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Board Characteristics and Exit Likelihood of Venture Capital Backed Firms: Evidence from India

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Table of Contents

Abstract

This paper assesses whether board characteristics of Venture Capital (VC) backed firms influence their likelihood of experiencing a successful exit in the form of an Initial Public Offering (IPO) or a Merger & Acquisition (M&A). Using a cox Proportional Hazards (PH) model on a sample of 2704 VC backed Indian firms that were tracked yearly from their first VC investment year, the analysis reveals that board size and board interlocks with domestic investors have a significant and positive impact on the exit likelihood of investees. Moreover, the average tenure of directors does not impact the exit likelihood of these investees. Further robustness analyses reveal that the impact of board interlocks is heterogenous and varies over time while the effect of board size is consistent across models. These findings yield several implications for startups and VC investors. Founders must consider the importance of board size to improve efficacy of their strategic plans and to increase their legitimacy. Furthermore, founders must embrace the idea of sacrificing some control over their board to investors as board interlocks provide positive signals to market participants regarding startup quality. Additionally, VC firms must optimize their portfolio to actively contribute to success of their investees. Finally, VC firms could use board size as an additional criterion to assess potential investees as it may indicate the willingness of the founding team to give up control and to expedite the exit process.

Keywords: Board Interlocks, Board Size, Cox Proportional Hazards (PH) Model, Initial Public Offering (IPO), Merger & Acquisition (M&A), Startups, Venture Capital (VC).

List of Abbreviations

GaWC	Globalization and World Cities
IPO	Initial Public Offering
M&A	Merger & Acquisition
MCA	Ministry of Corporate Affairs
NAICS	North American Industry Classification System
OLS	Ordinary Least Squares
PE	Private Equity
PH	Proportional Hazards
SIC	Standard Industry Classification
TRBC	Thomson Reuters Business Classification
TVC	Time Varying Coefficients
VC	Venture Capital
VIF	Variance Inflation Factor

1. Introduction

Startups are young private firms that are widely regarded as engines of economic growth because they drive innovation and generate employment (Acs et al., 2008). These firms receive funds from investors such as business angels and VC firms to scale their operations. Asymmetric information and agency problems are at the heart of investor-investee relationships given the limited history and early stage of development of startups relative to well-established firms (Gompers, 1995). To overcome such issues, VC firms employ several control methods such as syndication (co-investing with other firms) and staged financing (Tian, 2011). However, a key component of corporate governance is the board of directors. Although previous literature has highlighted several factors influencing exit likelihood of VC backed firms, there exists a lacuna regarding the impact of board characteristics on their exit likelihood, especially in the case of Indian startups (Garg, 2013; Mehta et al., 2021). Furthermore, most studies regarding the impact of board characteristics on firm performance have focused on public firms (Dalton et al., 2007). Yao and O'Neill (2022) asserted that startup boards differ significantly from public firm boards in terms of composition, experience, and background. For instance, startup boards often have no committees while public firm boards have well-established and formal committees. As few papers in the past have shed light on governance of startups and their exit likelihood, this paper adds to the VC literature by utilizing a unique dataset regarding Indian startups to assess the role of board characteristics on their exit likelihood. A successful exit occurs when the VC backed firm lists on a public stock exchange via an IPO or is involved in a trade sale via an M&A. Therefore, the research question of this paper is the following: *Do board characteristics of VC backed firms impact their likelihood of experiencing a successful exit?*

To answer the aforementioned research question, this paper employs a cox PH model on a sample of 2704 Indian startups that received their first VC investment between 2001 and 2021. The dataset, which is consolidated using four databases, includes annual information regarding exit status, board size, board interlocks, average board tenure, funding raised, number of investors, location, and financing stage of these startups. The analysis reveals that board size and board interlocks have a significant and positive impact on the exit likelihood of investees. Moreover, the average tenure of directors does not impact the exit likelihood of these investees. Further robustness analyses reveal that the impact of board interlocks is heterogenous and varies over time while the effect of board size is consistent. Board interlocks reduce the probability of exiting via an M&A initially; however, this probability increases over time. In contrast, board interlocks increase the probability of exiting via an IPO irrespective of time. Finally, firms headquartered in non-major cities benefit from board interlocks initially while firms headquartered in major cities benefit from interlocks over time.

The results found in this paper present several implications for founders of startups. Although founders prefer maintaining maximum control over their startups, they must consider the size of their board if their ambition is to experience a successful exit. Additionally, founders must embrace the idea of their investors taking up seats in their board as board interlocks provide positive signals to market participants regarding the quality of startups and increase their likelihood of going public or being involved in an M&A. The results also yield implications for investors. VC firms can improve the exit likelihood of their investees by taking up board positions in them and actively helping them. Finally, VC firms could use board size as an additional criterion to assess potential investees as it may indicate the willingness of the founding team to give up control and to expedite the exit process.

2. Background

2.1 Venture Capital (VC)

VC is a form of funding that is typically provided to companies with a high present value of growth opportunities (Gompers & Lerner, 2001). In the VC world, VC firms are investors while the companies they invest in are known as investees or portfolio firms. However, VC firms provide more than merely funding to portfolio firms. Hellmann and Puri (2002) stated that VC firms play a crucial role in corporate governance of startups. They screen startups by gathering information about them, which provides valuable insights regarding these startups to other market participants. Most VC firms also provide strategic guidance to their investees and help them in establishing relationships with influential customers, suppliers, and other investors (Hochberg et al., 2007; Peneder, 2010).

The VC cycle comprises of three stages (Gompers & Lerner, 1999). Firstly, VC firms raise funding from high-net-worth individuals and institutional investors. Once sufficient funding is obtained, they screen firms and invest in the most attractive ones. Finally, they monitor the performance of portfolio firms and decide on their exit strategy. This paper is concerned with the exit likelihood of VC backed firms, which relates to the third stage in the investment process.

Several exit opportunities are available to VC backed firms, which are discussed in the next section.

