from the CEO
Gender Dissimilarity	Independent Variable	0 – Gender similarity 1 – Gender dissimilarity	Indicates whether a CDO is dissimilar in gender from the CEO
Functional Background Dissimilarity	Independent Variable	0 – Functional background similarity 1 – Functional background dissimilarity	Indicates whether a CDO is dissimilar in functional background from the CEO
Educational Level Dissimilarity	Independent Variable	0 – Educational level similarity 1 – Educational level dissimilarity	Indicates whether a CDO is dissimilar in educational level from the CEO

3.2.3 Control Variables

To enhance the validity and generalizability of the findings, the following variables are controlled for, collected from the BoardEx, LSEG, and Orbis database. The following individual-level control variables were included. First, *CEO turnover* was included which is perceived as an individual leaving their CEO position within the TMT (e.g., Gentry et al., 2021). Within the literature, it has been shown that *CEO turnover* initiates turnover among other TMT members (Fee & Hadlock, 2004). Consequently, the departure of a CEO during the tenure of a CDO may lead to CDO turnover. *CEO turnover* was based on the end-of-role-date, operationalized as a binary variable, which was coded as 1 if the CEO left during the CDOs' tenure and 0 otherwise (e.g., Zhang et al., 2011). Second, researchers discovered that *CIO presence* is positively associated with CDO presence within a firm, particularly as the CDO's digital transformation process is linked to information and communication technologies (Kunisch et al., 2022). As a result, it is argued that the CDO and CIO have a complementary rather than substitutive roles. Therefore, a lack of *CIO presence* could limit an individual in the CDO role. Although the lack of *CIO presence* has not been empirically validated as a predictor of CDO turnover, this research will control for it. This variable was operationalized by assigning a binary value of 1 if a CIO was present and 0 otherwise.

Besides, the following firm-level control variables were included. First, *firm size* is controlled for as frequency of turnover is directly correlated to firm size (Grusky, 1963; Messersmith et al., 2014). It follows the reasoning that as larger companies employ a greater number of people, their turnover rate must be higher. This is operationalized based on the numbers of employees (e.g., Zhang & Rajagopalan, 2010). In addition, *TMT size* is controlled for as this is positively associated with executive turnover (Godthelp & Glunk, 2003; Zhang et al., 2011). This is operationalized using the number of executives inside a TMT at the start of the year. Thirdly, *firm age* is controlled for which is defined as the number of years the firm has existed. Older, more matured businesses tend to be resistant to change because they rely heavily on taken-for-granted resources, competitive advantages, and routines (Hannan & Freeman, 1984). Therefore, executives in these older companies tend to become entrenched in the routines and regulations, making them less adaptable to change. This unwillingness to change may discourage digital transformations, thus undermining the efforts of the CDO, which could influence CDO turnover. *Firm age* is operationalized based on the year of incorporation. Finally, *financial performance* was controlled for as research has demonstrated that poor firm performance and falling stock prices frequently led to turnover (e.g., Berns & Klarner, 2017;

Gentry et al., 2021; Mian, 2001). As a result, poor firm performance could influence CDO turnover. Return on assets data was used to operationalize *financial performance* (e.g., Zhang & Rajagopalan, 2010).

Furthermore, *industry type* was included as an industry-level control variable. This control variable is operationalized through its four-digit Standard Industrial Classification (SIC) code (e.g., Zajac & Westphal, 1996). Based on the SIC code, a variable was generated with the following categories: 1) Energy & Transformation, 2) Real estate & Construction, 3) Manufacturing, 4) Industrial Applications & Services, 5) Life Sciences, 6) Technology, 7) Trade & Services, 8) Finance, and 9) Commercial physical and Bio research.

Table 2. Overview Control Variables

Variable	Type	Values	Description
CEO Turnover	Control variable – individual level	0 – No CEO Turnover 1 – CEO Turnover	Indicates whether there has been a change in the Chief Executive Officer
CIO Presence	Control variable – individual level	0 – No CIO presence 1 – CIO presence	Indicates whether a Chief Information Officer is present within the firm
Firm Size	Control variable – firm level	In # of employees	Indicates firm size
TMT Size	Control variable – firm level	In # of individuals in the top management team	Indicates TMT size
Firm Age	Control variable – firm level	In # of years the firm has been in incorporation	Indicates firm age
Financial Performance	Control variable – firm level	in terms of return on assets (ROA)	Indicates firm performance
Industry Type	Control Variable – industry level	1 – Energy & Transformation 2 – Real estate & Construction 3 – Manufacturing 4 – Industrial Applications & Services 5 – Life Sciences 6 – Technology 7 – Trade & Services 8 – Finance 9 – Commercial Physical and Bio research	Indicates industry type based on SICCODE

3.3 Method of Analysis

A binary logistic regression analysis was performed to examine the relationship between demographic dissimilarities and CDO turnover (Hair et al., 2019). This analysis included both non-metric binary dependent- and independent variables, with a two-level category, for which a binary logistic model was specified. Within this specification, the predictive power of demographic dissimilarity on CDO turnover has been assessed. Even though there is a non-linear relationship between the independent variables and the likelihood of CDO turnover, this regression models estimate the probability of CDO turnover as a linear combination of the intercept with the binary independent variables (Hair et al., 2019). Therefore, the estimation equation is formulated as follows:

$$P(\text{CDO turnover}) = 1 / (1 + e^{-(\beta_0 + \beta_1 \text{age dissimilarity} + \beta_2 \text{gender dissimilarity} + \beta_3 \text{functional background dissimilarity} + \beta_4 \text{educational level dissimilarity})})$$

Within this equation $P(\text{CDO turnover})$ represents the probability of CDO turnover to be in category 1 given the values of demographic dissimilarity. β_0 represents the intercept term and $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients associated with the independent variables. Besides, e transforms the linear combination of predictors into a probability using the logistic function (Hair et al., 2019).

Furthermore, several assumptions have been considered. First, a sample size of >400 is ensured to make estimations with the maximum likelihood (MLE) that supports logistic regression. In addition, the following assumptions have been tested: 1) independence of residuals, 2) multicollinearity, 3) influential outliers, and 5) no complete/quasi-separation of data (see Appendix III).

3.4 Validity & Reliability

Validity was a primary consideration to ensure that the data measured what it was intended to measure (Hair et al., 2019). First, data accuracy has been considered by including variables that were relevant to CDO turnover and the research question. Similarly, variables were incorporated that have been used and validated by other researchers in similar studies. Second, source reputation and credibility were ensured by using well-recognized databases within the field of research. These databases are known for their data collection and validating data, which enhances the overall reliability and validity. Furthermore, dissimilarity measures were verified by combining tested approaches from published studies, ensuring the measures' robustness and validity. In addition, a long timeframe was adopted to capture the CDO turnover dynamics and

the impact of demographic dissimilarity on this outcome. Moreover, expert consultation was conducted to ensure the validity of the data and variables employed (Hair et al., 2019).

In addition, the current study's reliability has been assessed to ensure that the data and findings were consistent (Hair et al., 2019). First, credibility of database sources was ensured, which guarantees the credibility of the data. Secondly, a missing data analyses and completeness verification was performed to ensure that the study used a complete and verified dataset. Furthermore, reproducibility was assessed by rerunning the analysis to ensure that comparable results were obtained. Moreover, data processing transparency was guaranteed to provide insights into how the databases were transformed into the final dataset.

3.5 Ethics

Several steps have been taken to ensure research integrity. Primarily, during all phases of the study, the American Psychological Association (APA 7) guidelines were applied to adhere to ethical standards. Secondly, while the data collected from the databases is publicly available, anonymization has been considered by only using company and Board IDs, excluding all personal information of executives. Thirdly, biases and misrepresentations were avoided by evading selective reporting or ignoring certain findings. In addition, full transparency on the data analysis, cleaning, and recoding has been provided to ensure the findings are replicable and generalizable to current- and future research on executive turnover within TMTs.

Ch.4 Results

4.1 Data Analysis

Before the hypotheses were tested through the binary logistic regression, preliminary tests have been performed to assess the missing values and assumptions of logistic regression (Hair et al., 2019). A Little's MCAR (missing completely at random) test was performed of which the univariate statistics demonstrated that exceedingly high missing value percentages were present (see Appendix II). Besides, the results of the Little's MCAR test were statistically significant at a 5% significance level ($p = .000$), indicating that the missingness of the data were not completely at random. Therefore, further analyses have been performed to understand the missing values in which it was discovered that there were specific patterns among the missing values. For example, it was found that more recently incorporated firms had more missing values. These patterns and high percentages of missing data could have negative consequences for the size, statistical power, and validity as well as inducing biases in the interpretation of the results (Hair et al., 2019). Therefore, to protect the validity, reliability, and generalizability of the research and its findings, a partial list-wise deletion strategy was adopted to cope with the missing data mechanisms. In total 1334 observations were included within the current study to test the relationships between the individual demographic dissimilarities and CDO turnover. Overall, 227 CDO turnovers were observed in the timeframe of 2005 until 2023.

4.2 Result Estimation

The logistic regression was performed using SPSS 29.0 software. Appendix IV shows the case summary and variable coding of the analysis. To examine the independent variables' ability to predict CDO turnover, six models were incorporated into the analysis. The first model integrates the control variables. The second integrates age dissimilarity. The third integrates gender dissimilarity. The fourth integrates functional background dissimilarity. The fifth integrates educational level dissimilarity. The sixth model integrates all four dissimilarity variables simultaneously. Table 5 displays the regression outcomes of these models. With the purpose of understanding the outcomes, a thorough evaluation of the models has been executed (see Appendix V).

4.2.1 Descriptive statistics and Correlations

Tables 3 summarize the descriptive statistics for the variables. It reports that *CDO turnover* had a low occurrence within the S&P 1500 firms. Regarding the four independent dissimilarity variables, it can be observed that *age dissimilarity* (mean = .62) and *educational level dissimilarity* (mean = .61) both exhibit moderate dissimilarity among the CDO and CEO. In contrast to *functional background dissimilarity* (mean = .91) exhibiting larger demographic

dissimilarity between the CDO and CEO, *gender dissimilarity* (mean = .35) exhibits lower levels of dissimilarity between the two. Furthermore, while 55% of S&P 1500 firms had a *CIO* present, the majority of these did not experience *CEO turnover*. Additionally, findings on *firm size*, *TMT size*, *firm age*, and *firm performance* revealed variation among the S&P 1500 firms. Besides, a wide range of industries were represented, encompassing nine industries.

Table 3. Descriptive Statistics

Variable	Mode	Median	Mean	SD	Min.	Max.	N
CDO Turnover	0	0	.17	.376	0	1	1334
Age Dissimilarity	1	1	.62	.485	0	1	531
Gender Dissimilarity	0	0	.35	.477	0	1	1071
Functional Background Dissimilarity	1	1	.91	.288	0	1	1334
Educational Level Dissimilarity	1	1	.61	.487	0	1	955
CEO Turnover	0	0	.11	.315	0	1	1334
CIO Presence	1	1	.55	.498	0	1	1334
Firm Size	31000	21100	58805.80	87340.329	373	647500	1277
TMT Size	33	34	50.82	51.111	1	336	1332
Firm Age	21	27	39.79	38.586	-11	229	1319
Financial Performance	.96	5.66	6.4049	9.72209	-92.76	85.09	1289
Industry Type	7	6	5.58	2.251	1	9	1322

Table 4 reports the (inter)correlations among all the variables. The Pearson correlation coefficients indicate that there are no substantial concerns regarding multi-collinearity within this analysis, since all correlation coefficients are below the threshold of 0.8 (Hair et al., 2019). The highest correlations observed were between firm size and TMT size (.472), and between CIO presence and TMT size (.275). Furthermore, the variance inflation factor (VIF) was computed for each independent and control variable to assess multi-collinearity (see Appendix III). The collinearity diagnostics indicated that for all independent- and control variables, the tolerance values were close to 1 (ranging from .699 to .990) and VIF were close to 1 (ranging

from 1.010 to 1.432). Hence, these values shows that they adhered to the common thresholds indicating that multi-collinearity is not a significant issue in the regression model.

Table 4. Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. CDO Turnover	1											
2. CEO Turnover	-.161***	1										
3. Firm Size	-.059**	.087**	1									
4. Firm Performance	-.044	-.067**	.029	1								
5. Age Dissimilarity	.004	-.010	.047	-.020	1							
6. Gender Dissimilarity	.033	-.024	.006	-.082**	-.130**	1						
7. Functional Background Dissimilarity	.054**	-.020	-.054	-.006	.047	.017	1					
8. Educational Level Dissimilarity	-.008	.042	.061	-.031	.042	.068**	.018	1				
9. TMT Size	-.155***	.060**	.472***	-.050	-.009	.100***	-.234***	.012	1			
10. CIO Presence	-.089***	.036	.244***	.029	.037	-.034	-.064**	-.022	.275***	1		
11. Firm Age	-.004	.044	.198***	-.040	-.038	.076**	.107***	.020	.184**	.018	1	
12. Industry Type	-.029	.010	.133***	.001	.020	.050	.037	.098**	.164**	.090***	.002	1

Legend: * $p < .1$; ** $p < .05$; *** $p < .001$

4.2.2 Hypothesis Testing

Based upon the estimated results, the theoretically formulated hypotheses were tested upon the second, third, fourth, fifth and sixth model (see Table 55), in which the regression analysis controlled for the variables which may influence the relationship between demographic dissimilarity and CDO turnover. Figure 2 shows the conceptual model containing the findings on the hypotheses.

Table 5. Regression Analysis

	Model 1 <i>β/se</i>	Model 2 (H1) <i>β/se</i>	Model 3 (H2) <i>β/se</i>	Model 4 (H3) <i>β/se</i>	Model 5 (H4) <i>β/se</i>	Model 6 <i>β/se</i>
Independent Variables						
Age dissim.		-.043 (.331)				-.029 (.334)
Gender dissim.			.345 (.335)			.345 (.337)
Functional Background dissim.				-.290 (.616)		-.300 (.617)
Educational Level dissim.					.094 (.333)	.094 (.333)
Control Variables						
CEO turnover	-19.177 (5045.51)	-19.180 (5043.77)	-19.184 (5034.26)	-19.204 (5029.75)	-19.204 (5033.95)	-19.204 (5033.95)
CIO presence	-.493 (.334)	-.492 (.334)	-.475 (.334)	-.481 (.335)	-.472 (.336)	-.472 (.336)
Firm size	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)
TMT size	-.001 (.005)	-.001 (.005)	-.001 (.005)	-.001 (.005)	-.001 (.005)	-.001 (.005)
Firm age	.006 (.005)	.006 (.005)	.006 (.005)	.006 (.005)	.006 (.005)	.006 (.005)
Firm performance	-.017 (.018)	-.017 (.018)	-.017 (.018)	-.017 (.018)	-.016 (.018)	-.016 (.018)
Industry Type (1)	1.492** (.726)	1.490** (.726)	1.521** (.727)	1.559** (.733)	1.564** (.733)	1.564** (.733)
Industry Type (2)	.503 (.619)	.510 (.622)	.516 (.622)	.548 (.627)	.550 (.627)	.550 (.627)
Industry Type (3)	-.400 (1.177)	-.398 (1.177)	-.282 (1.182)	-.315 (1.185)	-.304 (1.186)	-.304 (1.186)

Legend: * $p < .1$, ** $p < .05$; *** $p < .01$

Note 1: Reference category 'Industry Type'; category 9.

Note 2: Reference category all independent variables; category 0.

	Model 1	Model 2 (H1)	Model 3 (H2)	Model 4 (H3)	Model 5 (H4)	Model 6
	β/se	β/se	β/se	β/se	β/se	β/se
Industry Type (3)	-.400 (1.177)	-.398 (1.177)	-.282 (1.182)	-.315 (1.185)	-.304 (1.186)	-.304 (1.186)
Industry Type (4)	-18.020 (10757.87)	-17.998 (10659.74)	-17.925 (10642.85)	-17.869 (10645.29)	-17.909 (10656.09)	-17.909 (10656.00)
Industry Type (5)	.659 (.767)	.655 (.767)	.627 (.767)	.511 (.813)	.498 (.812)	.498 (.812)
Industry Type (6)	.717 (.623)	.724 (.625)	.764 (.626)	.775 (.626)	.757 (.628)	.757 (.628)
Industry Type (7)	-1.177 (.919)	-1.174 (.919)	-1.169 (.922)	-1.116 (.929)	-1.133 (.934)	-1.133 (.934)
Industry Type (8)	-18.942 (28420.60)	-18.965 (28420.60)	-19.159 (28420.58)	-19.133 (28420.60)	-19.074 (28420.61)	-19.074 (28420.61)
N	1334	531	1071	1334	955	459
Model X2	30.546***	30.563**	31.605**	31.821**	31.901**	31.901**
Hosmer & Lemeshow	4.562	4.372	17.371**	14.431	4.026	4.026
Nagelkerke	.133	.133	.138	.139	.139	.139

Legend: * $p < .1$, ** $p < .05$; *** $p < .01$

Note 1: Reference category 'Industry Type'; category 9.