2.2 Exit Types

The below discussion is based on Cumming and MacIntosh (2003) and Gompers et al. (2008).

- *Initial Public Offering (IPO)*: In an IPO, a company's shares are listed on a stock exchange and offered to the public. An IPO is the most preferred type of exit for investors as it gives them flexibility regarding the timing of sale of their shares and the selling price.
- *Mergers and Acquisitions (M&A)*: Most startups are unable to list on a stock exchange because they get sold to a third party (usually, another company) through a merger or an acquisition.
- *Secondary Sales*: In this scenario, the VC firm's shares in the portfolio firm are sold to a third party, such as another investor or VC firm.
- *Buyback*: In this scenario, the investee firm buys the VC firm's shares.
- *Write-Offs*: In this scenario, the VC firm liquidates its equity in the investee firm without earning a profit.

Following Gompers et al. (2008), a successful exit occurs when the investee experiences an M&A or an IPO.

2.3 Venture Capital versus Private Equity (PE)

The distinction between VC and PE investments can sometimes be fuzzy; however, VC firms target younger startups than PE firms do (Mustafa, 2019). The average deal size of PE investments is much larger than that of VC investments. Furthermore, VC firms take on product and business model risks, which pertain to younger startups, while PE firms take on expansion risk, which pertains to mature startups. Therefore, this paper is concerned only with VC investments as they pertain to young startups.

3. Literature Review & Hypotheses Development

The VC-investee relation is seen as a typical agency relationship wherein the VC firm is the principal, and the investee is the agent (Panda & Dash, 2016). The risk of the founding team of the investee acting opportunistically is a salient feature of this relationship. Therefore, VC firms employ several governance mechanisms to minimize such risks. Some of these mechanisms include employing the staged financing method (wherein the VC firm can exercise the abandonment option in case of underperformance) and taking a seat on the board of the investee firm. Although the literature regarding determinants of exit likelihood for VC backed firms has grown steadily in recent years, the role of board characteristics has received little attention. This literature is especially scarce in the context of Indian firms. Mehta et al. (2021) highlighted that market conditions, deal characteristics, and VC related variables have a significant impact on the exit likelihood of VC backed firms. Furthermore, Dominic and Gopalaswamy (2019) highlighted that the exit likelihood of VC backed Indian firms is low due to the general illiquidity of the Indian market. On the other hand, Annamalai and Deshmukh (2011) found that VC investments in India are characterized by short investment durations as most VC funding is mostly available only to firms at a late stage of their development. However, they ignore the role of deal characteristics such as funding value and syndicate size. The study by Tripathi and Sharma (2018) comes close to this paper in terms of assessing the role of board interlocks between investees and investee on the investee's exit performance. However, their study was restricted to a logistic regression analysis of 111 firms that experienced an IPO or M&A between 2004 and 2013. Nevertheless, they found that board interlocks increase the probability of IPOs relative to M&A's. Finally, most papers studying the effect of board characteristics on startup performance have been limited to post-IPO performance of startups (Amini et al., 2022; Gogineni & Upadhyay, 2021). This paper sheds light on the effect of three board characteristics of VC backed firms on their exit likelihood: board interlocks with domestic investors, board size, and board tenure.

3.1 Board Interlocks

Board interlocks have a bearing on the exit likelihood of startups (Fried et al., 1998; Venugopal & Yerramilli, 2019). Garg (2013) highlighted that the compensation of investor directors is heavily influenced by exit events such as M&A's or IPOs of investees of which they are also board members. The presence of a director of the investor firm on the board of investee may enhance monitoring and minimize moral hazard on the part of the entrepreneur (Félix et al., 2012). Moreover, the director may also be more hands on and be able to provide regular advice to the entrepreneur regarding crucial matters (Nguyen & Vu, 2021). One of the key areas where VC directors add value to startups is their involvement in strategic decision making (Fried et al., 1998). Additionally, executives of investees are more likely to have a well-rounded view of their business and a clearer strategic vision of their business in the presence of a VC director (Garg, 2013). This is because these executives are likely to shift cognitive gears while preparing for board meetings to ensure that they have a well-defined long-term goal and portray a clear understanding of the business environment, which may help them uncover blind spots (Louis & Sutton, 1991; Zajac & Bazerman, 1991). Finally, VC investors look to maximize their returns and may push the investee to exit as soon as an opportunity becomes available, regardless of the exit type (Cumming et al., 2017). Previous studies in this area have highlighted the positive impact of board interlocks on exit likelihood of startups. For instance, Bernstein et al. (2016) found that US portfolio companies are more likely to exit when a VC partner takes up a position on their board. In a similar vein, Naoko and Yutaka (2016) found that having a board interlock with investors positively influences the IPO likelihood of Japanese startups.

On the other hand, board interlocks may lead to tension among inside and outside directors regarding the long-term strategic direction of the firm due to conflicting interests. These conflicts may result in lower likelihood of exiting via an M&A as internal directors may have prestige and autonomy considerations while VC directors may be driven by pure profit motive. Félix et al. (2012) found that European investee firms that have board interlocks with their investors take longer to experience an exit relative to other firms. However, they call for further research in the area as this finding contradicted their expectations and findings in previous studies. Therefore, it is expected that board interlocks with investors have a positive influence on exit likelihood and the following is proposed:

H1: Relative to other firms, those VC backed firms that have at least one board interlock with their domestic investors are more likely to experience a successful exit, keeping other variables fixed.[1]

3.2 Board Size

The role of board size (i.e., the number of directors) has been the focus of several studies related to performance of firms (Dalton et al., 1999; McIntyre et al., 2007). A large board size allows firms to develop influential relationships and learn from diverse experiences of directors. Moreover, firms with a large board are more likely to be well-rounded in terms of competencies as different directors can bring complementary skills to the table. Furthermore, as a venture progresses through different stages of its business development cycle, it is more likely to require

[1] Although it is expected that board interlocks with investors have a positive influence on the exit likelihood of VC backed firms regardless of the geography of investors, this paper studies interlocks with domestic investors only due to data limitations. Further information is available in section 4.1.

a larger board to tackle new issues such as pre-IPO due diligence, expanding to foreign markets, and raising funding at a fair valuation (Gan & Erikson, 2022). Wasserman (2008) highlighted that founders that give up control of their business by adding more board members are better off as their firms are far more valuable relative to other firms. Furthermore, Naoko and Yutaka (2016) found that board size positively influences the IPO likelihood of Japanese firms.

Conversely, a large board size implies that board members have larger leeway to shirk their responsibilities, which may exacerbate the agency problem (Hillman et al., 2011). As board size increases, the likelihood of conducting transparent and honest boardroom meetings reduces, which may allow executives to exhibit larger influence over strategic decisions (Lipton & Lorsch, 1992; Ryan & Wiggins, 2004). Yitshaki et al. (2021) found that board size is negatively associated with survival likelihood of high-tech startups due to higher coordination costs and increased likelihood of coalition formation within the board.

Although economic theory is divided regarding the above-mentioned perspectives, it is expected that board size positively influences exit likelihood of startups. This is because diminishing returns resulting from adding more directors is usually seen in large public firms while the average board size of startups is not large enough to experience such diminishing returns (Naoko & Yutaka, 2016). Hence, the following hypothesis is proposed:

H2: As board size of a VC backed firm increases, its exit likelihood increases, keeping other variables fixed.

3.3 Board Tenure

Board tenure is another key determinant of firm performance. Serving on the board of a firm for a long time allows directors to obtain crucial information regarding the company, which they can then use to contribute to strategic decision making (Reguera-Alvarado & Bravo, 2017). As tenure of board members in a company increases, they tend on align on long-term objectives and exit routes of the company (Kor & Sundaramurthy, 2008). This smoothens the exit process and reduces time to completion of the exit. On the other hand, serving on the board for a long duration may reduce the efficacy of outside board members as they may develop close ties with executives and reduce their monitoring frequency (Hillman et al., 2011; Miller, 1991).

Notwithstanding the contrasting perspectives in the literature, it is assumed that the former effect dominates in the case of startups as board members may need time to scale the business appropriately. These board members may be better equipped to discover teething issues and

understand market dynamics than directors with a short tenure. Furthermore, efficacy of monitoring is less important for startups as their need for funding from external sources serves as an additional control mechanism (Zaheer et al., 2019). Startups that exhibit inferior performance may find it difficult to raise funding and shut down. Therefore, the following is proposed:
H3: As average tenure of the directors of a VC backed firm increases, its exit likelihood increases, keeping other variables fixed.

4. Data and Methodology

4.1 Sample Construction

The dataset used in this paper is consolidated using four different data sources.[2] Therefore, several steps are performed to compose the final dataset.

Step 1

Data regarding VC investments in India between 2001 and 2021 is retrieved from the ThomsonOne (T1) VentureXpert database (ThomsonOne, 2001-2021). T1 provides information regarding VC investments such as execution date, investor names, investee name, investee location (city), investee founded date, investee industry, funding amount, stage of investment (seed, early stage, later/expansion stage), exit type (IPO, merger, etc.), and exit date. To retrieve the investments data, several filters are applied on the T1 platform. Firstly, the criterion 'Venture Capital deals' is selected to ensure that PE deals are not included in the sample. Secondly, consistent with previous studies in this area, only 'Seed', 'Early Stage', 'Expansion', and 'Later Stage' deals are selected to ensure that only VC deals are selected (Pintado et al., 2007; Sahlman, 1990; Swathi, 2018). Finally, only those companies that received their first VC investment between 01/01/2001 and 31/12/2021 are selected. The dataset retrieved from T1 after applying these filters encompasses 5814 investment rounds received by 3324 firms. The information regarding 'Investee Company City' is manually corrected due to missing and/or inaccurate information. For instance, 'Andheri' (a locality in the city of Mumbai) is mentioned as the location of some firms. Therefore, these cases are changed to Mumbai. Similarly, 'Maharashtra' (a state in India) is assigned to some cases. These cases are manually changed according to the registration information of the company.

[2] Three of the databases used are Thomson One VentureXpert (Investment data), Tracxn (for missing Investment value data), and Zauba Corp (for missing board data). The final database pertains to board data of Indian firms, which was provided by Professor Ajay Bhaskarabhatla.

Step 2

The next step is to combine the T1 dataset with board data of Indian firms, which was provided by Professor Ajay Bhaskarabhatla from the Erasmus School of Economics. This data contains board level information for Indian firms such as director name, Director Identification Number (DIN), director date of birth, director appointment date, director cessation date (if applicable), director gender, company name, and Company Identification Number (CIN). The DIN is a unique identification code assigned to each director by the Ministry of Corporate Affairs (MCA) in India (Ministry of Corporate Affairs, 2006). Similarly, the CIN is a unique identification code assigned to each corporate entity registered in India (Ministry of Corporate Affairs, 2013).

To merge the T1 and board information datasets, a common identifier is required. This is because the entity names as per T1 dataset and as per the board dataset are not identical. For instance, the abbreviations 'Pvt' or 'Ltd' are used in the T1 dataset while the board information dataset has the full words spelled out for 'Private' or 'Limited'. After adjusting for such changes, entity names are then matched to allocate the CIN for each firm in the T1 database. Out of the 3324 startups in the T1 dataset, the entity name is an exact match with the board data for only 1592 firms. For the remaining 1732 firms, the CIN is manually searched on the Zauba Corp website, which provides information regarding firms registered in India. However, CIN information is not available for 197 firms, which are thus deleted. Therefore, the number of investees with a valid CIN after performing this step is 3127.

The same approach is then applied for data regarding investors. No CINs are allocated to foreign investors as they are not registered with the MCA. Furthermore, the investors with missing CIN information are not deleted as this paper is interested in board level characteristics of investee firms. The CIN is only allocated to investor firms to identify if the investor and investee had any common directors in a given year.