Note 2: Reference category all independent variables; category 0.

Hypothesis 1 posits that *age dissimilarity* between the CDO and CEO should be positively related to CDO turnover. Within the regression analysis, it has been shown that in both the 2nd model ($B = -.043, p = .898$) and 6th model ($B = -.029, p = .930$), age dissimilarity has a non-statistically significant negative effect on CDO turnover. This indicates that within the current study, no support (NS) has been found for hypothesis 1.

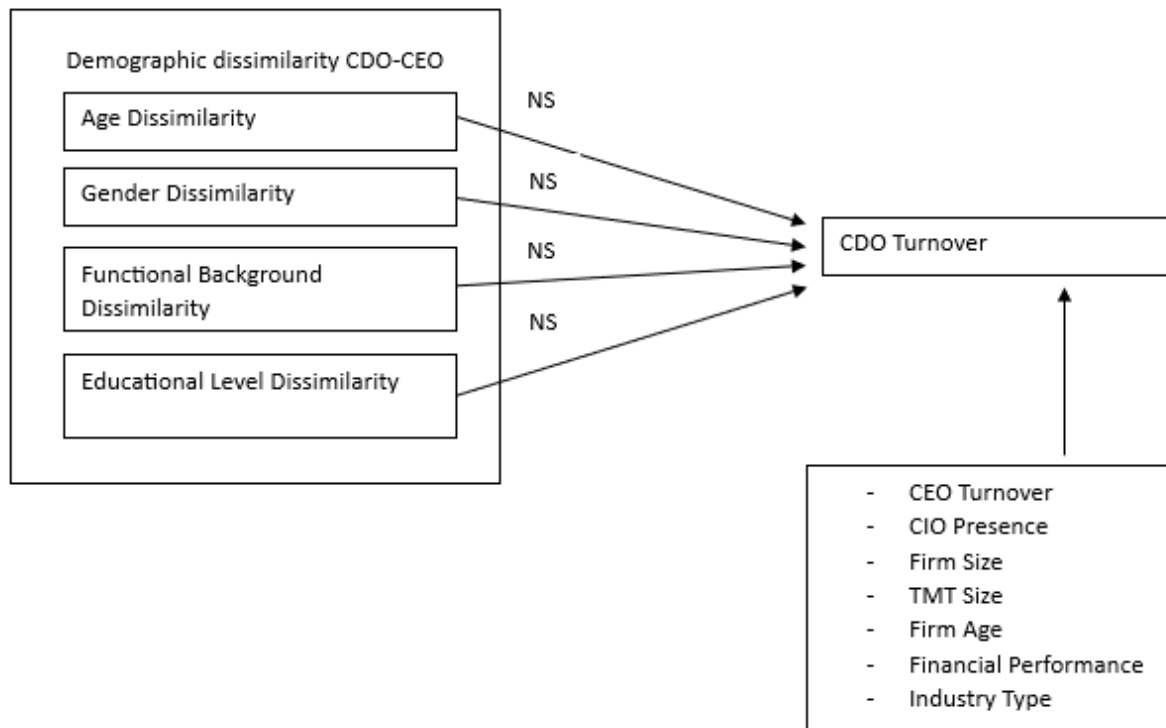
Hypothesis 2 posits that *gender dissimilarity* between the CDO and CEO should be positively related to CDO turnover. Within the regression analysis, it has been shown that in both the 3rd ($B = .345, p = .303$) and 6th model ($B = .345, p = .306$) gender dissimilarity has a non-statistically significant positive effect on CDO turnover. This indicates that within the current study, no support has been found for hypothesis 2.

Hypothesis 3 posits that *functional background dissimilarity* between the CDO and CEO should be positively related to CDO turnover. Within the current analysis, it has been shown that in both the 4th ($B = -.290, p = .638$) and 6th model ($B = -.300, p = .626$), functional background dissimilarity has a non-statistically significant negative effect on CDO turnover. This indicates that within the current study, no support has been found for hypothesis 3.

Hypothesis 4 posits that *educational level dissimilarity* between the CDO and CEO should be positively related to CDO turnover. Within the current analysis, it has been shown that in both the 5th ($B = .940, p = .777$) and 6th model ($B = .940, p = .777$), educational level dissimilarity has a non-statistically significant positive effect on CDO turnover. This indicates that within the current study, no support has been found for hypothesis 4.

Among the control variables, it has been shown that only category 1 ‘Energy & Transformation’ of *industry type* significantly predicts *CDO turnover* in all models ($B = 1.564, p = .033, \text{Exp}(B) = 1.564$). All other control variables do not have a statistically significant effect on CDO turnover.

Figure 2. Conceptual Model (results)



4.3 Supplementary Analysis

In the executed regression analysis, the individual effect of demographic dissimilarities on CDO turnover was examined. However, this approach had limitations in fully capturing the multifaceted nature of demographic dissimilarity. While it is common in TMT turnover research to examine these individual demographic attributes, some researchers advocate for measuring demographic dissimilarity as a composite construct to understand its impact on turnover outcomes more holistically (Tsui & Gutek, 1999). Especially given that individuals are composed of all single demographic attributes together.

Therefore, a supplementary analysis has been performed in which a composite measure has been generated for demographic dissimilarity between the CDO and CEO. This composite measure was treated as a metrically scaled variable coded as 0) no demographic attribute dissimilarity, 1) one demographic attribute dissimilarity, 2) two demographic attribute dissimilarities, 3) three demographic attribute dissimilarities, and 4) four demographic attribute dissimilarities. Table 6 shows the descriptive statistics of this variable. Based on this composite variable, the supplementary regression analysis has been performed, which was included as 7th model.

Table 6. Descriptive Statistics (composite)

Variable	Mode	Median	Mean	SD	Min.	Max.	N
Demographic Dissimilarity	1	1.88	2	.895	0	4	1334

Table 7 reports the correlations among all the variables. The Pearson correlation coefficients indicate that there are no substantial concerns regarding multi-collinearity within this analysis, given that all correlation coefficients are below the threshold of 0.8 (Hair et al., 2019). The highest observed correlation is between firm size and TMT size (.472). Furthermore, the collinearity diagnostics indicated that for the composite and control variables, the tolerance values (ranging from .730 to .987) and VIF values (ranging from 1.013 to 1.69) were close to 1, which adheres to the thresholds and therefore indicates that multi-collinearity is not an issue in the regression model (Appendix VI).

Table 7. Correlations (composite)

Variable	1	2	3	4	5	6	7	8	9
1. Composite demo. dissim Turnover	1								
2. CDO Turnover	-.148***	1							
3. CEO Turnover	.102***	-.161***	1						
4. Firm Size	.070**	-.059**	.087**	1					
5. Firm Performance	-.066**	-.044	-.067**	.029	1				
6. TMT Size	.073**	-.155***	.060**	.472***	-.050*	1			
7. CIO Presence	.047*	-.089***	.036	.244***	.029	.275***	1		
8. Firm Age	.089***	-.004	.044	.198***	-.040	.184***	.018	1	
9. Industry Type	.033	-.029	.010	.133***	.001	.164***	.090***	.002	1

Legend: * $p < .1$, ** $p < .05$, *** $p < .01$

Table 8 displays the regression analysis results, extending the initial regression analysis with the addition of model 7, which includes the composite variable (see Appendix VI). The significant composite measure of demographic dissimilarity ($B = -.357, p < .001$) suggests that higher overall demographic dissimilarity is associated with a lower likelihood of CDO turnover. With an odds ratio ($\text{Exp}(B)$) of .700, the findings suggest that the odds of CDO turnover decreases with 30% for each one-unit increase in demographic dissimilarity. Thus, the more demographic dissimilar, based on the four traits, the lower the likelihood of CDO turnover

With the inclusion of the composite measure, the model's explanatory power is increased given that the model's X^2 statistics is substantial higher in model 7 ($X^2 = 117.351$) compared to model 6 ($X^2 = 31.901$), indicating that the model fit is significantly improved. Besides, the Nagelkerke R^2 has increased in model 7 ($R^2 = .151$) compared to model 6 ($R^2 = .139$), suggesting that a larger portion of variance in CDO turnover is explained.

Furthermore, table 8 demonstrates that more control variables hold a statistically significant affect on CDO turnover with the inclusion of the composite. For example, TMT size has a significant negative affect on CDO turnover ($B = -.014, p < .001, \text{Exp}(B) = .986$). Firm age becomes a significant positive predictor in the composite model ($B = .004, p < 0.1, \text{Exp}(B) = 1.004$). Besides, firm performance becomes a significant negative predictor of CDO turnover ($B = -.022, p < .05, \text{Exp}(B) = .978$). Furthermore, industry category type 1 remains statistically significant in predicting CDO turnover ($B = 1.224, p < .001, \text{Exp}(B) = 3.401$). With the inclusion of the composite, category 5 also becomes statistically significant in predicting CDO turnover ($B = .734, p < .1, \text{Exp}(B) = 2.083$). All other control variables remain non-significant across the models.

Table 8. Regression Analysis (composite)

	Model 1	Model 2 (H1)	Model 3 (H2)	Model 4 (H3)	Model 5 (H4)	Model 6	Model 7
	β/se	β/se	β/se	β/se	β/se	β/se	β/se
Independent Variables							
Age dissim.		-.043 (.331)				-.029 (.334)	
Gender dissim.			.345 (.335)			.345 (.337)	
Functional Background dissim.				-.290 (.616)		-.300 (.617)	
Educational Level dissim.					.094 (.333)	.094 (.333)	
Dissimilarity Composite							-.357*** (.098)
Control Variables							
CEO turnover	-19.177 (5045.51)	-19.180 (5043.77)	-19.184 (5034.26)	-19.204 (5029.75)	-19.204 (5033.95)	-19.204 (5033.95)	-19.725 (3394.45)
CIO presence	-.493 (.334)	-.492 (.334)	-.475 (.334)	-.481 (.335)	-.472 (.336)	-.472 (.336)	-.225 (.171)
Firm size	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)
TMT size	-.001 (.005)	-.001 (.005)	-.001 (.005)	-.001 (.005)	-.001 (.005)	-.001 (.005)	-.014*** (.003)
Firm age	.006 (.005)	.006 (.005)	.006 (.005)	.006 (.005)	.006 (.005)	.006 (.005)	.004* (.002)
Firm performance	-.017 (.018)	-.017 (.018)	-.017 (.018)	-.017 (.018)	-.016 (.018)	-.016 (.018)	-.022** (.009)
Industry Type (1)	1.492** (.726)	1.490** (.726)	1.521** (.727)	1.559** (.733)	1.564** (.733)	1.564** (.733)	1.224** (.472)

Legend: * $p < .1$, ** $p < .05$; *** $p < .01$

Note 1: Reference category 'Industry Type'; category 9.

Note 2: Reference category all independent variables; category 0.

	Model 1	Model 2 (H1)	Model 3 (H2)	Model 4 (H3)	Model 5 (H4)	Model 6	Model 7
	<i>β/se</i>	<i>β/se</i>	<i>β/se</i>	<i>β/se</i>	<i>β/se</i>	<i>β/se</i>	<i>β/se</i>
Industry Type (2)	.503 (.619)	.510 (.622)	.516 (.622)	.548 (.627)	.550 (.627)	.550 (.627)	.469 (.378)
Industry Type (3)	-.400 (1.177)	-.398 (1.177)	-.282 (1.182)	-.315 (1.185)	-.304 (1.186)	-.304 (1.186)	.462 (.417)
Industry Type (4)	-18.020 (10757.87)	-17.998 (10659.74)	-17.925 (10642.85)	-17.869 (10645.29)	-17.909 (10656.09)	-17.909 (10656.00)	.459 (.598)
Industry Type (5)	.659 (.767)	.655 (.767)	.627 (.767)	.511 (.813)	.498 (.812)	.498 (.812)	.734* (.400)
Industry Type (6)	.717 (.623)	.724 (.625)	.764 (.626)	.775 (.626)	.757 (.628)	.757 (.628)	.513 (.361)
Industry Type (7)	-1.177 (.919)	-1.174 (.919)	-1.169 (.922)	-1.116 (.929)	-1.133 (.934)	-1.133 (.934)	.264 (.388)
Industry Type (8)	-18.942 (28420.60)	-18.965 (28420.60)	-19.159 (28420.58)	-19.133 (28420.60)	-19.074 (28420.61)	-19.074 (28420.61)	-.140 (.721)
N	1334	531	1071	1334	955	459	1334
Model X2	30.546***	30.563**	31.605**	31.821**	31.901**	31.901**	117.351***
Hosmer & Lemeshow	4.562	4.372	17.371**	14.431	4.026	4.026	15.792
Nagelkerke	.133	.133	.138	.139	.139	.139	.151

Legend: * $p < .1$, ** $p < .05$; *** $p < .01$

Note 1: Reference category 'Industry Type'; category 9.

Note 2: Reference category all independent variables; category 0.

Ch.5 Discussion

The influence of demographic dissimilarities in the CDO-CEO vertical dyad on CDO turnover has not received sufficient attention, creating a research gap in turnover studies. Therefore, the current study expanded upon relational demography, proposing that when CDOs and CEOs are demographically dissimilar, CDOs are more likely to leave. Particularly considering that dissimilarities in demographic traits affect the attitudes and behaviours of executives, which negatively influences feelings of attraction and integration, often lowering levels of communication - all of which could lead to executive turnover (Tsui et al., 1992; Tsui et al., 2002). Contrasting to the expectations, the findings demonstrated that individual demographic dissimilarities do not significantly affect CDO turnover. Hence, the proposed hypotheses are not supported, suggesting that correlations between demographic dissimilarity and CDO turnover may not be as clear first suggested. However, findings also showed that overall demographic dissimilarity between the CDO and CEO does have a significant negative effect on CDO turnover.

5.1 Demographic Dissimilarity Effect

Current research on demographic dissimilarity and executive turnover has primarily focused on the influence of individual demographic traits, demonstrating that demographic dissimilarities between superiors and subordinates on a single trait is associated with increased executive turnover (e.g., Tsui et al., 1992; Westphal & Zajac, 1995). For instance, age dissimilarity was found to cause cognitive differences, resulting in less shared values, attitudes, and beliefs, reducing social integration, and increasing subordinate turnover (O'Reilly et al., 1989; Tsui et al., 1992; Westphal & Zajac, 1995). Similarly, gender dissimilarity was found to limit attraction, cohesion, and frequency of communication, which raises turnover rates (Tsui & O'Reilly, 1989). Additionally, functional background dissimilarity was found to increase turnover by fostering different attitudes, behaviours, and perspectives, resulting in less communication and more power struggles (Tsui et al., 1992; Westphal & Zajac, 1995; Zhang et al., 2011). Furthermore, although existing research on educational level dissimilarity is mixed, the general view is that it causes cognitive differences which may limit decision-making, performance, and social attraction, thereby increasing turnover (e.g., Tsui et al., 1992). As a result, existing research proposed that dissimilarities in individual demographic traits are positively correlated with executive turnover.

In examining the relationship between demographic dissimilarity and CDO turnover, it was therefore hypothesized that age, gender, functional background, and educational level

dissimilarities between the CDO and CEO would be positively associated with CDO turnover. Despite these expectations, the study lacked statistical evidence to support the hypotheses. Consequently, the results of the current study do not align with existing findings in this field of research, suggesting that individual demographic dissimilarities are not significant predictors of CDO turnover. Nevertheless, the current study's supplementary analysis revealed that the effect of dissimilarity as a composite was significantly negatively related to CDO turnover. In contrast to the initial expectations, this implies that as overall demographic dissimilarity on the four traits increases, the likelihood of CDO turnover decreases.

One possible explanation for this phenomenon may be that by conceptualizing demographic dissimilarities as a combined effect rather than as the individual effects of the separate demographic variables, a significant relationship between overall demographic dissimilarity and CDO turnover can be established. In contrast to existing research that discovered that demographic dissimilarity, treated as separate traits, increases non-CEO turnover (Tsui et al., 1992; Westphal & Zajac, 1995), non-significant effects of individual demographic trait dissimilarities were found, despite the fact that CDOs and CEOs were more dissimilar than similar on these traits. Hence, existing findings do not seem to apply to the CDO-CEO dyad. Therefore, the absence of a significant effect could be attributed to a need for a shift in theorization in which demographic dissimilarity should be considered as a profile. Especially since individuals are composed of all single demographic attributes combined (Tsui & Gutek, 1999). Besides, while individual dissimilarities do not have a significant effect, the composite may accumulate the effects to the point where their influences become meaningful and statistically significant in predicting CDO turnover (Tsui & Gutek, 1999). Consequently, the different findings for overall and individual demographic dissimilarity emphasize the importance of the concept's conceptual clarity (e.g., Tsui et al., 1992), in which utilising demographic dissimilarity as a composite measure is a better way to assess the relationship within the CDO-CEO dyad.