Step 3

Upon obtaining the relevant CINs for investees, the board information dataset is matched with the T1 dataset using CIN as the common identifier. However, upon performing this step, it is identified that the board information dataset does not contain information for 831 investees (out of 3127 firms). Therefore, the board data such as director name, DIN, director appointment date, and director cessation date are added manually by looking up the company on Zauba Corp. Using this process, board data is retrieved for 777 firms while the remaining 54 firms are excluded from the sample.[3] Therefore, the total number of investees after performing this step is 3073. This process is then repeated for investor firms; however, investors with no information regarding directors are not excluded.

Step 4

Furthermore, the T1 dataset indicates that 1071 of the remaining 3073 firms received an investment value of USD 0 in at least one investment round. However, this is unrealistic. Therefore, the investment value for such cases is manually retrieved from Tracxn, which provides reliable data on VC deals, especially in India (Mathew & Rault-Chodankar, 2019; Retterath & Braun, 2020). This process is extremely challenging as the registration name of firms does not always match the name of the firm as per Tracxn. For instance, the information for the company GCT Technologies Private Limited (CIN: U72900DL2018PTC328654) is available under the name of Galaxycard on the Tracxn platform. These aliases are identified using the LinkedIn profiles of directors or through Google search.[4] The investment values are retrieved for 798 firms while the remaining 273 cases are deleted. Therefore, the remaining number of investee firms after performing this step is 2800.

Step 5

Nine firms in the sample experienced an exit before their first VC investment date. Hence, these cases are deleted and the remaining number of investees after performing this step is 2791.

Step 6

Finally, those firms that were incorporated more than 25 years before their first VC investment date are deleted as these firms may not be entrepreneurial and may be considered as distinct from startups (Boelen, 2021). The remaining number of investees after performing this step is 2704.

Step 7

The T1 platform is also used to retrieve data regarding exits. A total of 621 exits were announced in India between 2001 and 2021. However, only 261 of these exits pertain to the sample

[3] Unfortunately, data regarding the date of birth and gender of the directors is not available on the Zauba platform. Therefore, the board characteristics studied in this paper are board size, board interlocks, and average tenure of directors.

[4] For this case, the term 'GCT TECHNOLOGIES PRIVATE LIMITED funding Eaglewings' was searched on google as Eaglewings was one of the investors as per the T1 dataset. The first result highlighted the following article https://www.vccircle.com/fintech-startup-galaxycard-bags-seed-funding-from-samyakth-capital-others, which shows that the product offered by GCT TECHNOLOGIES PRIVATE LIMITED is Galaxycard.

of 2704 firms in this dataset. Therefore, 2443 firms did not experience an exit. This dataset on exits is merged with the T1 dataset. As discussed in section 2.2, the different types of successful exit routes for VC backed firms in this sample are IPO and M&A.

The final sample encompasses 4826 investment rounds received by 2704 firms. These investment rounds were funded by 1336 different investors, out of which 404 firms were domestic while the remaining 932 firms were foreign. This sample is set up as an unbalanced panel dataset wherein each investee is tracked yearly from the year of its first VC investment. The last observation year for firms depends on whether they went out of business or continued operating. In this sample, the first possible observation year is 2001 while the last possible observation year is 2021. The total number of observations generated is 17,594. Table A1 (Appendix A) summarizes the different steps employed to construct the final dataset. Furthermore, table A2 (Appendix A) provides a breakdown of startups based on their industry classification (Panel A) and on the year of their first investment (Panel B). Finally, table A3 (Appendix A) provides a breakdown of startup exits based on their industry classification (Panel A) and on the year of their exit (Panel B).

4.2 Model – Survival Analysis

To test the effect of board characteristics on exit likelihood of Indian firms, a survival analysis technique is utilized. In this technique, the outcome variable (*Exit*) is modelled as the time until the event of interest takes place (Dominic & Gopalaswamy, 2019; Félix et al., 2012). The remaining part of this section, along with sections 4.2.1 and 4.2.2 are based on DeMaris (2004) and Allison (2010).

Unlike the Ordinary Least Squares (OLS) regression model, the survival analysis model does not rely on the assumption that the residuals are distributed normally. Another significant advantage of the survival analysis model over other models such as OLS and Logistic regression is its ability to handle censored data. In the context of this analysis, right-censoring is of key interest as only 261 (out of 2704) firms experienced an exit. Right censoring occurs when the event of interest (in this case, exit) occurs at time beyond the observation period (in this case, after 31/12/2021). The underlying assumption here is that if the number of periods was large enough, the exit event for each remaining firm would eventually have been observed.

Survival analysis models make use of the survival function S(t), which indicates the probability that an event does not occur before a certain time t. Given that the survival function is a probability, it falls between the interval [0,1]. Therefore, the survival function is modelled as:

$$S(t) = 1 - F(t) = P(T > t) \tag{1}$$

Another key component of survival analysis models is the hazard rate, which indicates the rate of failure. The hazard rate is the probability that an event will take place at time t, given that the event has not already occurred before time *t*. In this analysis, the hazard rate would highlight the probability that an investee experiences an exit at a certain time, given that it has not exited already. The hazard rate can either vary over time or remain constant over the study period. The hazard rate is modelled as the ratio of the probability density function and the survival function (DeMaris, 2004):

$$h(t) = \lim_{\Delta t \to 0} P(t < T \leq t + \Delta t \mid T > t) = \frac{f(t)}{S(t)} \tag{2}$$

4.2.1 Non-Parametric Estimation: Kaplan-Meier Survival Curve

The Kaplan-Meier estimator is a non-parametric technique to estimate the survival function. The Kaplan-Meier estimate at any time *t* is based on the following formula:

$$S(t_j) = \left(\frac{Total\ number\ of\ subjects_j - Number\ of\ subjects\ that\ experienced\ failure_j}{Total\ number\ of\ subjects_j}\right)$$