Besides, while the effects of individual demographic dissimilarities only become influential when treated as a combination of demographics, the absence of significant individual effects could also be attributed to the underlying meaning that CDOs and CEOs attach to these traits. For instance, although past research assumed that individuals attach the same value to demographic traits, recent research has demonstrated that individuals ascribe various meanings to these traits (Tsui & Gutek, 1999). For example, gender was initially assumed to be an equally important social category for both males and females, but more recent research has indicated

that gender has become a more prominent trait for females than for males. Hence, this underlying meaning is essential because the value assigned to these social categories and traits influences individuals' categorization, attraction, and social identity with others (Tsui & Gutek, 1999), determining how they respond to demographic dissimilarities. Gender dissimilarities, for instance, may not cause turnover if gender is not regarded as a significant social category for assessing dissimilarities. Therefore, by ignoring these subjective interpretations and the underlying meaning CDOs and CEOs attach to demographic dissimilarities, the influence of their demographic dissimilarities may not have been accurately captured, resulting in non-significant findings for the individual traits. Though, the composite measure may still have a substantial effect by capturing the overall influence of demographic dissimilarity. Nevertheless, further research into the underlying social interpretation of demographic dissimilarities among CDOs and CEOs is needed to better understand their effects on turnover.

Overall, the composite measure results indicates that, whilst demographic dissimilarity among other non-CEOs was found to cause turnover, it reduced CDO turnover, which theoretically implies that the impact of demographic dissimilarity on turnover varies by role. This phenomenon may be attributed to the characteristics of CDOs. Research has shown that not only do CDOs come from varied backgrounds and demographic characteristics, but they also hold varying cross-functional responsibilities that require regular interaction and cooperation with other functional executives (Kunisch et al., 2022; Péladeau & Acker, 2019). Since this will most likely result in relationships with demographically dissimilar executives, CDOs must be more resilient to these dissimilarities and their associated consequences. For example, as a CDOs' ability to achieve a digital transformation necessitates a shift in the status quo (Rickards et al., 2015), this will result in opposition, power struggles, and communication issues, which may be exacerbated by demographic dissimilarities. Besides, because they must form cross-organisational relationship, they must maintain adaptability to manage demographic gaps while also fostering effective communication and engagement to overcome the hurdles and differences associated with behaviours, values, and beliefs (e.g., Tsui et al., 1992). Therefore, these differences are less likely to deter a CDO from pursuing its transformational strategy, and hence do not directly contribute to CDO turnover. Overall, this suggests that, while demographic dissimilarity discourages other non-CEO executives from staying, due to mismatches, and reduced attraction (e.g., Tsui et al., 1992; Westphal & Zajac, 1995), CDOs appear to be more resilient to the effects of demographic dissimilarities, making them more likely to stay.

The findings on the composite measure of demographic dissimilarity also imply that increased similarity between CDOs and CEOs is associated with a higher likelihood of CDO turnover. This contradicts existing research in which similarity is associated with a lower likelihood of executive turnover (O'Reilly et al., 1989). Especially as similarity is associated with enhanced social attraction, communication, and cohesion in which individuals are more likely to behave similarly as well as hold similar values, opinions, and beliefs (Cunningham, 2007; Ibarra, 1992; Westphal & Zajac, 1995). This theoretically implies that the impact of demographic similarity on turnover is different for CDOs compared to other executives. Firms appointing a CDO role within its TMT require someone who can challenge the status quo from a more disruptive perspective than the firm's present approach (Rickards et al., 2015). Besides, CDOs are often appointed when CEOs acknowledge that their current approach and perspective cannot integrate the necessary digital transformation (Rickards et al., 2015). Therefore, this suggests that if firms appoint a too demographically similar CDO to the CEO, it may undermine the CDOs' effectiveness and ability to drive change. Especially as these similarities reflect resemblances in experiences, values, opinions, and beliefs, which may result in a similar problem-solving or workstyle approach as currently adopted in the firm (Wagner et al., 1984; Westphal & Zajac, 1995). As a result, demographic similarity is likely to result in cognitive similarity with the CEO, limiting its ability to deviate from the CEO's current approach and complicating challenging the status quo to integrate the digital transformation, increasing their likelihood of leaving.

5.2 Theoretical Contributions

This study makes several contributions to the literature. First, a contribution to CDO- and non-CEO turnover has been made. As TMT turnover studies have primarily focused on understanding the individual-level drivers of CEO turnover (e.g., Busenbark et al., 2016; Zhu & Shen, 2016), research has overlooked the broader spectrum of TMT executives, resulting in an incomplete understanding of non-CEO turnover. Besides, given the limited research on the role and turnover dynamics of CDOs, studies lacked understanding of their individual-level drivers, despite their significant role in the firm's digital transformation (e.g., Firk et al., 2021; Wade & Obwegeser, 2019). Therefore, to contribute to CDO turnover research, the current study has been undertaken as one of the first linked to relational demography. The research has demonstrated that although CDO-CEO individual demographic dissimilarity does not significantly predict CDO turnover, the overall demographic dissimilarity finds a significant effect. This negative significant relationship, contradicting with relational demography,

suggests that whereas demographic dissimilarity among other non-CEOs causes turnover, here it reduces CDO turnover. Hence, the study provides new perspectives on the effect of demographic dissimilarity on CDO turnover as individual-level driver. Besides, it implies that future research should be performed to investigate other individual-level drivers of CDO turnover.

Secondly, the study contributes to Tsui et al.'s (1992) relational demography by providing insight into how demographic differences within the CDO-CEO vertical dyad influences CDO turnover. This broadens the scope of relational demography by extending the dyadic level to the CDO-CEO dyad. The study builds on the existing argumentation that demographic dissimilarity will influence individual's behaviours (e.g., Tsui & O'Reilly, 1989; Westphal & Zajac, 1995; Zhang et al., 2011) which could negatively affect individual's recognition in social identities and levels of attraction, possibly resulting in CDO turnover. After applying a relational demography way of measuring CDO turnover, the study found non-statistically significant findings, which limits the interpretation and confirmation of the theory. Then again, a negative significant effect of overall demographic dissimilarity on CDO turnover has been found. This contradicts existing research on relational demography suggesting that as demographic dissimilarity increases, CDO turnover decreases. As a result, this advances relational demography by demonstrating that not all non-CEO roles, like the CDO, can be well explained by the traditional reasoning on demographic dissimilarity.

Finally, the current study contributes to understanding how demographic dissimilarity should be measured and integrated within relational demography studies. Although the current study's initial approach is consistent with the traditional relational demography approach (e.g., Tsui et al., 2002; Tsui & O'Reilly, 1989), the current study takes on a novel approach by testing the relationship between demographic dissimilarity and CDO turnover as a composite (e.g., Zhang et al., 2011). Remarkably, a negative significant relationship was discovered between CDO turnover and the composite, which contradicts the assumptions based on relational demography. Hence, by considering individuals as represented by a demographic profile rather than individual demographic variables, a better understanding of the effect of demographic dissimilarity on executive turnover can be gained. Therefore, the study contributes to Tsui et al.'s (1992) relational demography by demonstrating that overall dissimilarity in demographic traits between the CEO and CDO can also reduce CDO turnover.

5.3 Practical Implications

Several implications can be drawn from this research. First, demographic dissimilarities between CDOs and CEOs, based on the composite, hold a significant negative influence on CDO turnover. This implies that demographic dissimilarities, and thus behavioural, attitude, and value disparities, will reduce CDO turnover (e.g., Tsui et al., 1992). Hence, it may be suggested that firms should purposefully recruit dissimilar individuals within the CDO-CEO dyad. Especially as it has also been demonstrated that demographic similarity between the CDO and CEO will increase CDO turnover, as it may undermine the CDOs' effectiveness and ability to drive change. Although this may initially cause resistance and barriers to attraction, integration, and cohesion (e.g., Westphal & Zajac, 1995), it may eventually allow different opinions, values, perspectives, and experiences to be combined, potentially improving performance and digital transformation. (e.g., Bengtsson et al., 2020). Therefore, this approach strengthens CDO retention and digital transformation, which is both beneficial for the CDOs as well as for the firm.

A second implication is that although demographic dissimilarity between the CDO and CEO reduces CDO turnover, other studies showed that it increases other non-CEOs turnover (O'Reilly et al., 1989; Tsui et al., 1992; Wagner et al., 1984). Hence, firms should become aware of both the negative and positive influences of demographic dissimilarities on executive turnover. For instance, becoming aware of how demographic dissimilarity within vertical dyads impact interactions and cohesiveness can aid in understanding variations in behaviours, attitudes, and values. Beyond simply raising awareness, firms should implement initiatives like training programs to better comprehend demographic differences and improve workplace dynamics to harmonize attraction, integration, and communication within dissimilar dyads. This is critical for the company's digital transformation as well as organisational performance dynamics, strategic direction, and firm success (Messersmith et al., 2014).

5.4 Limitations & Future Research

Within the study, several limitations should be acknowledged. First, the current study is limited by the sole use of archival secondary data. While this data provided useful information sources and the data collection approach used was consistent with the work of others (e.g., Gentry et al., 2021), this approach resulted in a dataset containing significant numbers of missing data, which has decreased the analysis's statistical power. The insufficient data may have made the research more susceptible to bias and reliability issues, especially as it could involve measurement errors (Hair et al., 2019). Besides, the low sample size may have constrained the

model's predictive power in finding a statistically significant effect. Furthermore, the small sample size may be less representative of the total population, limiting its generalizability. As a result, in future studies, it would be worth studying the proposed relationship based on a larger sample size.

Secondly, the model's predictive power was insufficient to predict the CDO turnover results, which could have influenced the results given the underrepresentation of this group. This introduces the risk of biased or inaccurate predictions, which could have influenced the interpretation of the current study's findings (Hair et al., 2019). Therefore, future research should focus on other analytical approaches to provide a more complete dataset to capture and understand CDO turnover causes within S&P 1500 firms.

Third, as different firms define the CDO role in varying ways, the current study includes several synonyms or alternative role descriptions. Even though these roles are included based on extensive search methods, it could be possible that descriptions are included that do not accurately reflect the CDO role. Since this may negatively influence replicability and generalizability of the current study, full coding transparency will be provided (see Appendix I). Furthermore, no distinction between voluntary and involuntary CDO turnover has been made (e.g., Messersmith et al., 2014), which could be of importance to understand CDO turnover and the influence of demographic dissimilarity. Therefore, future research should further test this relationship while controlling for voluntary or involuntary turnover.

Another limitation of the current study is the conceptual understanding of demographic dissimilarity and its influence on CDO turnover. Initially, the study approached demographic dissimilarity by examining the individual effects of age, gender, educational level, and functional background dissimilarity separately. However, supplementary analysis inspired by Tsui and Gutek (1999) was performed as it was argued that demographic dissimilarity should be assessed based on the overall demographic profile of individuals. Given that the supplementary analysis revealed a significant effect on CDO turnover, which was initially not found among the individual effects of demographic dissimilarities, reconceptualizing demographic dissimilarity may allow for a more accurate understanding of its influence. Especially by capturing the accumulated effect of demographic dissimilarities. Therefore, future research could adopt this approach to explore the overall effect of demographic dissimilarities on turnover among for instance other non-CEOs. Furthermore, since it has been argued that the subjective interpretation of demographic traits and dissimilarities could

influence how demographic dissimilarity is perceived (e.g., Tsui & Gutek, 1999), future research could explore its moderating effect on the relationship between demographic dissimilarity and executive, or CDO, turnover. Especially as by understanding how this moderates the relationship, valuable insights into the dissimilarity mechanisms underlying turnover could be obtained.

In addition, since the complementary analysis showed that CDO turnover reduces when demographic dissimilarities exist between the CDO and CEO, while controlling for both firm- and industry-related characteristics, other variables may drive the phenomenon of CDO turnover. Therefore, future research should examine the effect of other predictors on CDO turnover to understand the high turnover rates of these CDOs (Wade & Obwegeser, 2019). This emphasises the complexities of the relationship between the predictors and CDO turnover, emphasising the necessity for future research to better understand this phenomenon.

A final limitation of the current study is that it only conducts a single comparison to determine whether demographic dissimilarities affect CDO turnover. Although the analysis of demographic differences within the vertical dyad between the CDO and CEO is essential to understanding CDO turnover, demographic dissimilarity with other TMT members might also have an influence. Therefore, a multiplicity perspective could have been adopted by comparing it with other roles closely related to the CDO (e.g., Firk et al., 2021).

Conclusion

The current study builds on relational demography of Tsui et al. (1992) by testing the relationship between demographic dissimilarity and CDO turnover within S&P 1500 firms. The study explores how individual demographic differences between CDOs and CEOs influences CDO turnover. The findings show that individual dissimilarities do not significantly predict CDO turnover, suggesting that previous research on demographic dissimilarity may not be fully applicable to the CDO role. However, when demographic dissimilarity is considered as a composite profile, there is a significant negative relationship with CDO turnover. This implies that as CDOs and CEOs become more demographically dissimilar, it reduces CDO turnover. As a result, the study provides new perspectives on the effect of demographic dissimilarity on CDO turnover as individual-level driver. Besides, it shows that by considering CDOs as represented by a demographic profile rather than individual demographic variables, a better understanding of the effect of demographic dissimilarity on their turnover can be gained.

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Appendices

Appendix I – Data Coding Scheme

clear

set more off

//PREPARING THE DATASTREAM DATA

import excel "C:\Stata\Veerle Rengeling (CDO Turnover)\LSEG fresh, Veerle Rengeling.xlsx", sheet("As Values") firstrow clear.

drop if ISIN == ""

//drop duplicates

bysort ISIN: gen dup = _n

drop if dup > 1

drop dup

//reshape from wide to long format

destring EMP2005-ROA2023, replace force

reshape long EMP ROA, i(ISIN) j(Year)

//save the file

save "C:\Stata\Veerle Rengeling (CDO Turnover)\Datastream Data.dta", replace

//PREPARING FUNCTIONAL BACKGROUND DATA

use "C:\Stata\Veerle Rengeling (CDO Turnover)\Employment Details NA.dta", clear

gen CDO_Tech_background = 1 if (strpos(Sector, "Electronic & Electrical Equipment") | strpos(Sector, "Information Technology Hardware") | strpos(Sector, "Software & Computer Services")) & (strpos(RoleName, "CDO") | strpos(RoleName, "Digital"))

gen CEO_Tech_background = 1 if (strpos(Sector, "Electronic & Electrical Equipment") | strpos(Sector, "Information Technology Hardware") | strpos(Sector, "Software & Computer Services")) & (strpos(RoleName, "CEO") | strpos(RoleName, "Chief Executive Officer"))

drop if CDO_Tech_background == . & CEO_Tech_background == .

replace CDO_Tech_background = 0 if CDO_Tech_background == .

replace CEO_Tech_background = 0 if CEO_Tech_background == .

```

gen YearStartRole = year(DateStartRole)
drop if DateStartRole == .n

bysort DirectorID: gen dup = _n
drop if dup > 1
drop dup

gen DurationYears = 2024 - YearStartRole
expand DurationYears
bysort DirectorID: gen Year = mod(_n-1,DurationYears)+YearStartRole
sort DirectorID Year
drop CompanyName-NED DateStartRole-ISIN YearStartRole-DurationYears

save "C:\Stata\Veerle Rengeling (CDO Turnover)\Functional Background.dta", replace
//PREPARING STANDARD DEVIATION OF AGE DATA
use "C:\Stata\Veerle Rengeling (CDO Turnover)\SD Age - NA.dta", clear
,

gen Year = year(AnnualReportDate)
drop AnnualReportDate
bysort CompanyID Year: gen dup = _n
drop if dup > 1
drop dup

Save "C:\Stata\Veerle Rengeling (CDO Turnover)\SD Age (CLEANED).dta", replace
//PREPARING TMT DATA
use "C:\Stata\Veerle Rengeling (CDO Turnover)\Composition of Officers - NA.dta", clear

gen YearStartRole = year(DateStartRole)
drop if missing(DateStartRole)
drop DateStartRole

```

```

gen YearEndRole = year(DateEndRole)
replace YearEndRole = 2024 if DateEndRole == .c
drop if missing(DateEndRole)
drop DateEndRole

gen DurationYears = YearEndRole - YearStartRole + 1
expand DurationYears

sort DirectorID CompanyID YearStartRole YearEndRole
bysort DirectorID CompanyID YearStartRole YearEndRole: gen Year = mod(_n-
1,DurationYears)+YearStartRole
keep if Seniority == "Senior Manager"
bysort CompanyID Year: gen TMT_Size = _N
bysort CompanyID Year: gen dup = _n
drop if dup > 1
drop dup
drop DirectorID RoleName Seniority YearStartRole YearEndRole DurationYears

save "C:\Stata\Veerle Rengeling (CDO Turnover)\TMT Size.dta", replace
//PREPARING CIO DUMMY
use "C:\Stata\Veerle Rengeling (CDO Turnover)\Composition of Officers - NA.dta", clear

gen YearStartRole = year(DateStartRole)
drop if missing(DateStartRole)
drop DateStartRole

gen YearEndRole = year(DateEndRole)
replace YearEndRole = 2024 if DateEndRole == .c
drop if missing(DateEndRole)
drop DateEndRole

gen DurationYears = YearEndRole - YearStartRole + 1