In the absence of censoring (which is usually unlikely), the Kaplan-Meier curve is merely the empirical distribution of the data. It is a univariate method of estimating survival over time, and hence, not adjusted for multiple covariates in a model. However, it provides useful information while comparing survival between groups. The Kaplan-Meier estimation technique has three assumptions (Kishore et al., 2010). Firstly, observations that are censored have the same survival probability as those that continue to be observed in the sample. Secondly, observations have the same survival probability regardless of their timing of joining the study. Finally, the event occurs at the time specified in the dataset. This assumption may not be satisfied in cases where observations are followed up periodically. However, this is not a cause for concern in this paper as the Kaplan-Meier curve is only used to provide descriptive information regarding the sample rather than to test the hypotheses mentioned in section 3. Moreover, observing firms on a yearly basis is in line with previous literature regarding VC backed firms as the level of granularity is detailed enough to analyze the exit likelihood of these firms (Clarysse et al., 2011; Yao & O'Neill, 2022).

In this paper, the Kaplan-Meier survival curves are estimated separately for investees that had at least one board interlock with their domestic investors versus those that did not.

Furthermore, the log-rank test is used to compare the difference in survival across these two groups. This test measures and compares the expected and actual events for each group. The null hypothesis under the log-rank test is that the difference in survival probability between these two groups is not statistically significant.

4.2.2 Semi-Parametric Estimation: The Cox PH Model

The cox PH model has been frequently used to analyze VC investments and exit likelihood of startups (Cumming & Johan, 2010; Cumming & MacIntosh, 2001; Gompers & Lerner, 1999). It is a semi-parametric method to perform survival analysis which allows for a multivariate regression approach. The hazard rate of an event, which is estimated using partial likelihood estimation, for individual *i* at time *t* when the model has *n* covariates is modelled as:

$$h_i t = h_0(t) * (e^{(\beta_1 x_{1it} + \cdots + \beta_n x_{nit})}) \tag{3}$$

When all covariates take the value of 0, the hazard rate of the event occurring for each individual is $h_0(t)$, which is known as the baseline hazard rate. A key component of this model is the hazard ratio, which is the ratio of the hazard rates of different individuals. The hazard ratio between two individuals *i* and *j* at time *t* when the model has n covariates is modelled as:

$$\widehat{HR} = \frac{h_i t}{h_j t} = \frac{h_0(t) * (e^{(\beta_1 x_{1it} + \cdots + \beta_n x_{nit})})}{h_0(t) * (e^{(\beta_1 x_{1jt} + \cdots + \beta_n x_{njt})})} \tag{4}$$

Assuming that x_1 is a binary variable and that individuals *i* and *j* differ only in terms of their values of x_1, wherein *i* takes the value 1 while *j* takes value 0, the hazard ratio simplifies to:

$$\widehat{HR} = e^{\beta_1} \tag{5}$$

Moreover, since the term $h_0(t)$ is cancelled out in equation (4) in the numerator and denominator while computing the hazard ratio, the cox PH model does not require any assumption to be met regarding the shape of the baseline hazard function. However, a critical assumption of this model is the PH assumption. Under this assumption, the hazard ratio for each variable is time-invariant, as also indicated in equation (5). To test whether the PH assumption holds, this paper analyzes the Schoenfeld residuals test for each explanatory variable separately and the global cox PH model (Allison, 2010; Hess, 1995; Pommet, 2017). If the Schoenfeld residuals for an explanatory variable exhibit a non-random time trend (i.e., correlated with time), the PH assumption is said to be violated for that variable.

4.3 Variables

4.3.1 Dependent Variable

Exit

Given that the cox PH model is used in this paper, the dependent variable is the hazard that a firm experiences a successful exit (IPO or M&A) in a given year. Therefore, *Exit* is a binary variable that takes value 1 if the firm experienced an IPO or an M&A during a given year and 0 otherwise.[5] As highlighted in section 4.1, only 261 firms experienced an exit. Out of the remaining 2443 firms, one firm was declared defunct before 2021 while the remaining 2442 firms survived. These 2442 firms are said to be right-censored, as explained in section 4.2.

4.3.2 Board Characteristics

Interlock

Interlock is measured as a binary variable that takes value 1 for a year if there was at least one common director serving the board of an investee and that of its domestic investors during that year and 0 otherwise.

Board Size

Board Size measures the number of active directors sitting on an investee's board each year. Therefore, this variable is discrete in nature as it can only take whole number and non-negative values.

Tenure

Tenure measures the average duration (in years) served on an investee's board each year by active board members. Therefore, this variable is continuous in nature.

4.3.3 Control Variables

Location

Giot and Schwienbacher (2007) asserted that locating in a well-developed entrepreneurial cluster improves the likelihood of VC backed firms to experience an exit. They argue that such firms can establish influential business contacts quickly and learn from firms with similar entrepreneurial goals, which drastically reduces information and monitoring costs for investors. This finding was verified by Chen et al. (2010), who documented that VC-backed firms located in the traditional VC centers in the United States (San Francisco, Boston, and New York) are more

[5] If a firm experiences the exit, all observations for subsequent years pertaining to that firm are automatically dropped in survival analysis models.

likely to experience an IPO relative to firms located in other cities. Hence, it is expected that firms headquartered in a major Indian city are more likely to experience an exit relative to firms that are headquartered in other locations, keeping other variables fixed.

Following the procedure employed by Goerzen et al. (2013), all Indian cities that were categorized as ‘Alpha’, ‘Beta’, or ‘Gamma’ in the year 2020 by the Globalization and World Cities (GaWC) network are identified as major cities in this paper. The GaWC network has released a world-cities ranking list for 2000, 2004, 2008, 2010, 2012, 2016, 2018, and 2020 (Loughborough University, 2020). However, in the context of India, the same eight cities have appeared in the major cities list since 2012 as per the GaWC classification. These eight cities are Ahmedabad, Bangalore, Chennai, Delhi, Hyderabad, Kolkata, Mumbai, and Pune (The Globalization and World Cities Research Network, 2020). Therefore, *Location* is a binary variable that takes value 1 if the investee is headquartered in a major city and 0 otherwise.