```

```

expand DurationYears

sort DirectorID CompanyID YearStartRole YearEndRole

by sort DirectorID CompanyID YearStartRole YearEndRole: gen Year = mod(_n-1,DurationYears)+YearStartRole

gen CIO_dummy = 1 if strpos(RoleName,"CIO") | strpos(RoleName,"Chief Information Officer")

bysort CompanyID Year: fillmissing CIO_dummy, with(any)

bysort CompanyID Year: gen dup = _n

drop if dup > 1

drop dup

drop if CIO_dummy != 1

drop DirectorID RoleName Seniority YearStartRole YearEndRole DurationYears

save "C:\Stata\Veerle Rengeling (CDO Turnover)\CIO Dummy.dta", replace

//PREPARING Year of Incorporation

import excel "C:\Stata\Veerle Rengeling (CDO Turnover)\ISIN Firm Age (Orbis) - Rengeling, V..xlsx", sheet("Results") firstrow clear

gen YearOfIncorporation = substr(Dateofincorporation, -4, 4)

destring YearOfIncorporation, replace force

rename ISINnumber ISIN

drop if ISIN == ""

drop A CompanynameLatinalphabet Dateofincorporation BvDIDnumber F G

save "C:\Stata\Veerle Rengeling (CDO Turnover)\Year of Incorporation.dta", replace

//START OF MAIN CODE

use "C:\Stata\Veerle Rengeling (CDO Turnover)\Employment Details NA.dta", clear

ssc install fillmissing, replace

drop if ISIN == ""

```

```

//filtering out CDO's and CEO's

keep if strpos(RoleName,"CDO") | strpos(RoleName,"Digital") | strpos(RoleName,"CEO") |
strpos(RoleName,"Chief Executive Officer")

drop if strpos(RoleName,"Marketing") | strpos(RoleName,"Director") |
strpos(RoleName,"Media") | strpos(RoleName,"Banking") | strpos(RoleName,"Design") |
strpos(RoleName,"Product") | strpos(RoleName,"Payment") |
strpos(RoleName,"Communications")

//creating the Experience variable (for functional background)

bysort DirectorID CompanyID DateStartRole DateEndRole RoleName: gen dup = _n
drop if dup > 1
drop dup
sort DirectorID DateStartRole

by DirectorID: gen CDO_Experience = 1 if (Sector[_n-1] == "Information Technology
Hardware" | Sector[_n-1] == "Software & Computer Services" | Sector[_n-1] ==
"Telecommunication Services") & (strpos(RoleName,"CDO") | strpos(RoleName,"Digital"))

bysort DirectorID: replace CDO_Experience = 1 if CDO_Experience[_n-1] == 1

replace CDO_Experience = 0 if CDO_Experience == .

//Resume to Panel data

gen YearStartRole = year(DateStartRole)
drop if missing(DateStartRole)
drop DateStartRole

gen YearEndRole = year(DateEndRole)
replace YearEndRole = 2024 if DateEndRole == .c
drop if missing(DateEndRole)
drop DateEndRole

gen DurationYears = YearEndRole - YearStartRole + 1

//generate CDO and CEO dummy's

```

```

gen CDO_Dummy = 1 if strpos(RoleName,"CDO") | strpos(RoleName,"Digital")
replace CDO_Dummy = 0 if CDO_Dummy == .

gen CEO_Dummy = 1 if strpos(RoleName,"CEO") | strpos(RoleName,"Chief Executive
Officer")
replace CEO_Dummy = 0 if CEO_Dummy == .

//expand the dataset
expand DurationYears

//generate the Year variable
sort DirectorID CompanyID YearStartRole YearEndRole
bysort DirectorID CompanyID YearStartRole YearEndRole: gen Year = mod(_n-
1,DurationYears)+YearStartRole

//
merge m:1 DirectorID Year using "C:\Stata\Veerle Rengeling (CDO Turnover)\Functional
Background.dta"
drop if _merge == 2
drop _merge

bysort CompanyID Year: fillmissing CDO_Tech_background, with(any)
bysort CompanyID Year: fillmissing CEO_Tech_background, with(any)

//generate the CDO_Turnover variable
gen CDO_Turnover = 1 if Year == YearEndRole & CDO_Dummy == 1
replace CDO_Turnover = 0 if CDO_Turnover == .

//generate the CEO_Turnover variable
gen CEO_Turnover = 1 if Year == YearEndRole & CEO_Dummy == 1
replace CEO_Turnover = 0 if CEO_Turnover == .

//drop duplicates

```

```

bysort DirectorID CompanyID Year: gen dup = _n
drop if dup > 1
drop dup

//drop unnecessary variables
drop  CompanyName  BrdPosition  FulltextDescription  NED  Sector  YearStartRole
YearEndRole  DurationYears

//order for readability
order CompanyID DirectorID Year RoleName ISIN

//merge with Individual Details
merge m:1 DirectorID using "C:\Stata\Veerle Rengeling (CDO Turnover)\Individual Details
NA.dta"
keep if _merge == 3
drop _merge

//generate the Age variable
gen YOB = substr(DOB, -4, 4)
destring YOB, replace force
drop DOB
gen Age = Year - YOB

//split up the demographic details between the CDO's and CEO's so we can have them both in
the same observation on a company level
gen CDO_Gender = Gender if CDO_Dummy == 1
gen CDO_Nationality = Nationality if CDO_Dummy == 1
gen CDO_Age = Age if CDO_Dummy == 1

gen CEO_Gender = Gender if CEO_Dummy == 1
gen CEO_Nationality = Nationality if CEO_Dummy == 1

```

```

gen CEO_Age = Age if CEO_Dummy == 1

bysort CompanyID Year: fillmissing CDO_Gender, with(any)
bysort CompanyID Year: fillmissing CDO_Nationality, with(any)
bysort CompanyID Year: fillmissing CDO_Age, with(any)

bysort CompanyID Year: fillmissing CEO_Gender, with(any)
bysort CompanyID Year: fillmissing CEO_Nationality, with(any)
bysort CompanyID Year: fillmissing CEO_Age, with(any)

//Merging with education data
merge m:1 DirectorID using "C:\Stata\Veerle Rengelink (CDO Turnover)\Education
Level.dta"
drop if _merge == 2
drop _merge
gen CDO_Education = education_level if CDO_Dummy == 1
bysort CompanyID Year: fillmissing CDO_Education, with(any)
gen CEO_Education = education_level if CEO_Dummy == 1
bysort CompanyID Year: fillmissing CEO_Education, with(any)
drop education_level

//drop observations that do not have information on the CDO
drop if CDO_Gender == ""

//Aggregate to firm level
bysort CompanyID Year: gen dup = _n
drop if dup > 1
drop dup

//drop unnecessary variables

```

```
drop DirectorID RoleName CDO_Dummy CEO_Dummy Title DOD Gender Nationality YOB
Age NetworkSize
```

```
drop CEO_Nationality
```

```
merge 1:m ISIN Year using "C:\Stata\Veerle Renglink (CDO Turnover)\Datastream Data.dta"
```

```
keep if _merge == 3
```

```
drop _merge
```

```
//Create Age Dissimilarity variable
```

```
merge 1:1 CompanyID Year using "C:\Stata\Veerle Renglink (CDO Turnover)\SD Age
(CLEANED).dta"
```

```
drop if _merge == 2
```

```
drop _merge
```

```
gen AgeDifference = CDO_Age - CEO_Age
```

```
replace AgeDifference = 0 if AgeDifference == .
```

```
gen AgeDissim = 1 if abs(AgeDifference) > STDEVAge
```

```
replace AgeDissim = 0 if abs(AgeDifference) <= STDEVAge
```

```
replace AgeDissim = . if CDO_Age == . | CEO_Age == . | STDEVAge == .
```

```
drop AgeDifference
```

```
*replace AgeDissim = 0 if AgeDissim == .
```

```
//Create Gender Dissimilarity
```

```
gen GenderDissim = 1 if (CDO_Gender == "F" & CEO_Gender == "M") | (CDO_Gender ==
"M" & CEO_Gender == "F")
```

```
replace GenderDissim = 0 if (CDO_Gender == "M" & CEO_Gender == "M") | (CDO_Gender
== "F" & CEO_Gender == "F")
```

```
*replace GenderDifference = 0 if GenderDifference == .
```

```
//Create Background Dissimilarity variable
```

```

gen FuncBackDissim = 1 if (CDO_Tech_background == 1 & CEO_Tech_background == 0) |
(CDO_Tech_background == 0 & CEO_Tech_background == 1)

replace FuncBackDissim = 0 if (CDO_Tech_background == 1 & CEO_Tech_background ==
1)

*replace FuncBackSim = 0 if FuncBackSim == .

//Create Education Dissimilarity variable

gen EducationDissim = 1 if CDO_Education != CEO_Education

replace EducationDissim = 0 if CDO_Education == CEO_Education

replace EducationDissim = . if CDO_Education == . | CEO_Education == .

gen EducationDissimLev1 = 1 if abs(CDO_Education - CEO_Education) == 1

replace EducationDissimLev1 = 0 if EducationDissimLev1 == .

replace EducationDissimLev1 = . if CDO_Education == . | CEO_Education == .

gen EducationDissimLev2 = 1 if abs(CDO_Education - CEO_Education) == 2

replace EducationDissimLev2 = 0 if EducationDissimLev2 == .

replace EducationDissimLev2 = . if CDO_Education == . | CEO_Education == .

gen EducationDissimLev3 = 1 if abs(CDO_Education - CEO_Education) == 3

replace EducationDissimLev3 = 0 if EducationDissimLev3 == .

replace EducationDissimLev3 = . if CDO_Education == . | CEO_Education == .

merge 1:1 CompanyID Year using "C:\Stata\Veerle Rengeling (CDO Turnover)\TMT
Size.dta"

drop if _merge == 2

drop _merge

merge 1:1 CompanyID Year using "C:\Stata\Veerle Rengeling (CDO Turnover)\CIO
Dummy.dta"

drop if _merge == 2

drop _merge

replace CIO_dummy = 0 if CIO_dummy == .

```

```

merge m:1 ISIN using "C:\Stata\Veerle Rengeling (CDO Turnover)\Year of Incorporation.dta"
drop if _merge == 2
drop _merge

gen FirmAge = Year - YearOfIncorporation
drop YearOfIncorporation

//EXPORT
save "C:\Stata\Veerle Rengeling (CDO Turnover)\FINAL DATASET.dta", replace
export excel using "\\ru.nl\wrkgrp\UBN-Managementwetenschappen\Databases map\Vragen
en instructie\2024\Rengeling, Veerle (CDO Turnover)\FINAL DATASET.xlsx",
firstrow(variables) replace

//EDUCATIONAL Level
use "C:\Stata\Veerle Rengeling (CDO Turnover)\Education Details NA (ALL).dta", clear

tostring AwardDate, force replace
gen year = substr(AwardDate,1,4)
gen month = substr(AwardDate,5,2)
gen day = substr(AwardDate,7,2)
destring year month day, force replace
gen Awarddate = mdy(month,day,year)
format Awarddate %td
drop year day month AwardDate
rename Awarddate AwardDate

duplicates drop
*(52,728 observations deleted)

*fixing degree_year
gen degree_year = year(AwardDate)

```

*checking if any DirectorID missing -> No DirectorIDs missing
drop if missing(DirectorID)

drop FullTextDescription

duplicates drop

*(8 observations deleted)

rename Qualification qualification

*If Institution is a university or something else

gen Institution = "University" if (strpos(CompanyName,"University")>0)

replace Institution = "Other" if Institution == ""

gen bachelors = 0

gen phd = 0

gen masters = 0

gen morethanbachelors = 0

gen someunived = 0

label variable bachelors "Bachelor's Degree Dummy"

label variable masters "Master's Degree Dummy"

label variable phd "PhD Degree Dummy"

label variable morethanbachelors ">Bachelor's Degree Dummy"

label variable someunived "Any University Education Dummy"

*classify those who have a bachelor's degree

foreach x in "AA" "AB" "ACA" "AS" "B A" "B Acc" "B.Proc" "BA" "BB" "BC" "Bachelor"
"BE" "BF" "BJ" "BM" ///

```
"BP" "BS" "BT" "BV" "Baccalaureate" "Baccalaureus" "D Univ" "DB" "DC" "DD" "DIC"
"DE" "DP" "Degree" "Dipl Ing" ///
```

```
"DECF" "DECS" "DESS" "BTech" "BSocSc" "BTEC" "BVSc" "BSc" "BSEE" "Architect"
"DESCAF" "AB" "AA" ///
```

```
"Dipl Kfm" "Dipl.-kfm" "Diploma" "Diplom-Kaufmann" "Dipl me" "Licentiate" "Lizentiat"
///
```

```
"LLB" "LLL" "Lic" "Liz" "MBB" "MBCbB" "MBS" "SB" "Undergraduate" "Honors
Business Administration" ///
```

```
"BVSc" "BJ" "Registered Nurse" "Industrial Engineering" "Honors Business Administration"
"Geological Engineer" ///
```

```
"Electrical Engineering" "Engineering Program" "European Engineer" "Industrial
Engineering" "IEng" "Mechanical Engineering" "Metallurgy Engineering" {
```

```
    replace bachelors = 1 if strpos(qualification, "`x`" ) > 0
```

```
}
```

```
foreach x in "Undergraduate" "Baccalaureate" {
```

```
    replace bachelors = 1 if strpos(CompanyName, "`x`" ) > 0
```

```
}
```

```
foreach x in "Graduated" {
```

```
    replace bachelors = 1 if strpos(qualification, "`x`" ) > 0 & strpos(CompanyName,
"Univer" )
```

```
}
```

```
*classify those who have a master's degree
```

```
*includes MBA
```

```
foreach x in "Master" "LLM" "M Arch" "MA" "MCJ" "MCom" "ME" "MFA" "MHA" "MP"
///
```

```
"MRC" "MS" "MTech" "Magister" "MBA" "M Arch" "MBB" "DEA" {
```

```
    replace masters = 1 if strpos(qualification, "`x`" ) > 0
```

```
}
```

```
*classify those who have a phd
```

```
foreach x in "Candidate" "Doctor" "DBA" "DEng" "D Univ" "DM" "DIC" "DComm" "DM"  
"DPhil" "DSc" "DSO" "Doctorate" "Dr" ///
```

```
"Dr Ing" "Habilitation" "JD" "Laurea" "LLD" "MD" "PEng" "PMD" "PhD" "PharmD" "SJD"  
"ScD" ///
```

```
"VMD" "DComm" "PMD" "DEng" "DPhil" "DDS" {  
    replace phd = 1 if strpos(qualification, "`x`" ) > 0  
}
```

*classify those who have more than just bachelors

```
foreach x in "Post Graduate" "Graduate Certificate" "Graduate Diploma" "Post Baccalaureate"  
///
```

```
"Post Doctoral" "Postgraduate" "Postdoctoral" "Post Doctoral" "Graduate  
Management" {  
    replace morethanbachelors = 1 if strpos(qualification, "`x`" ) > 0  
}
```

```
replace morethanbachelors = 1 if phd == 1 | masters == 1
```

*dummy if they studied at all

```
replace someunived = 1 if morethanbachelors == 1 | bachelors == 1 | masters == 1 | phd == 1
```

```
replace someunived = 1 if qualification == "Studied"
```

```
replace someunived = 1 if Institution == "University" & qualification == "Attended"
```

```
replace someunived = 1 if Institution == "University" & qualification == "Completed"
```

*education level including MBA

```
gen education_level = 0
```

```
replace education_level = 1 if bachelors == 1
```

```
replace education_level = 2 if masters == 1
```

```
replace education_level = 3 if phd == 1
```

```
label variable education_level "Education Level - 1:BS / 2:MS+MBA / 3:PhD"
```

```
gen Amount_education = 12 if education_level == 0
```

```
replace Amount_education = 16 if education_level == 1
```

```

replace Amount_education = 18 if education_level == 2
replace Amount_education = 21 if education_level == 3

label variable Amount_education "number of years of formal education for each CEO: a high
school diploma was coded as 12 years, an undergraduate degree as 16 years, a master's degree
as 18 years, and a PhD as 21 years."

bys DirectorID: egen max_education = max(Amount_education)
keep if max_education == Amount_education
bys DirectorID: gen dup = cond(_N==1,0,_n)
drop if dup > 1
drop dup max_education

keep DirectorID degree_year bachelors phd masters morethanbachelors someunived
education_level Amount_education

drop degree_year-someunived Amount_education

save "C:\Stata\Veerle Rengeling (CDO Turnover)\Education Level.dta", replace

```

Appendix II – Missing Value Analysis

Table 9. Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes ^a	
				Count	Percent	Low	High
EMP	1277	58805.80	87340.329	57	4.3	0	132
TMT_Size	1332	50.82	51.111	2	.1	0	99
FirmAge	1319	39.79	38.586	15	1.1	0	126
ROA	1289	6.4049	9.72209	45	3.4	32	35
CDO_Turnover	1334			0	.0		
AgeDissim	531			803	60.2		
GenderDissim	1071			263	19.7		
FuncBackDissim	1334			0	.0		
EducationDissim	955			379	28.4		
CEO_Turnover	1334			0	.0		
CIO_Presence	1334			0	.0		
SICCODEcat	1322			12	.9		

a. Little's MCAR test: Chi-Square = 38.002, DF = 13, Sig. = .000

Appendix III – Assumption Testing

Before the binary logistic regression analysis based on panel data can be performed, several fundamental presumptions must be satisfied (Hair et al., 2019). First, an important consideration is the independence of observations. This indicates that there is no relationship between the value of CDO turnover for one observation and the value of CDO turnover on another observations (Hair et al., 2019). This has been considered and ensured within the study design and random sampling method. Secondly, The degree of multicollinearity between the independent and control variables was assessed because strong correlations might negatively impact parameter estimates and standard errors, which can impede the model's ability to accurately predict results and estimate coefficients (Hair et al., 2019). The collinearity diagnostics, which can be found in Table 10, indicates that for all independent- and control variables the tolerance values were close to 1 (ranging from .699 to .990) and variance inflation factors (VIF) were close to 1 (ranging from 1.010 to 1.432). These adhere to the common thresholds indicating that multicollinearity is not a significant issue in the regression model. As a result, the independent and control variables lack multicollinearity with one another and show low redundancy. Thirdly, influential outliers had to be assessed that may disproportionately influence the outcomes of the analysis. Therefore, a z-scores have been calculated to determine how many standard deviations (SDs) a data point is away from the

mean of the dataset (Hair et al., 2019). Following the computation of z-scores for every data point, the SD from the mean z-score of ± 3 was used as the threshold to detect significant outliers (Hair et al., 2019). This means that outliers outside of 3 SDs were excluded in the binary logistic regression. Finally, the assumption that there was no complete separation, meaning that no independent variable could perfectly predict CDO turnover, was adhered to which was assessed for in the binary logistic regression (Hair et al., 2019).

Table 10. Multi-collinearity Diagnostics

		Coefficients ^a					Collinearity Statistics	
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Tolerance	VIF
		B	Std. Error	Beta				
1	(Constant)	.104	.049		2.111	.035		
	AgeDissim Age Dissimilarity between CDO/CEO	-.002	.029	-.004	-.076	.939	.988	1.012
	GenderDissim Gender Dissimilarity between CDO/CEO	.031	.031	.048	1.008	.314	.986	1.014
	FuncBackDissim Functional Background Dissimilarity between CDO/CEO	-.012	.045	-.013	-.274	.784	.994	1.006
	EducationDissim Educational Level Dissimilarity between CDO/CEO	.002	.029	.003	.068	.946	.994	1.006
2	(Constant)	.190	.067		2.830	.005		
	AgeDissim Age Dissimilarity between CDO/CEO	.000	.029	.000	-.010	.992	.984	1.016
	GenderDissim Gender Dissimilarity between CDO/CEO	.029	.031	.044	.934	.351	.975	1.026
	FuncBackDissim Functional Background Dissimilarity between CDO/CEO	-.022	.048	-.023	-.467	.641	.875	1.143
	EducationDissim Educational Level Dissimilarity between CDO/CEO	.009	.029	.015	.311	.756	.962	1.039
	CEO_Turnover CEO Turnover	-.120	.043	-.132	-2.810	.005	.990	1.010
	EMP Firm Size in # of employees	1.835E-8	.000	.005	.096	.923	.775	1.291
	ROA Firm Performance in return on assets	-.001	.002	-.024	-.509	.611	.958	1.044
	TMT_Size TMT size	.000	.000	-.019	-.346	.730	.699	1.432
	FirmAge Firm age in terms of year of incorporation	9.779E-6	.000	.001	.025	.980	.914	1.094
	CIO_Presence CIO presence	-.030	.030	-.049	-1.002	.317	.928	1.078
	SICCODEcat Industry Type (categorical)	-.007	.006	-.056	-1.171	.242	.940	1.063

a. Dependent Variable: CDO_Turnover CDO Turnover

Appendix IV – Case Summary & Variable Coding

Table 11. Case Processing Summary

Unweighted Cases ^a		N	Percent
Selected Cases	Included in Analysis	459	34.4
	Missing Cases	875	65.6
	Total	1334	100.0
Unselected Cases		0	.0
Total		1334	100.0

a. If weight is in effect, see classification table for the total number of cases.

Table 12. Dependent Variable Coding

Original Value	Internal Value
0 No CDO Turnover	0
1 CDO Turnover	1

Table 13. Categorical Variable(s) Coding

		Categorical Variables Codings								
		Frequency	(1)	(2)	(3)	Parameter coding				
			(4)	(5)	(6)	(7)	(8)			
SICCODEcat Industry Type (categorical)	1 Energy & Transformation	44	.000	.000	.000	.000	.000	.000	.000	.000
	2 Real estate & Construction	26	1.000	.000	.000	.000	.000	.000	.000	.000
	3 Manufacturing	101	.000	1.000	.000	.000	.000	.000	.000	.000
	4 Industrial Applications & Services	14	.000	.000	1.000	.000	.000	.000	.000	.000
	5 Life Sciences	12	.000	.000	.000	1.000	.000	.000	.000	.000
	6 Technology	53	.000	.000	.000	.000	1.000	.000	.000	.000
	7 Trade & Services	141	.000	.000	.000	.000	.000	1.000	.000	.000
	8 Finance	66	.000	.000	.000	.000	.000	.000	1.000	.000
	9 Commercial physical and Bio research	2	.000	.000	.000	.000	.000	.000	.000	1.000
EducationDissim Educational Level Dissimilarity between CDO/CEO	0 Functional background similarity CDO-CEO	198	.000							
	1 Functional background dissimilarity CDO-CEO	261	1.000							
CIO_Presence CIO presence	0 No CIO present	185	.000							
	1 CIO present	274	1.000							
AgeDissim Age Dissimilarity between CDO/CEO	0 Age similarity CDO-CEO	180	.000							
	1 Age dissimilarity CDO-CEO	279	1.000							
GenderDissim Gender Dissimilarity between CDO/CEO	0 Gender similarity CDO-CEO	314	.000							
	1 Gender dissimilarity CDO-CEO	145	1.000							
FuncBackDissim Functional Background Dissimilarity between CDO/CEO	0 Educational level similarity CDO-CEO	52	.000							
	1 Educational level dissimilarity CDO-CEO	407	1.000							
CEO_Turnover CEO Turnover	0 No CEO Turnover	401	.000							
	1 CEO Turnover	58	1.000							

Appendix V – Binary Logistic Regression Analysis

Logistic Regression model 0 – Constant

Analysing the iteration history of the base model, consisting solely of the constant, it reveals that the MLE process ends at the fifth iteration, yielding an intercept (-2.171) free of predictors (Table 14). The initial -2 Log likelihood (-2LL) in this model is 303.231, indicating a suboptimal model fit, with a -2LL closer to 0 indicating a more desirable fit. This discrepancy raises the concern regarding the model’s ability to predict CDO turnover effectively when only the constant is included.

An additional concern of the current study is detected in the ‘classification table’ of the first model in which the SPSS software fails to estimate the predicted CDO turnover with a value of 1, given the representation of such cases is insufficient (Table 15). This indicates a trade-off in the model’s predictive power, especially regarding correct classification of cases with a CDO turnover of 1. This inadequate representation of CDO turnover cases, due to the high percentage of missing values, introduces the risk of biased or inaccurate predictions, necessitating cautious interpretation of the model’s findings (e.g., Hair et al., 2019).

Furthermore, analysing the ‘variables in the equation’ model, incorporating the Wald test to determine the statistical significance of each IV, reveals that the constant model has a Wald statistic of 198.816 with 1 degree of freedom ($p < .001$) (Table 16). This Wald statistic indicates that the constant is statistically significant at the 5% significance level. This suggests that the constant by itself still offers predictive information about the dependent variable, even considering the concerns mentioned above.

Table 14. Iteration History - Model 0

Iteration	-2 Log likelihood	Coefficients Constant
Step 0 1	319.804	-1.590
2	303.706	-2.066
3	303.232	-2.167
4	303.231	-2.171
5	303.231	-2.171

- a. Constant is included in the model.
- b. Initial -2 Log Likelihood: 303.231
- c. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Table 15. Classification Table - Model 0

	Observed	Predicted	CDO_Turnover CDO Turnover		Percentage Correct
			0 No CDO Turnover	1 CDO Turnover	
Step 0	CDO_Turnover CDO Turnover	0 No CDO Turnover	412	0	100.0
		1 CDO Turnover	47	0	.0
Overall Percentage					89.8

a. Constant is included in the model.

b. The cut value is .500

Table 16. Variables in the Equation - Model 0

	B	S.E.	Wald	df	Sig.	Exp(B)
Step 0 Constant	-2.171	.154	198.816	1	<.001	.114

Logistic Regression model 1 – Constant with Control Variables

Analysing the iteration history of the first model, consisting of the constant and the control variables, it reveals that the MLE process ends at the twentieth iteration and produces an intercept (-2.191) (Table 17). The -2LL in the second model is 272.685, indicating a suboptimal model fit, with a -2LL closer to 0 indicating a more desirable fit. Comparing the -2LL of this model in comparison to the initial model, a small decrease can be detected which indicates that the subsequent model provides a slightly better fit to the data, indicating an improvement of the model fit (Hair et al., 2019).

With the add of the control variables, the logistic regression analysis provides the Hosmer and Lemeshow test, which can be interpreted for model fit. Within the current study, this test yielded a chi-square statistic of $X^2 = 4.562$ (df = 8, p = .803), indicating a satisfactory fit of the observed data (Table 18). This suggests that the observed and predicted probabilities of the outcome variable align across different levels of the control variables. The analysis also provided the omnibus test in which the model yielded a chi-square statistic of $X^2 = 30.546$ (df = 14, p = .006), suggesting that the model contains statistical significance (Table 19). This indicates that the logistic regression model is statistically significant, suggesting that some of the control variables significantly predicts the outcome variable. As a result, these test results suggest statistical significance for the model.

In addition, the logistic regression within the second model also provides the ‘model summary’ in which it can be observed how much variation in the dependent variable can be explained by the model. The Cox & Snell R Square (.064) and Nagelkerke R Square (.133) indicate that a

small amount of variation in CDO turnover is explained by the control variables included in the model (Table 20).

Furthermore, analysing the ‘variables in the equation’ model (Table 21), incorporating the Wald test to determine the statistical significance of each control variable, reveals that the constant model is still statistically significant ($p < .001$) to the prediction. When examining the Wald test for the relationship between CDO turnover and various control variables, the following results were found, assessed at a 5% confidence interval. First, *CEO turnover* had a non-statistically significant effect on CDO turnover ($B = -19.177$, $p = .977$). Second, *CIO presence* did not significantly predict CDO turnover ($B = -.493$, $p = .140$). In addition, *firm size* did not have a statistically significant impact on CDO turnover ($B = .000$, $p = .630$). Furthermore, *firm age* was not shown to be a statistically significant predictor of CDO turnover ($B = .006$, $p = .226$). Similarly, *financial performance* was found to not be a statistically significant predictor of CDO turnover ($B = -.017$, $p = .349$). In contrast, the first category (energy & transformation) of the control variable *Industry Type* was discovered to be a statistically significant predictor of CDO turnover ($B = 1.492$, $p = .040$). Nonetheless, all other categories of the control variable industry type were shown to be non-significant predictors of CDO turnover. These results suggest that out of all control variables, only one category of industry type significantly predicts CDO turnover.

Table 17. Iteration History - Model 1

Iteration	-2 Log likelihood	Constant	Coefficients													
			CEO Turnover (1)	CIO presence (1)	Firm Size in # of employees	TMT size	Firm age in terms of year of incorporation	Firm Performance in return on assets	Industry Type (categorical)(1)	Industry Type (categorical)(2)	Industry Type (categorical)(3)	Industry Type (categorical)(4)	Industry Type (categorical)(5)	Industry Type (categorical)(6)	Industry Type (categorical)(7)	Industry Type (categorical)(8)
Step 1	307.791	-1.572	-.481	-.183	.000	.000	.002	-.006	.678	.196	-.120	-.152	.216	.254	-.211	-.416
2	280.784	-2.049	-1.213	-.375	.000	.000	.004	-.012	1.224	.396	-.271	-.484	.470	.530	-.559	-1.046
3	275.142	-2.176	-2.175	-.477	.000	-.001	.006	-.016	1.454	.492	-.379	-1.163	.630	.688	-.967	-1.938
4	273.558	-2.190	-3.175	-.493	.000	-.001	.006	-.017	1.488	.502	-.399	-2.068	.657	.715	-1.154	-2.934
5	273.006	-2.191	-4.176	-.493	.000	-.001	.006	-.017	1.491	.502	-.400	-3.037	.659	.717	-1.177	-3.939
6	272.903	-2.191	-5.176	-.493	.000	-.001	.006	-.017	1.492	.502	-.400	-4.026	.659	.717	-1.177	-4.941
7	272.728	-2.191	-6.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-5.022	.659	.717	-1.177	-5.942
8	272.701	-2.191	-7.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-6.021	.659	.717	-1.177	-6.942
9	272.690	-2.191	-8.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-7.020	.659	.717	-1.177	-7.942
10	272.687	-2.191	-9.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-8.020	.659	.717	-1.177	-8.942
11	272.685	-2.191	-10.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-9.020	.659	.717	-1.177	-9.942
12	272.685	-2.191	-11.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-10.020	.659	.717	-1.177	-10.942
13	272.685	-2.191	-12.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-11.020	.659	.717	-1.177	-11.942
14	272.685	-2.191	-13.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-12.020	.659	.717	-1.177	-12.942
15	272.685	-2.191	-14.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-13.020	.659	.717	-1.177	-13.942
16	272.685	-2.191	-15.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-14.020	.659	.717	-1.177	-14.942
17	272.685	-2.191	-16.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-15.020	.659	.717	-1.177	-15.942
18	272.685	-2.191	-17.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-16.020	.659	.717	-1.177	-16.942
19	272.685	-2.191	-18.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-17.020	.659	.717	-1.177	-17.942
20	272.685	-2.191	-19.177	-.493	.000	-.001	.006	-.017	1.492	.503	-.400	-18.020	.659	.717	-1.177	-18.942

a. Method: Enter
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 303.231
d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 18. Hosmer and Lemeshow Test - Model 1

Step	Chi-square	df	Sig.
1	4.562	8	.803

Table 19. Omnibus Test - Model 1

		Chi-square	df	Sig.
Step 1	Step	30.546	14	.006
	Block	30.546	14	.006
	Model	30.546	14	.006

Table 20. Model Summary - Model 1

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	272.685 ^a	.064	.133

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 21. Variables in the Equation - Model 1

		Variables in the Equation						95% C.I. for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1 ^a	CEO Turnover(1)	-19.177	5045.511	.000	1	.997	.000	.000	.
	CIO presence(1)	-.493	.334	2.180	1	.140	.611	.318	1.175
	Firm Size in # of employees	.000	.000	.232	1	.630	1.000	1.000	1.000
	TMT size	-.001	.005	.027	1	.869	.999	.989	1.009
	Firm age in terms of year of incorporation	.006	.005	1.466	1	.226	1.006	.996	1.016
	Firm Performance in return on assets	-.017	.018	.876	1	.349	.983	.950	1.018
	Industry Type (categorical)			10.343	8	.242			
	Industry Type (categorical) (1)	1.492	.726	4.222	1	.040	4.444	1.071	18.440
	Industry Type (categorical) (2)	.503	.619	.658	1	.417	1.653	.491	5.565
	Industry Type (categorical) (3)	-.400	1.177	.115	1	.734	.671	.067	6.729
	Industry Type (categorical) (4)	-18.020	10657.874	.000	1	.999	.000	.000	.
	Industry Type (categorical) (5)	.659	.767	.737	1	.391	1.932	.429	8.695
	Industry Type (categorical) (6)	.717	.623	1.324	1	.250	2.048	.604	6.941
	Industry Type (categorical) (7)	-1.177	.919	1.639	1	.200	.308	.051	1.868
	Industry Type (categorical) (8)	-18.942	28420.600	.000	1	.999	.000	.000	.
	Constant		-2.191	.602	13.227	1	<.001	.112	

a. Variable(s) entered on step 1: CEO Turnover, CIO presence, Firm Size in # of employees, TMT size, Firm age in terms of year of incorporation, Firm Performance in return on assets, Industry Type (categorical).