Funding

The investment value is a crucial determinant of the exit likelihood of a startup. Cumming and Johan (2008a) argued that holding an investment for a long time increases the marginal cost incurred by investors as VC investments are typically illiquid in the short run. Hence, VC investors look to minimize the duration taken by portfolios to exit. In a similar vein, Giot and Schwienbacher (2007) identified that as funding available to US investees increases, the time taken to exit decreases. Furthermore, large investment amounts received by investees may also signal to the market regarding their quality and future growth opportunities, which may facilitate a faster exit (Espenlaub et al., 2015). Therefore, it is expected that as funding amount increases, exit likelihood increases, keeping other variables fixed.

This variable measures the total funding amount received by an investee up until the observation year and is valued in USD millions. Hence, *Funding* represents the cumulative funding for an investee and is a continuous variable.

Later Stage

The investment stage of a firm in a given year could play a huge role in influencing its exit likelihood. This is because the investment stage can be used by investors and market participants to assess project specific risk. If a firm is at the seed stage as opposed to expansion stage, it may need to raise additional funding and gain more market expertise to develop its business model and offerings (Panda & Gopalaswamy, 2020). Several papers have shown that the financing stage of

VC backed firms affects their exit likelihood. For instance, Cumming and Johan (2008b) found that Canadian VC backed early-stage firms are less likely to go public than later-stage firms. Therefore, it is expected that relative to other firms, those firms that are at a later funding stage are more likely to experience an exit, keeping other variables fixed.

Following Félix et al. (2012), *Later Stage* is a binary variable that takes value 1 if the investee was at the 'Expansion' or 'Later' stage and 0 if it was at the 'Seed' or 'Early' stage at the end of a given year.

Investors

Previous studies have shown that syndicate size significantly impacts exit likelihood of VC backed firms (Dai et al., 2012; Khurshed et al., 2020). This is because investee firms can leverage the network of each investor to build influential connections. Moreover, the investee may be able to gain valuable information on best practices as a larger syndicate is more likely to have complementary skills (Félix et al., 2012; Nguyen & Vu, 2021). Finally, a larger syndicate may also be able to successfully lobby the entrepreneur to sell in case of declining performance (Espenlaub et al., 2015). Therefore, it is expected that as syndicate size increases, exit likelihood increases, keeping other variables fixed.

In this paper, this variable represents the total number of unique investors that the investee has received funding from until the observation year. Therefore, it measures the cumulative number of unique investors and can only take discrete non-negative values.

Industry Fixed Effects

Finally, systematic risks and differences across industries are controlled for using industry fixed effects. This is because exit might be more viable and easier in some industries relative to others (Giot & Schwienbacher, 2007; Wang & Wang, 2012). An economic sector is assigned to each investee using the Thomson Reuters Business Classification (TRBC) given that the T1 database does not have complete information regarding North American Industry Classification System (NAICS) and Standard Industrial Classification (SIC) codes, which are most widely used in VC literature, for Indian startups (Bani-Harouni et al., 2021).

Keeping in mind the basic equation form of the cox PH model (see equation 3) and the above-mentioned variables, the final equation estimated in this paper regarding the hazard of exit for firm *i* at time *t* is of the following form:

$$h_i(t) = h_0(t) * \left(e^{\left(\beta_1 Interlock_{it} + \beta_2 Board\ Size_{it} + \beta_3 Tenure_{it} + \beta X_{it} + \mu_i\right)}\right) \quad (6)$$

In this equation, $h_0(t)$ represents the baseline hazard function while X is a vector of control variables discussed in section 4.3.3. Finally, μ_i controls for industry fixed effects.

4.4 Descriptive Statistics

Table 1

Summary Statistics

Variable	Definition	Mean	SD	Min	Max
(1) Exit	Binary = 1 if the investee experienced a successful exit in that year	0.01	0.12	0.00	1.00
(2) Interlock	Binary = 1 if the investee had at least one common board member with a domestic investor during the year	0.11	0.31	0.00	1.00
(3) Board Size	Count of number of directors serving on the board of the investee firm at the end of the year	4.24	2.47	0.00	18.00
(4) Tenure	The average tenure of active board members of the investee firm at the end of the year	5.98	3.99	0.00	30.24
(5) Investors	The total number of unique investors that had invested in the investee firm in that year or prior	2.53	2.41	1.00	41.00
(6) Funding[6]	The cumulative funding received by an investee until a given year	22.72	152.22	0.00	9708.50
(7) Later Stage	Binary = 1 if the investee was at the 'Expansion' or 'Later' funding stage by the end of the year	0.60	0.49	0.00	1.00
(8) Location	Binary = 1 if the investee is headquartered in a major city	0.79	0.40	0.00	1.00

Note. The number of observations for all variables is 17,594.

Table 1 illustrates the summary statistics of different variables used in the cox PH model. The mean value of *Exit* indicates that only 1% of the observations relate to a successful exit event.

[6] The lowest funding value is USD 0.0014 million.

The mean value of *Interlock* indicates that 11% of the observations relate to cases wherein an investee has at least one interlock with its domestic VC investor. The mean value of *Board Size* indicates that the average number of board members is 4.24. Finally, the mean value of *Tenure* implies that the average tenure of board members is 5.98 years.

Table 2

Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Exit	1.00							
(2) Interlock	0.02***	1.00						
(3) Board Size	0.07***	0.15***	1.00					
(4) Tenure	-0.03***	-0.08***	0.10***	1.00				
(5) Investors	0.04***	0.12***	-0.01*	-0.14***	1.00			
(6) Funding	0.03***	0.02***	0.05***	0.01*	0.39***	1.00		
(7) Later Stage	0.02***	0.04***	0.33***	0.33***	0.04***	0.08***	1.00	
(8) Location	0.01	0.05***	-0.01*	-0.01*	0.02**	-0.01	-0.06***	1.00

Note. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively.