Logistic Regression Model 2 – Constant, Control Variables and Age Dissimilarity

Analysing the iteration history of the second model, which encompasses the constant, the control variables, and age dissimilarity as independent variable, the MLE process ends at the twentieth iteration and produces an intercept (-2.168) (Table 22). The -2LL in the third model

is 272.668, indicating a slightly better fit compared to the second model, suggesting an improvement in model fit (e.g., Hair et al., 2019).

The Hosmer and Lemeshow test has been provided by the analysis which yielded a chi-square statistic of $X^2 = 4.372$ (df = 8, p = .822), indicating that the logistic regression model adequately fits the observed data (Table 23). Within the third model, the omnibus test of the logistic regression yielded a chi-square statistic of $X^2 = 30.563$ (df = 15, p = .010), indicating statistical significance of the logistic regression model as whole (Table 24). This suggest that at least one predictor variable significantly predicts the outcome variable. In addition, the logistic regression provides the ‘model summary’, indicating a small amount of variation in CDO turnover is explained by the independent variable, with Cox & Snell R Square (.064) and Nagelkerke R Square (.133) coefficients (Table 25).

Furthermore, analysing the ‘variables in the equation’ model (Table 26), while *age dissimilarity* has been added as independent variable, it has been shown that the constant model remains statistically significant (p < .001) to the prediction. Besides, the statistical significance values of the control variables remain similar in which the category ‘energy & transformation’ of the control variable *industry type* still statistically significantly predicts CDO Turnover. Furthermore, when examining the Wald test for the relationship between *CDO turnover* and *age dissimilarity* between the CDO and CEO, it was found that it does not statistically significant predict CDO turnover (B = -.043, p = .898).

Table 22. Iteration History - Model 2

Iteration	-2 Log likelihood	Coefficients															Age Dissimilarity between CDO/CEO(1)
		Constant	CEO Turnover (t)	CIO presence (t)	Firm Size in # of employees	TMT size	Firm age in terms of year of incorporation	Firm Performance in return on assets	Industry Type (categorical)(1)	Industry Type (categorical)(2)	Industry Type (categorical)(3)	Industry Type (categorical)(4)	Industry Type (categorical)(5)	Industry Type (categorical)(6)	Industry Type (categorical)(7)	Industry Type (categorical)(8)	
1	307.786	-1.566	-.481	-.183	.000	.000	.002	-.008	.877	.198	-.119	-.148	.215	.256	-.211	-.421	-.011
2	280.774	-2.036	-1.214	-.374	.000	.000	.004	-.012	1.222	.401	-.269	-.474	.468	.535	-.557	-1.060	-.025
3	275.126	-2.156	-2.177	-.476	.000	-.001	.006	-.016	1.451	.499	-.377	-.145	.626	.695	-.964	-1.958	-.038
4	273.542	-2.168	-3.178	-.491	.000	-.001	.006	-.017	1.487	.510	-.397	-2.047	.654	.722	-1.151	-2.956	-.043
5	272.990	-2.168	-4.179	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-3.015	.655	.724	-1.174	-3.961	-.043
6	272.787	-2.168	-5.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-4.004	.655	.724	-1.174	-4.963	-.043
7	272.712	-2.168	-6.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-5.000	.655	.724	-1.174	-5.964	-.043
8	272.684	-2.168	-7.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-6.999	.655	.724	-1.174	-6.964	-.043
9	272.674	-2.168	-8.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-8.998	.655	.724	-1.174	-7.964	-.043
10	272.670	-2.168	-9.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-7.998	.655	.724	-1.174	-8.964	-.043
11	272.669	-2.168	-10.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-8.998	.655	.724	-1.174	-9.965	-.043
12	272.668	-2.168	-11.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-9.998	.655	.724	-1.174	-10.965	-.043
13	272.668	-2.168	-12.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-10.998	.655	.724	-1.174	-11.965	-.043
14	272.668	-2.168	-13.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-11.998	.655	.724	-1.174	-12.965	-.043
15	272.668	-2.168	-14.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-12.998	.655	.724	-1.174	-13.965	-.043
16	272.668	-2.168	-15.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-13.998	.655	.724	-1.174	-14.965	-.043
17	272.668	-2.168	-16.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-14.998	.655	.724	-1.174	-15.965	-.043
18	272.668	-2.168	-17.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-15.998	.655	.724	-1.174	-16.965	-.043
19	272.668	-2.168	-18.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-16.998	.655	.724	-1.174	-17.965	-.043
20	272.668	-2.168	-19.180	-.492	.000	-.001	.006	-.017	1.490	.510	-.398	-17.998	.655	.724	-1.174	-18.965	-.043

a. Method: Enter
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 272.685
d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 23. Hosmer and Lemeshow Test – Model 2

Step	Chi-square	df	Sig.
1	4.372	8	.822

Table 24. Omnibus Test – Model 2

		Chi-square	df	Sig.
Step 1	Step	.017	1	.898
	Block	.017	1	.898
	Model	30.563	15	.010

Table 25. Model Summary - Model 2

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	272.668 ^a	.064	.133

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 26. Variables in the Equation - Model 2

Step 1 ^a		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
	CEO Turnover(1)	-19.180	5043.774	.000	1	.997	.000	.000	.
	CIO presence(1)	-.492	.334	2.169	1	.141	.612	.318	1.177
	Firm Size in # of employees	.000	.000	.229	1	.632	1.000	1.000	1.000
	TMT size	-.001	.005	.027	1	.870	.999	.989	1.009
	Firm age in terms of year of incorporation	.006	.005	1.452	1	.228	1.006	.996	1.016
	Firm Performance in return on assets	-.017	.018	.888	1	.346	.983	.950	1.018
	Industry Type (categorical)			10.336	8	.242			
	Industry Type (categorical) (1)	1.490	.726	4.212	1	.040	4.437	1.069	18.410
	Industry Type (categorical) (2)	.510	.622	.672	1	.412	1.666	.492	5.640
	Industry Type (categorical) (3)	-.398	1.177	.114	1	.735	.672	.067	6.745
	Industry Type (categorical) (4)	-17.998	10659.738	.000	1	.999	.000	.000	.
	Industry Type (categorical) (5)	.655	.767	.728	1	.394	1.925	.428	8.660
	Industry Type (categorical) (6)	.724	.625	1.340	1	.247	2.062	.606	7.025
	Industry Type (categorical) (7)	-1.174	.919	1.632	1	.201	.309	.051	1.873
	Industry Type (categorical) (8)	-18.965	28420.596	.000	1	.999	.000	.000	.
	Age Dissimilarity between CDO/CEO(1)	-.043	.331	.017	1	.898	.958	.500	1.835
	Constant	-2.168	.627	11.960	1	<.001	.114		

a. Variable(s) entered on step 1: Age Dissimilarity between CDO/CEO.

Logistic Regression model 3 – Constant, Control Variables and Gender Dissimilarity
 Analysing the iteration history of the third model, which encompasses the constant, the control variables, and gender dissimilarity as independent variable, the MLE process ends at the twentieth iteration and produces an intercept (-2.323) (Table 27). The -2LL in the third model

is 271.626, indicating a slightly better fit compared to the second model, suggesting an improvement in model fit (e.g., Hair et al., 2019).

The Hosmer and Lemeshow test has been provided by the analysis which yielded a chi-square statistic of $X^2 = 17.371$ (df = 8, p = .026), indicating that the logistic regression model does not adequately fits the observed data (Table 28). However, within the third model, the omnibus test of the logistic regression yielded a chi-square statistic of $X^2 = 31.605$ (df = 16, p = .011), indicating statistical significance of the logistic regression model as whole (Table 29). This suggest that at least one predictor variable significantly predicts the outcome variable. In addition, the logistic regression provides the ‘model summary’, indicating a small amount of variation in CDO turnover is explained by the independent variable, with Cox & Snell R Square (.067) and Nagelkerke R Square (.138) coefficients (Table 30).

Furthermore, analysing the ‘variables in the equation’ model (Table 31), while *gender dissimilarity* has been added as independent variable, it has been shown that the constant model remains statistically significant (p < .001) to the prediction. Besides, with the adding of *gender dissimilarity* as independent variable, age dissimilarity remains non-significant. Besides, the statistical significance values of the control variables remain similar in which the category ‘energy & transformation’ of the control variable *industry type* still statistically significantly predicts CDO Turnover. Furthermore, when examining the Wald test for the relationship between *CDO turnover* and *gender dissimilarity* between the CDO and CEO, it was found that it does not statistically significant predict CDO turnover (B = .345, p = .303).

Table 27. Iteration History - Model 3

Iteration	-2 Log likelihood	Constant	Coefficients																
			CEO Turnover (1)	CIO presence (1)	Firm Size in # of employees	TMT size	Firm age in terms of year of incorporation	Firm Performance in return on assets	Industry Type (categorical)(1)	Industry Type (categorical)(2)	Industry Type (categorical)(3)	Industry Type (categorical)(4)	Industry Type (categorical)(5)	Industry Type (categorical)(6)	Industry Type (categorical)(7)	Industry Type (categorical)(8)	Age Dissimilarity between CDO&CEO(1)	Gender Dissimilarity between CDO&CEO(1)	
Step 1	1	307.284	-1.617	-.484	-.180	.000	.000	.002	-.006	.682	.208	-.076	-.128	.206	.271	-.198	-.496	-.003	1.22
2	279.858	-2.143	-1.219	-.365	.000	.000	.004	-.012	1.239	.416	-.181	-.432	.449	.585	-.537	-1.210	-.008	.254	
3	274.094	-2.300	-2.153	-.462	.000	-.001	.006	-.016	1.460	.508	-.265	-1.897	.600	.732	-.950	-2.147	-.016	.331	
4	272.502	-2.322	-3.184	-.475	.000	-.001	.006	-.017	1.518	.516	-.282	-1.980	.626	.761	-1.144	-3.151	-.019	.345	
5	271.949	-2.323	-4.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-2.945	.627	.763	-1.169	-4.158	-.019	.345	
6	271.745	-2.323	-5.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-3.932	.627	.764	-1.169	-5.158	-.019	.345	
7	271.670	-2.323	-6.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-4.927	.627	.764	-1.169	-6.159	-.019	.345	
8	271.642	-2.323	-7.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-5.926	.627	.764	-1.169	-7.159	-.019	.345	
9	271.632	-2.323	-8.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-6.925	.627	.764	-1.169	-8.159	-.019	.345	
10	271.628	-2.323	-9.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-7.925	.627	.764	-1.169	-9.159	-.019	.345	
11	271.627	-2.323	-10.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-8.925	.627	.764	-1.169	-10.159	-.019	.345	
12	271.626	-2.323	-11.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-9.925	.627	.764	-1.169	-11.159	-.019	.345	
13	271.626	-2.323	-12.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-10.925	.627	.764	-1.169	-12.159	-.019	.345	
14	271.626	-2.323	-13.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-11.925	.627	.764	-1.169	-13.159	-.019	.345	
15	271.626	-2.323	-14.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-12.925	.627	.764	-1.169	-14.159	-.019	.345	
16	271.626	-2.323	-15.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-13.925	.627	.764	-1.169	-15.159	-.019	.345	
17	271.626	-2.323	-16.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-14.925	.627	.764	-1.169	-16.159	-.019	.345	
18	271.626	-2.323	-17.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-15.925	.627	.764	-1.169	-17.159	-.019	.345	
19	271.626	-2.323	-18.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-16.925	.627	.764	-1.169	-18.159	-.019	.345	
20	271.626	-2.323	-19.184	-.475	.000	-.001	.006	-.017	1.521	.516	-.282	-17.925	.627	.764	-1.169	-19.159	-.019	.345	

a. Method: Enter
b. Constant is included in the model
c. Initial -2 Log Likelihood: 272.668
d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 28. Hosmer and Lemeshow Test - Model 3

Step	Chi-square	df	Sig.
1	17.371	8	.026

Table 29. Omnibus Test - Model 3

		Chi-square	df	Sig.
Step 1	Step	1.042	1	.307
	Block	1.042	1	.307
	Model	31.605	16	.011

Table 30. Model Summary – Model 3

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	271.626 ^a	.067	.138

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 31. Variables in the Equation - Model 3

Step 1 ^a		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
	CEO Turnover(1)	-19.184	5034.256	.000	1	.997	.000	.000	.
	CIO presence(1)	-.475	.334	2.022	1	.155	.622	.323	1.197
	Firm Size in # of employees	.000	.000	.259	1	.611	1.000	1.000	1.000
	TMT size	-.001	.005	.019	1	.890	.999	.989	1.009
	Firm age in terms of year of incorporation	.006	.005	1.396	1	.237	1.006	.996	1.016
	Firm Performance in return on assets	-.017	.018	.912	1	.340	.983	.949	1.018
	Industry Type (categorical)			10.449	8	.235			
	Industry Type (categorical) (1)	1.521	.727	4.381	1	.036	4.577	1.102	19.019
	Industry Type (categorical) (2)	.516	.622	.687	1	.407	1.675	.495	5.674
	Industry Type (categorical) (3)	-.282	1.182	.057	1	.811	.754	.074	7.655
	Industry Type (categorical) (4)	-17.925	10642.852	.000	1	.999	.000	.000	.
	Industry Type (categorical) (5)	.627	.767	.668	1	.414	1.872	.416	8.423
	Industry Type (categorical) (6)	.764	.626	1.489	1	.222	2.146	.630	7.314
	Industry Type (categorical) (7)	-1.169	.922	1.606	1	.205	.311	.051	1.894
	Industry Type (categorical) (8)	-19.159	28420.582	.000	1	.999	.000	.000	.
	Age Dissimilarity between CDO/CEO(1)	-.019	.333	.003	1	.955	.982	.511	1.884
	Gender Dissimilarity between CDO/CEO(1)	.345	.335	1.061	1	.303	1.412	.732	2.724
	Constant	-2.323	.644	13.015	1	<.001	.098		

a. Variable(s) entered on step 1: Gender Dissimilarity between CDO/CEO.

Logistic Regression model 4 – Constant, Control Variables and Functional Background Dissimilarity

Analysing the iteration history of the fourth model, which encompasses the constant, the control variables, and functional background dissimilarity as independent variable, the MLE process ends at the twentieth iteration and produces an intercept (-2.033) (Table 32). The -2LL in the third model is 271.410, indicating a slightly better fit compared to the second model, suggesting an improvement in model fit (e.g., Hair et al., 2019).

The Hosmer and Lemeshow test has been provided by the analysis which yielded a chi-square statistic of $X^2 = 14.443$ (df = 8, p = .071), indicating that the logistic regression model does adequately fits the observed data (Table 33). Besides, the omnibus test of the logistic regression yielded a chi-square statistic of $X^2 = 31.821$ (df = 17, p = .016), indicating statistical significance of the logistic regression model as whole (Table 34). This suggest that at least one predictor variable significantly predicts the outcome variable. In addition, the logistic regression provides the ‘model summary’, indicating a small amount of variation in CDO turnover is explained by the independent variable, with Cox & Snell R Square (.067) and Nagelkerke R Square (.139) coefficients (Table 35).

Furthermore, analysing the ‘variables in the equation’ model (Table 36), while *functional background dissimilarity* has been added as independent variable, it has been shown that the constant model remains statistically significant (p = .022) to the prediction. Besides, with the adding of *functional background dissimilarity* as independent variable, the other independent variables remain non-significant. Besides, the statistical significance values of the control variables remain similar in which the category ‘energy & transformation’ of the control variable *industry type* still statistically significantly predicts CDO Turnover. Furthermore, when examining the Wald test for the relationship between *CDO turnover* and *functional background dissimilarity* between the CDO and CEO, it was found that it does not statistically significant predict CDO turnover (B = -.290, p = .638).

Table 32. Iteration History - Model 4

Iteration	Coefficients																		
	-2 Log likelihood	Constant	CEO Turnover (1)	CIO presence (1)	Firm Size in # of employees	TMT size	Firm age in terms of year of incorporation	Firm Performance in return on assets	Industry Type (categorical)1	Industry Type (categorical)2	Industry Type (categorical)3	Industry Type (categorical)4	Industry Type (categorical)5	Industry Type (categorical)6	Industry Type (categorical)7	Industry Type (categorical)8	Age Dissimilarity between CDO/CEO1	Gender Dissimilarity between CDO/CEO1	Functional Background Dissimilarity between CDO/CEO1
Step 1	307.197	-1.529	-.489	-.180	.000	.000	.002	-.006	.694	.218	-.092	-.114	.163	.276	-.184	-.487	-.005	.121	-.092
2	279.691	-1.948	-.1231	-.367	.000	-.001	.004	-.012	1.265	.439	-.212	-.398	.361	.575	-.594	-.190	-.014	.266	-.201
3	273.884	-2.029	-.2201	-.466	.000	-.001	.005	-.016	1.516	.538	-.299	-.1035	.488	.744	-.902	-.2122	-.026	.337	-.273
4	272.288	-2.033	-.3203	-.491	.000	-.001	.006	-.017	1.555	.548	-.315	-.1924	.510	.773	-.1092	-.3125	-.031	.352	-.288
5	271.734	-2.033	-.4204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.2088	.511	.775	-.1115	-.4130	-.031	.353	-.290
6	271.530	-2.033	-.5204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.3876	.511	.775	-.1116	-.5132	-.031	.353	-.290
7	271.454	-2.033	-.6204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.4871	.511	.775	-.1116	-.6133	-.031	.353	-.290
8	271.427	-2.033	-.7204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.5870	.511	.775	-.1116	-.7133	-.031	.353	-.290
9	271.416	-2.033	-.8204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.6869	.511	.775	-.1116	-.8133	-.031	.353	-.290
10	271.413	-2.033	-.9204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.7869	.511	.775	-.1116	-.9133	-.031	.353	-.290
11	271.411	-2.033	-1.0204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.8869	.511	.775	-.1116	-1.0133	-.031	.353	-.290
12	271.411	-2.033	-1.1204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-.9869	.511	.775	-.1116	-1.1133	-.031	.353	-.290
13	271.411	-2.033	-1.2204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.0869	.511	.775	-.1116	-1.2133	-.031	.353	-.290
14	271.410	-2.033	-1.3204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.1869	.511	.775	-.1116	-1.3133	-.031	.353	-.290
15	271.410	-2.033	-1.4204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.2869	.511	.775	-.1116	-1.4133	-.031	.353	-.290
16	271.410	-2.033	-1.5204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.3869	.511	.775	-.1116	-1.5133	-.031	.353	-.290
17	271.410	-2.033	-1.6204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.4869	.511	.775	-.1116	-1.6133	-.031	.353	-.290
18	271.410	-2.033	-1.7204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.5869	.511	.775	-.1116	-1.7133	-.031	.353	-.290
19	271.410	-2.033	-1.8204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.6869	.511	.775	-.1116	-1.8133	-.031	.353	-.290
20	271.410	-2.033	-1.9204	-.481	.000	-.001	.006	-.017	1.559	.548	-.315	-1.7869	.511	.775	-.1116	-1.9133	-.031	.353	-.290

a. Method: Enter
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 271.626
d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 33. Hosmer and Lemeshow Test - Model 4

Step	Chi-square	df	Sig.
1	14.443	8	.071

Table 34. Omnibus Test - Model 4

Step 1	Step	Chi-square	df	Sig.
	Step	.216	1	.642
	Block	.216	1	.642
	Model	31.821	17	.016

Table 35. Model Summary - Model 4

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	271.410 ^a	.067	.139

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 36 Variables in the Equation - Model 4

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Step 1 ^a								
CEO Turnover(1)	-19.204	5029.753	.000	1	.997	.000	.000	.
CIO presence(1)	-.481	.335	2.063	1	.151	.618	.321	1.192
Firm Size in # of employees	.000	.000	.258	1	.612	1.000	1.000	1.000
TMT size	-.001	.005	.056	1	.813	.999	.989	1.009
Firm age in terms of year of incorporation	.006	.005	1.306	1	.253	1.006	.996	1.016
Firm Performance in return on assets	-.017	.018	.871	1	.351	.983	.949	1.019
Industry Type (categorical)			10.625	8	.224			
Industry Type (categorical) (1)	1.559	.733	4.526	1	.033	4.753	1.131	19.981
Industry Type (categorical) (2)	.548	.627	.764	1	.382	1.730	.506	5.914
Industry Type (categorical) (3)	-.315	1.185	.071	1	.790	.730	.072	7.444
Industry Type (categorical) (4)	-17.869	10645.286	.000	1	.999	.000	.000	.
Industry Type (categorical) (5)	.511	.813	.395	1	.530	1.666	.339	8.192
Industry Type (categorical) (6)	.775	.626	1.534	1	.216	2.170	.637	7.395
Industry Type (categorical) (7)	-1.116	.929	1.443	1	.230	.328	.053	2.024
Industry Type (categorical) (8)	-19.133	28420.601	.000	1	.999	.000	.000	.
Age Dissimilarity between CDO/CEO(1)	-.031	.334	.009	1	.926	.970	.504	1.865
Gender Dissimilarity between CDO/CEO(1)	.353	.336	1.105	1	.293	1.423	.737	2.748
Functional Background Dissimilarity between CDO/CEO(1)	-.290	.616	.221	1	.638	.748	.224	2.503
Constant	-2.033	.888	5.240	1	.022	.131		

a. Variable(s) entered on step 1: Functional Background Dissimilarity between CDO/CEO.

Logistic Regression model 5 – Constant, Control Variables and Educational Level Dissimilarity

Analysing the iteration history of the fifth model, which encompasses the constant, the control variables, and educational level dissimilarity as independent variable, the MLE process ends at the twentieth iteration and produces an intercept (-2.075) (Table 37). The -2LL in the third model is 271.330, indicating a slightly better fit compared to the second model, suggesting an improvement in model fit (e.g., Hair et al., 2019).

The Hosmer and Lemeshow test has been provided by the analysis which yielded a chi-square statistic of $X^2 = 4.026$ ($df = 8$, $p = .855$), indicating that the logistic regression model does adequately fits the observed data (Table 38). Besides, the omnibus test of the logistic regression yielded a chi-square statistic of $X^2 = 31.901$ ($df = 18$, $p = .023$), indicating statistical significance of the logistic regression model as whole (Table 39). This suggest that at least one predictor variable significantly predicts the outcome variable. In addition, the logistic

regression provides the ‘model summary’, indicating a small amount of variation in CDO turnover is explained by the independent variable, with Cox & Snell R Square (.067) and Nagelkerke R Square (.139) coefficients (Table 40).

Furthermore, analysing the ‘variables in the equation’ model (Table 41), while *educational level dissimilarity* has been added as independent variable, it has been shown that the constant model remains statistically significant ($p = .021$) to the prediction. Besides, with the adding of *educational level dissimilarity* as independent variable, the other independent variables remain non-significant. Besides, the statistical significance values of the control variables remain similar in which the category ‘energy & transformation’ of the control variable *industry type* still statistically significantly predicts CDO Turnover. Furthermore, when examining the Wald test for the relationship between *CDO turnover* and *educational level dissimilarity* between the CDO and CEO, it was found that it does not statistically significant predict CDO turnover ($B = .094, p = .777$).

Table 37. Iteration History - Model 5

Iteration	-2 Log Likelihood	Constant	CEO Turnover (t)	CDO presence (t)	Firm Size in # of employees	TMT size	Coefficients													
							Firm age in terms of year of incorporation	Firm Performance in return on assets	Industry Type (categorical)(1)	Industry Type (categorical)(2)	Industry Type (categorical)(3)	Industry Type (categorical)(4)	Industry Type (categorical)(5)	Industry Type (categorical)(6)	Industry Type (categorical)(7)	Industry Type (categorical)(8)	Age Dissimilarity between CDO/CEO(t)	Gender Dissimilarity between CDO/CEO(t)	Functional Background Dissimilarity between CDO/CEO(t)	Educational Level Dissimilarity between CDO/CEO(t)
1	307.138	-1.551	-4.991	-178	000	000	002	005	3700	220	086	-1.124	164	270	-160	-460	006	116	-304	044
2	279.593	-1.988	-1.233	-360	000	-001	004	-012	1.574	441	-200	-421	356	662	-516	-1.138	-015	251	-208	082
3	273.882	-2.071	-2.201	-458	000	-001	005	-016	1.523	541	-287	-1.088	476	726	-918	-2.082	-025	329	-284	094
4	272.286	-2.075	-3.203	-472	000	-001	006	-016	1.581	550	-304	-1.081	497	765	-1.109	-3.088	-029	344	-289	094
5	271.653	-2.075	-4.204	-473	000	-001	006	-016	1.584	550	-304	-2.928	498	757	-1.133	-4.071	-029	345	-300	094
6	271.449	-2.075	-5.204	-472	000	-001	006	-016	1.584	550	-304	-3.916	498	757	-1.133	-5.073	-029	345	-300	094
7	271.374	-2.075	-6.204	-472	000	-001	006	-016	1.584	550	-304	-4.912	498	757	-1.133	-6.073	-029	345	-300	094
8	271.346	-2.075	-7.204	-472	000	-001	006	-016	1.584	550	-304	-5.910	498	757	-1.133	-7.074	-029	345	-300	094
9	271.336	-2.075	-8.204	-472	000	-001	006	-016	1.584	550	-304	-6.909	498	757	-1.133	-8.074	-029	345	-300	094
10	271.332	-2.075	-9.204	-472	000	-001	006	-016	1.584	550	-304	-7.909	498	757	-1.133	-9.074	-029	345	-300	094
11	271.331	-2.075	-10.204	-472	000	-001	006	-016	1.584	550	-304	-8.909	498	757	-1.133	-10.074	-029	345	-300	094
12	271.331	-2.075	-11.204	-472	000	-001	006	-016	1.584	550	-304	-9.909	498	757	-1.133	-11.074	-029	345	-300	094
13	271.330	-2.075	-12.204	-472	000	-001	006	-016	1.584	550	-304	-10.909	498	757	-1.133	-12.074	-029	345	-300	094
14	271.330	-2.075	-13.204	-472	000	-001	006	-016	1.584	550	-304	-11.909	498	757	-1.133	-13.074	-029	345	-300	094
15	271.330	-2.075	-14.204	-472	000	-001	006	-016	1.584	550	-304	-12.909	498	757	-1.133	-14.074	-029	345	-300	094
16	271.330	-2.075	-15.204	-472	000	-001	006	-016	1.584	550	-304	-13.909	498	757	-1.133	-15.074	-029	345	-300	094
17	271.330	-2.075	-16.204	-472	000	-001	006	-016	1.584	550	-304	-14.909	498	757	-1.133	-16.074	-029	345	-300	094
18	271.330	-2.075	-17.204	-472	000	-001	006	-016	1.584	550	-304	-15.909	498	757	-1.133	-17.074	-029	345	-300	094
19	271.330	-2.075	-18.204	-472	000	-001	006	-016	1.584	550	-304	-16.909	498	757	-1.133	-18.074	-029	345	-300	094
20	271.330	-2.075	-19.204	-472	000	-001	006	-016	1.584	550	-304	-17.909	498	757	-1.133	-19.074	-029	345	-300	094

a. Method Enter
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 271.410
d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 38. Hosmer and Lemeshow Test - Model 5

Step	Chi-square	df	Sig.
1	4.026	8	.855

Table 39. Omnibus Test - Model 5

Step 1	Step	Chi-square	df	Sig.
	Step	.080	1	.777
	Block	.080	1	.777
	Model	31.901	18	.023

Table 40. Model Summary - Model 5

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	271.330 ^a	.067	.139

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 41. Variables in the Equation - Model 5

Step 1 ^a		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
	CEO Turnover(1)	-19.204	5033.946	.000	1	.997	.000	.000	.
	CIO presence(1)	-.472	.336	1.979	1	.159	.623	.323	1.204
	Firm Size in # of employees	.000	.000	.282	1	.595	1.000	1.000	1.000
	TMT size	-.001	.005	.055	1	.815	.999	.989	1.009
	Firm age in terms of year of incorporation	.006	.005	1.339	1	.247	1.006	.996	1.016
	Firm Performance in return on assets	-.016	.018	.820	1	.365	.984	.949	1.019
	Industry Type (categorical)			10.650	8	.222			
	Industry Type (categorical) (1)	1.564	.733	4.549	1	.033	4.779	1.135	20.117
	Industry Type (categorical) (2)	.550	.627	.769	1	.380	1.734	.507	5.930
	Industry Type (categorical) (3)	-.304	1.186	.066	1	.798	.738	.072	7.542
	Industry Type (categorical) (4)	-17.909	10656.088	.000	1	.999	.000	.000	.
	Industry Type (categorical) (5)	.498	.812	.376	1	.540	1.645	.335	8.082
	Industry Type (categorical) (6)	.757	.628	1.452	1	.228	2.131	.623	7.298
	Industry Type (categorical) (7)	-1.133	.934	1.473	1	.225	.322	.052	2.008
	Industry Type (categorical) (8)	-19.074	28420.612	.000	1	.999	.000	.000	.
	Age Dissimilarity between CDO/CEO(1)	-.029	.334	.008	1	.930	.971	.505	1.868
	Gender Dissimilarity between CDO/CEO(1)	.345	.337	1.050	1	.306	1.412	.730	2.732
	Functional Background Dissimilarity between CDO/CEO(1)	-.300	.617	.237	1	.626	.741	.221	2.481
	Educational Level Dissimilarity between CDO/CEO(1)	.094	.333	.080	1	.777	1.099	.572	2.111
	Constant	-2.075	.899	5.335	1	.021	.126		

a. Variable(s) entered on step 1: Educational Level Dissimilarity between CDO/CEO.

Logistic Regression model 6 – Constant, Control Variables and Demographic Dissimilarity
 Analysing the iteration history of the sixth model, which encompasses the constant, the control variables, and all independent demographic dissimilarity variables, the MLE process ends at the twentieth iteration and produces an intercept (-2.075) (Table 42). The -2LL in the third

model is 271.330, indicating a slightly better fit compared to the last models, suggesting an improvement in model fit (e.g., Hair et al., 2019).

The Hosmer and Lemeshow test has been provided by the analysis which yielded a chi-square statistic of $X^2 = 4.026$ ($df = 8$, $p = .855$), indicating that the logistic regression model adequately fits the observed data (Table 43). Within the third model, the omnibus test of the logistic regression yielded a chi-square statistic of $X^2 = 31.901$ ($df = 18$, $p = .023$), indicating statistical significance of the logistic regression model as whole (Table 44). This suggest that at least one predictor variable significantly predicts the outcome variable. In addition, the logistic regression provides the ‘model summary’, indicating a small amount of variation in CDO turnover is explained by the independent variable, with Cox & Snell R Square (.067) and Nagelkerke R Square (.139) coefficients (Table 45).

Furthermore, analysing the ‘variables in the equation’ model (Table 46), with the inclusion of all four *demographic dissimilarity* variables have been added, it has been shown that the constant model remains statistically significant ($p = .021$) to the prediction. Besides, with the adding of these variables, the statistical significance values of the control variables remain similar in which the category ‘energy & transformation’ of the control variable *industry type* still statistically significantly predicts CDO Turnover.

When examining the Wald test for the relationship between CDO turnover and various dissimilarities between the CDO and CEO, the following results were found, assessed at a 5% confidence interval. Age dissimilarity between CDO and CEO does not significantly predict CDO turnover ($B = -.029$, $p = .930$). Similarly, gender dissimilarity between CDO and CEO also did not exhibit a significant association with CDO turnover ($B = .345$, $p = .306$). Additionally, functional background dissimilarity between CDO and CEO did not significantly influence CDO turnover ($B = -.300$, $p = .626$), nor did educational level dissimilarity between CDO and CEO ($B = .094$, $p = .777$). Comparing the findings on all four demographic dissimilarity independent variables compared to the inclusion of these variables individually, it has been shown that the magnitude and statistical significance remains relatively similar.