Table 2 illustrates the pairwise correlations between different variables used in the cox PH model. The highest correlation between the covariates is 0.39 (between *Funding* & *Investors*). Furthermore, the maximum Variance Inflation Factor (VIF) of all covariates used in tables 3, 4, and 5 is 1.30 (for *Later Stage*), which is well below the generally accepted level of 10 (Hair et al., 2013). Evidently, high multicollinearity is unlikely to be a problem in the analysis.

5. Results

5.1 Non-Parametric Estimation Results

5.1.1 Smoothed Hazard Estimate

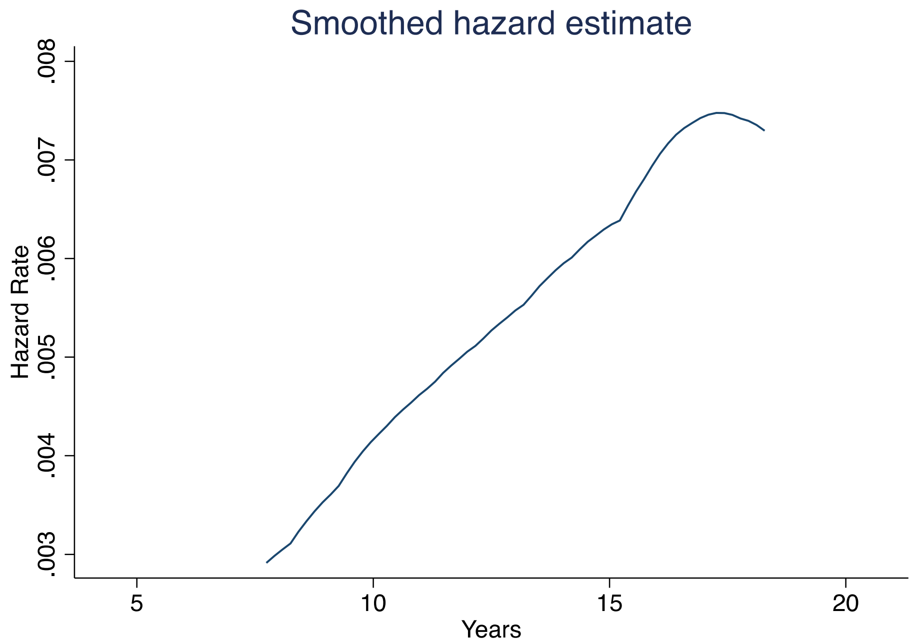

Figure 1. Smoothed Hazard Estimate of Successful Exits
Note. Number of subjects is 2704 and number of failures (successful exits) is 261. Analysis time is shown in intervals of five years. Total analysis time at risk is 55,259 and total number of periods is 21. The last exit is observed at t = 21 years.

Figure 1 illustrates the hazard of exit for investees over time (in years). Although the relation is non-monotonic when viewed in totality, the depicted relationship is positive between years 7 to 17. The probability of exit for a given investee initially increases steadily from 0.3% in year 7 to about 0.75% in year 17. After year 17, this probability drops slightly. Therefore, the figure shows that likelihood of exit increases over time; however, the probability of exit for companies that have not exited within 17 years of their first funding reduces slightly. This result is logical as firms can gather information about the market and establish best practices over time to maximize their exit likelihood. However, firms that have not exited for a long period may see their chances of exiting decline. Over time, startups may lose their competitive advantage as large competitors may imitate their methods or startups with new technologies may enter the market, rendering the previous ones obsolete. Another possible explanation for this phenomenon is that many firms prefer to stay private rather than going public to maintain confidentiality and avoid high regulatory compliance costs that public firms must bear (Chemmanur et al., 2020).

5.1.2 Kaplan-Meier Survival Curve: All Investments

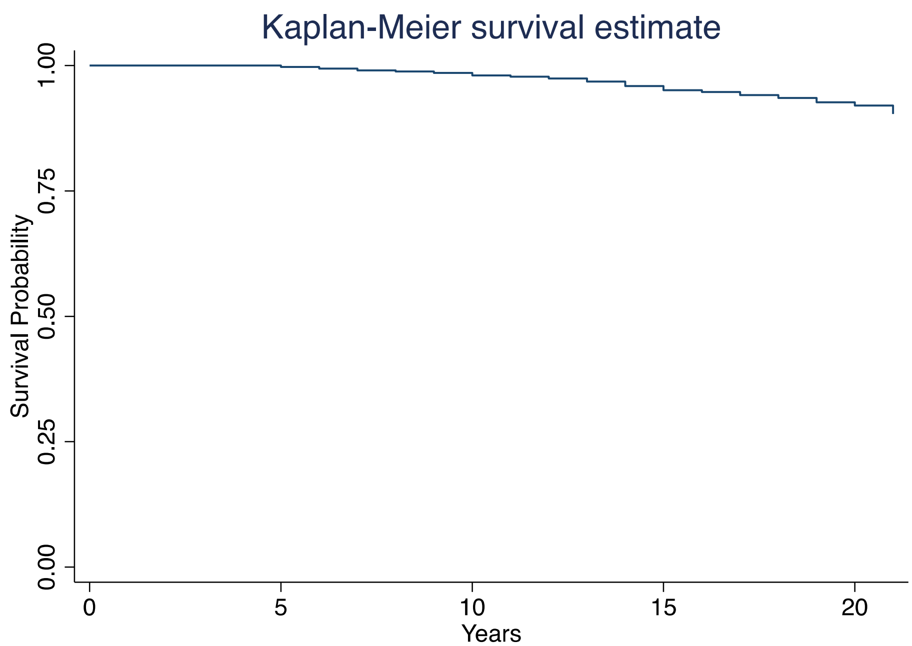

Figure 2. Kaplan-Meier survival curve, ungrouped
Note. Analysis time is shown in intervals of five years. The total number of observations is 17,594 and number of unique firms is 2704. Total analysis time at risk is 55,259 and total number of periods is 21. 261 firms experienced an exit while the remaining 2443 firms did not.