Table 42. Iteration History - Model 6

Iteration	-2 Log Likelihood	Constant	CEO Turnover (1)	CIO presence (1)	Firm Size in # of employees	TMT size	Coefficients												Age Dissimilarity between CDO/CEO(1)	Gender Dissimilarity between CDO/CEO(1)	Functional Background Dissimilarity between CDO/CEO(1)	Educational Level Dissimilarity between CDO/CEO(1)
							Firm age in terms of year of incorporation	Firm Performance in return on assets	Industry Type (categorical)(1)	Industry Type (categorical)(2)	Industry Type (categorical)(3)	Industry Type (categorical)(4)	Industry Type (categorical)(5)	Industry Type (categorical)(6)	Industry Type (categorical)(7)	Industry Type (categorical)(8)	Industry Type (categorical)(9)	Industry Type (categorical)(10)				
Step 1	1	307.128	-1.551	-.491	-.178	.000	.000	.002	-.005	.700	.220	-.886	-.124	.164	.270	-.180	-.480	.119	-.094	.044		
2	279.593	-1.988	-1.233	-.360	.000	-.001	.004	-.012	1.274	.441	-.200	-.421	.356	.562	-.516	-1.138	-.015	.251	-.208	.082		
3	273.992	-2.071	-2.201	-.458	.000	-.001	.005	-.016	1.523	.541	-.287	-1.068	.476	.726	-.916	-2.062	-.025	.329	-.284	.094		
4	272.296	-2.075	-3.203	-.472	.000	-.001	.006	-.016	1.561	.550	-.304	-1.961	.497	.755	-1.109	-3.066	-.029	.344	-.299	.094		
5	271.653	-2.075	-4.204	-.473	.000	-.001	.006	-.016	1.564	.550	-.304	-2.928	.498	.757	-1.133	-4.071	-.029	.345	-.300	.094		
6	271.449	-2.075	-5.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-3.916	.498	.757	-1.133	-5.073	-.029	.345	-.300	.094		
7	271.374	-2.075	-6.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-4.912	.498	.757	-1.133	-6.073	-.029	.345	-.300	.094		
8	271.346	-2.075	-7.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-5.910	.498	.757	-1.133	-7.074	-.029	.345	-.300	.094		
9	271.336	-2.075	-8.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-6.909	.498	.757	-1.133	-8.074	-.029	.345	-.300	.094		
10	271.332	-2.075	-9.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-7.909	.498	.757	-1.133	-9.074	-.029	.345	-.300	.094		
11	271.331	-2.075	-10.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-8.909	.498	.757	-1.133	-10.074	-.029	.345	-.300	.094		
12	271.331	-2.075	-11.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-9.909	.498	.757	-1.133	-11.074	-.029	.345	-.300	.094		
13	271.330	-2.075	-12.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-10.909	.498	.757	-1.133	-12.074	-.029	.345	-.300	.094		
14	271.330	-2.075	-13.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-11.909	.498	.757	-1.133	-13.074	-.029	.345	-.300	.094		
15	271.330	-2.075	-14.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-12.909	.498	.757	-1.133	-14.074	-.029	.345	-.300	.094		
16	271.330	-2.075	-15.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-13.909	.498	.757	-1.133	-15.074	-.029	.345	-.300	.094		
17	271.330	-2.075	-16.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-14.909	.498	.757	-1.133	-16.074	-.029	.345	-.300	.094		
18	271.330	-2.075	-17.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-15.909	.498	.757	-1.133	-17.074	-.029	.345	-.300	.094		
19	271.330	-2.075	-18.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-16.909	.498	.757	-1.133	-18.074	-.029	.345	-.300	.094		
20	271.330	-2.075	-19.204	-.472	.000	-.001	.006	-.016	1.564	.550	-.304	-17.909	.498	.757	-1.133	-19.074	-.029	.345	-.300	.094		

a. Method Enter
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 271.330
d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 43. Hosmer and Lemeshow Test - Model 6

Step	Chi-square	df	Sig.
1	4.026	8	.855

Table 44. Omnibus Test - Model 6

Step	Model	Chi-square	df	Sig.
1	Model	31.901	18	.023

Table 45. Model Summary - Model 6

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	271.330 ^a	.067	.139

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 46. Variables in the Equation - Model 6

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Step 1 ^a								
CEO Turnover(1)	-19.204	5033.946	.000	1	.997	.000	.000	.
CIO presence(1)	-.472	.336	1.979	1	.159	.623	.323	1.204
Firm Size in # of employees	.000	.000	.282	1	.595	1.000	1.000	1.000
TMT size	-.001	.005	.055	1	.815	.999	.989	1.009
Firm age in terms of year of incorporation	.006	.005	1.339	1	.247	1.006	.996	1.016
Firm Performance in return on assets	-.016	.018	.820	1	.365	.984	.949	1.019
Industry Type (categorical)			10.650	8	.222			
Industry Type (categorical) (1)	1.564	.733	4.549	1	.033	4.779	1.135	20.117
Industry Type (categorical) (2)	.550	.627	.769	1	.380	1.734	.507	5.930
Industry Type (categorical) (3)	-.304	1.186	.066	1	.798	.738	.072	7.542
Industry Type (categorical) (4)	-17.909	10656.088	.000	1	.999	.000	.000	.
Industry Type (categorical) (5)	.498	.812	.376	1	.540	1.645	.335	8.082
Industry Type (categorical) (6)	.757	.628	1.452	1	.228	2.131	.623	7.298
Industry Type (categorical) (7)	-1.133	.934	1.473	1	.225	.322	.052	2.008
Industry Type (categorical) (8)	-19.074	28420.612	.000	1	.999	.000	.000	.
Age Dissimilarity between CDO/CEO(1)	-.029	.334	.008	1	.930	.971	.505	1.868
Gender Dissimilarity between CDO/CEO(1)	.345	.337	1.050	1	.306	1.412	.730	2.732
Functional Background Dissimilarity between CDO/CEO(1)	-.300	.617	.237	1	.626	.741	.221	2.481
Educational Level Dissimilarity between CDO/CEO(1)	.094	.333	.080	1	.777	1.099	.572	2.111
Constant	-2.075	.899	5.335	1	.021	.126		

a. Variable(s) entered on step 1: Age Dissimilarity between CDO/CEO, Gender Dissimilarity between CDO/CEO, Functional Background Dissimilarity between CDO/CEO, Educational Level Dissimilarity between CDO/CEO.

Appendix VI – Supplementary Analysis

Table 47. Collinearity Diagnostics

		CDO_CEO_Dissim Composite - CDO/CEO demographic dissimilarity	CDO_Turnover CDO Turnover	CEO_Turnover CEO Turnover	EMP Firm Size in # of employees	ROA Firm Performance in return on assets	TMT_Size TMT size	CIO_Presence CIO presence	FirmAge Firm age in terms of year of incorporation	SICCODEcat Industry Type (categorical)
CDO_CEO_Dissim Composite - CDO/CEO demographic dissimilarity	Pearson Correlation	1	-.148**	.102**	.070*	-.066*	.073**	.047	.089**	.033
	Sig. (2-tailed)		<.001	<.001	.013	.019	.007	.083	.001	.224
	N	1334	1334	1334	1277	1289	1332	1334	1319	1322
CDO_Turnover CDO Turnover	Pearson Correlation	-.148**	1	-.161**	-.059*	-.044	-.155**	-.089**	-.004	-.029
	Sig. (2-tailed)	<.001		<.001	.036	.116	<.001	.001	.873	.298
	N	1334	1334	1334	1277	1289	1332	1334	1319	1322
CEO_Turnover CEO Turnover	Pearson Correlation	.102**	-.161**	1	.087**	-.067*	.060*	.036	.044	.010
	Sig. (2-tailed)	<.001	<.001		.002	.016	.029	.193	.109	.716
	N	1334	1334	1334	1277	1289	1332	1334	1319	1322
EMP Firm Size in # of employees	Pearson Correlation	.070*	-.059*	.087**	1	.029	.472**	.244**	.198**	.133**
	Sig. (2-tailed)	.013	.036	.002		.306	<.001	<.001	<.001	<.001
	N	1277	1277	1277	1277	1271	1277	1277	1265	1271
ROA Firm Performance in return on assets	Pearson Correlation	-.066*	-.044	-.067*	.029	1	-.050	.029	-.040	.001
	Sig. (2-tailed)	.019	.116	.016	.306		.071	.301	.152	.965
	N	1289	1289	1289	1271	1289	1289	1289	1276	1282
TMT_Size TMT size	Pearson Correlation	.073**	-.155**	.060*	.472**	-.050	1	.275**	.184**	.164**
	Sig. (2-tailed)	.007	<.001	.029	<.001	.071		<.001	<.001	<.001
	N	1332	1332	1332	1277	1289	1332	1332	1319	1322
CIO_Presence CIO presence	Pearson Correlation	.047	-.089**	.036	.244**	.029	.275**	1	.018	.090**
	Sig. (2-tailed)	.083	.001	.193	<.001	.301	<.001		.506	.001
	N	1334	1334	1334	1277	1289	1332	1334	1319	1322
FirmAge Firm age in terms of year of incorporation	Pearson Correlation	.089**	-.004	.044	.198**	-.040	.184**	.018	1	.002
	Sig. (2-tailed)	.001	.873	.109	<.001	.152	<.001	.506		.940
	N	1319	1319	1319	1265	1276	1319	1319	1319	1309
SICCODEcat Industry Type (categorical)	Pearson Correlation	.033	-.029	.010	.133**	.001	.164**	.090**	.002	1
	Sig. (2-tailed)	.224	.298	.716	<.001	.965	<.001	.001	.940	
	N	1322	1322	1322	1271	1282	1322	1322	1309	1322

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Table 48. Multi-collinearity Analysis

Model		Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error				Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.262	.031		8.333	<.001	.201	.324		
	CEO_Turnover CEO Turnover	-.178	.034	-.145	-5.209	<.001	-.245	-.111	.986	1.014
	EMP Firm Size in # of employees	1.473E-7	.000	.034	1.076	.282	.000	.000	.746	1.340
	ROA Firm Performance in return on assets	-.002	.001	-.053	-1.903	.057	-.004	.000	.987	1.013
	TMT_Size TMT size	-.001	.000	-.148	-4.569	<.001	-.002	-.001	.730	1.369
	CIO_Presence CIO presence	-.033	.022	-.044	-1.528	.127	-.076	.009	.907	1.103
	FirmAge Firm age in terms of year of incorporation	.000	.000	.023	.821	.412	.000	.001	.948	1.055
	SICCODEcat Industry Type (categorical)	-.002	.005	-.012	-.440	.660	-.011	.007	.967	1.034
2	(Constant)	.346	.037		9.370	<.001	.274	.419		
	CEO_Turnover CEO Turnover	-.166	.034	-.135	-4.875	<.001	-.233	-.099	.979	1.021
	EMP Firm Size in # of employees	1.548E-7	.000	.036	1.138	.255	.000	.000	.746	1.340
	ROA Firm Performance in return on assets	-.002	.001	-.060	-2.161	.031	-.004	.000	.984	1.016
	TMT_Size TMT size	-.001	.000	-.144	-4.494	<.001	-.001	-.001	.730	1.370
	CIO_Presence CIO presence	-.030	.022	-.040	-1.390	.165	-.072	.012	.905	1.104
	FirmAge Firm age in terms of year of incorporation	.000	.000	.032	1.134	.257	.000	.001	.943	1.061
	SICCODEcat Industry Type (categorical)	-.002	.005	-.011	-.380	.704	-.011	.007	.967	1.034
	CDO_CEO_Dissim Composite - CDO/CEO demographic dissimilarity	-.049	.011	-.118	-4.261	<.001	-.071	-.026	.977	1.024

a. Dependent Variable: CDO_Turnover CDO Turnover

Logistic Regression model 7 – Constant, Control Variables and Demographic Dissimilarity Composite

Analysing the iteration history of the seventh model, which encompasses the constant, the control variables, and the composite of demographic dissimilarity, the MLE process ends at the twentieth iteration and produces an intercept (-.731) (Table 49). The -2LL in the third model is 1002.589, indicating a relatively optimal model fit in comparison to all other models (e.g., Hair et al., 2019).

The Hosmer and Lemeshow test has been provided by the analysis which yielded a chi-square statistic of $X^2 = 15.792$ (df = 8, p = .045) (Table 50). Although a non-significant p-value is aimed to be obtained with the Hosmer and Lemeshow test in order to find a good model fit, the p-value of 0.045 is marginally significant, indicating that it is on the edge of a good model fit. Within the third model, the omnibus test of the logistic regression yielded a chi-square statistic of $X^2 = 117.351$ (df = 15, p <.001), indicating statistical significance of the logistic regression model as whole (Table 51). This suggest that at least one predictor variable significantly predicts the outcome variable. In addition, the logistic regression provides the ‘model summary’, indicating a small amount of variation in CDO turnover is explained by the independent variable, with Cox & Snell R Square (.089) and Nagelkerke R Square (.151) coefficients (Table 52).

Furthermore, analysing the ‘variables in the equation’ model (Table 53), with the inclusion of the composite, it has been shown that the constant model just does not remain statistically significant ($p = .051$) to the prediction. Though, a significant effect of the composite on CDO turnover has been found ($B = -.357, p < .001$), suggesting that higher overall demographic dissimilarity is associated with a lower likelihood of CDO turnover. With an odds ratio ($\text{Exp}(B)$) of .700, the findings suggest that the odds of CDO turnover decreases with 30% for each one-unit increase in demographic dissimilarity

Furthermore, more control variables hold a statistically significant affect on CDO turnover with the inclusion of the composite (Table 53). TMT size has a significant negative affect on CDO turnover ($B = -.014, p < .001, \text{Exp}(B) = .986$). Firm age becomes a significant positive predictor in the composite model ($B = .004, p < 0.1, \text{Exp}(B) = 1.004$). Besides, firm performance becomes a significant negative predictor in the composite model ($B = -.022, p < .05, \text{Exp}(B) = .978$). Furthermore, industry category type 1 remains statistically significant in predicting CDO turnover ($B = 1.224, p < .001, \text{Exp}(B) = 3.401$). With the inclusion of the composite, category 5 also becomes statistically significant in predicting CDO turnover ($B = .734, p < .1, \text{Exp}(B) = 2.083$). All other control variables remain non-significant across both models.

Table 49. Iteration History – Model 7

Iteration	-2 Log likelihood	Constant	CEO Turnover (t)	Firm Size in # of employees	Firm Performance in return on assets	TMT size	Coefficients								Composite-CDO CEO demographic dissimilarity		
							CDO presence (t)	Firm age in terms of year of incorporation	Industry Type (categorical)(1)	Industry Type (categorical)(2)	Industry Type (categorical)(3)	Industry Type (categorical)(4)	Industry Type (categorical)(5)	Industry Type (categorical)(6)		Industry Type (categorical)(7)	Industry Type (categorical)(8)
Step 1	1071.172	-.887	-.673	.000	-.010	-.004	-.142	.002	.588	-.243	.299	.194	.295	.251	.167	-.062	-.193
2	1018.946	-.838	-1.576	.000	-.017	-.009	-.218	.003	1.001	.411	.442	.351	.564	.432	.259	-.117	-.324
3	1007.183	-.752	-2.633	.000	-.020	-.013	-.226	.004	1.170	.461	.460	.432	.699	.496	.267	-.137	-.357
4	1004.167	-.733	-3.686	.000	-.022	-.014	-.224	.004	1.213	.467	.461	.455	.729	.509	.264	-.138	-.357
5	1003.161	-.731	-4.711	.000	-.022	-.014	-.225	.004	1.222	.469	.462	.458	.733	.512	.264	-.140	-.357
6	1002.798	-.731	-5.720	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
7	1002.666	-.731	-6.724	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
8	1002.617	-.731	-7.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
9	1002.599	-.731	-8.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
10	1002.592	-.731	-9.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
11	1002.590	-.731	-10.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
12	1002.589	-.731	-11.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
13	1002.589	-.731	-12.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
14	1002.589	-.731	-13.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
15	1002.588	-.731	-14.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
16	1002.589	-.731	-15.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
17	1002.589	-.731	-16.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
18	1002.589	-.731	-17.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
19	1002.589	-.731	-18.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357
20	1002.589	-.731	-19.725	.000	-.022	-.014	-.225	.004	1.224	.469	.462	.459	.734	.513	.264	-.140	-.357

a. Method: Enter
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 1016.491
d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 50. Hosmer and Lemeshow Test – Model 7

Step	Chi-square	df	Sig.
1	15.792	8	.045

Table 51. Omnibus Test – Model 7

Step 1		Chi-square	df	Sig.
	Step	13.902	1	<.001
	Block	13.902	1	<.001
	Model	117.351	15	<.001

Table 52. Model Summary – Model 7

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1002.589 ^a	.089	.151

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 53. Variables in the Equation – Model 7

Step 1 ^a		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
	CEO Turnover(1)	-19.725	3394.453	.000	1	.995	.000	.000	.
	Firm Size in # of employees	.000	.000	.935	1	.334	1.000	1.000	1.000
	Firm Performance in return on assets	-.022	.009	5.933	1	.015	.978	.961	.996
	TMT size	-.014	.003	17.990	1	<.001	.986	.980	.993
	CIO presence(1)	-.225	.171	1.734	1	.188	.799	.572	1.116
	Firm age in terms of year of incorporation	.004	.002	2.930	1	.087	1.004	.999	1.009
	Industry Type (categorical)			9.611	8	.293			
	Industry Type (categorical) (1)	1.224	.472	6.730	1	.009	3.401	1.349	8.575
	Industry Type (categorical) (2)	.469	.378	1.544	1	.214	1.599	.763	3.351
	Industry Type (categorical) (3)	.462	.417	1.225	1	.268	1.587	.701	3.595
	Industry Type (categorical) (4)	.459	.598	.589	1	.443	1.582	.490	5.109
	Industry Type (categorical) (5)	.734	.400	3.368	1	.066	2.083	.951	4.559
	Industry Type (categorical) (6)	.513	.361	2.021	1	.155	1.670	.823	3.388
	Industry Type (categorical) (7)	.264	.388	.464	1	.496	1.302	.609	2.783
	Industry Type (categorical) (8)	-.140	.721	.038	1	.846	.869	.211	3.574
	Composite - CDO/CEO demographic dissimilarity	-.357	.098	13.249	1	<.001	.700	.578	.848
	Constant	-.731	.375	3.801	1	.051	.481		

a. Variable(s) entered on step 1: Composite - CDO/CEO demographic dissimilarity.