Figure 2 shows the survival probability over time. At time 0, the probability of surviving was 1. Naturally, this probability reduces over time as firms begin to exit. At period 21, the survival probability was approximately 0.9. This implies that 90% of the firms in this sample did not experience a successful exit by 2021.

5.1.3 Kaplan-Meier Survival Curve: Interlock = 1 vs. Interlock = 0

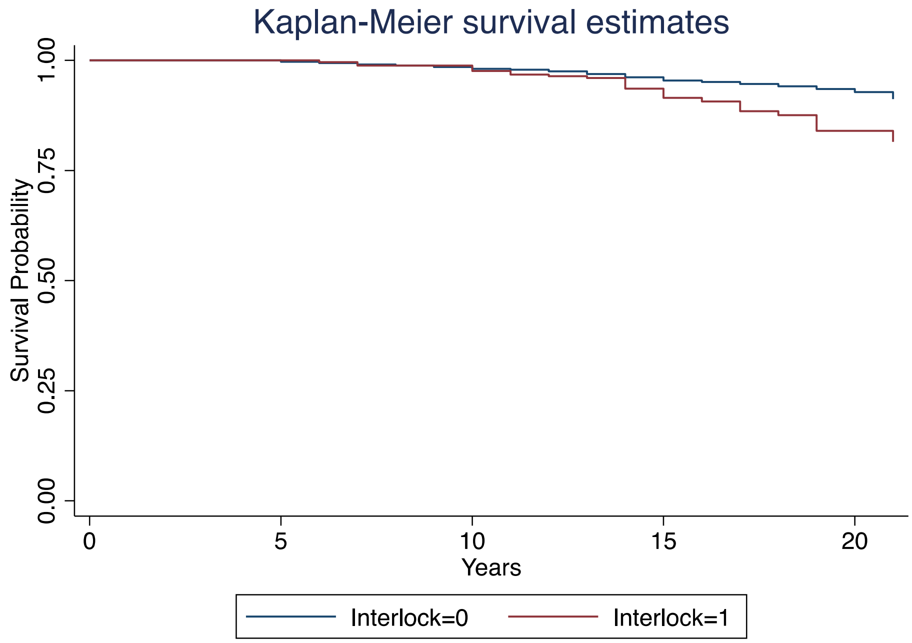

Figure 3. Kaplan-Meier survival curve, Interlocks vs. No Interlocks
Note. Analysis time is shown in intervals of five years. The total number of observations is 17,594 and number of unique firms is 2704. Total analysis time at risk is 55,259 and total number of periods is 21. 261 firms experienced an exit while the remaining 2443 firms did not. The difference between the curves is statistically significant at the 1% significance level as the chi^2 (1) value is 23.33.

Figure 3 compares the survival probability over time for firms that had at least one board interlock with their domestic investors with that of firms that had no board interlocks with their domestic investors. Evidently, the survival probability of both groups reduces over time. However, the survival probability reduces faster for firms with board interlocks than for firms without an interlock. For instance, at time 21, the survival probability of firms with board interlocks was about 0.80 while that of firms without interlocks was about 0.90. The log-rank test (discussed in section 4.2.1) indicates that this difference in survival probabilities between the two groups is statistically significant at the 1% level.

5.2 Semi-Parametric Estimation Results

This section presents the regression results of the cox PH model to analyze the impact of board characteristics of VC backed firms on their exit likelihood.

Table 3

Estimated Coefficients for Hazard of Exit

Variables	(1) Exit	(2) Exit	(3) Exit
Time Invariant Coefficients			
Board Interlock = 1	0.2928	0.3368*	0.3322*
	[0.1808]	[0.1799]	[0.1802]
Board Size	0.3041***	0.2996***	0.3000***
	[0.0242]	[0.0239]	[0.0239]
Tenure	-0.0364*	-0.0234	-0.0236
	[0.0207]	[0.0200]	[0.0199]
Investors	0.0027	0.0159	0.0158
	[0.0298]	[0.0287]	[0.0288]
Funding	0.0005	0.0005	0.0005
	[0.0003]	[0.0003]	[0.0003]
Location = 1	0.1834	0.1768	0.1764
	[0.1637]	[0.1616]	[0.1618]
Later Stage = 1	0.7269***	[Omitted due to stratification]	3.6403***
	[0.1622]		[0.6177]
Time Variant Coefficients (TVC)			
Later Stage = 1	-	-	-0.1889***
	-	-	[0.0366]
Observations	16,070	16,070	16,070
Number of Firms/Clusters	2,704	2,704	2,704
Number of Failures	261	261	261
Time at Risk	55,259	55,259	55,259
Industry Fixed Effects	Yes	Yes	Yes
Stratified	No	Yes	No

Note. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. Standard errors, which are clustered at the firm level, are depicted in square brackets. Number of clusters in each model is 2704. Efron approximation method is used to break ties (Gimmon & Levie, 2021). The dataset contains 17,594 observations; however, 1524 observations relate to observations belonging to a period after the exit was observed. Hence, these cases are dropped automatically. Total analysis time at risk is 55,259 and total number of periods is 21. Model 2 is stratified based on the *Later Stage* variable. In Model 3, the Time Varying Coefficients (TVCs) have been interacted with t (linear function of time) to account for the time trend.

Table 3 presents the results of the cox PH model. Model 1 presents the results of the base model (see equation 6). However, the Schoenfeld residuals test (explained in section 4.2.2) indicates that the PH assumption was not met for the variable *Later Stage*. Moreover, the test for the overall model is significant at the 1% level, which implies that the PH assumption is violated for the model. This indicates that the results in model 1 cannot be used for statistical inference. Two options are available to overcome this problem (Kleinbaum, 2011).

The first method involves stratifying the model based on the variables that do not meet the PH assumption. In this method, the baseline hazard function (i.e., $h_0(t)$), is allowed to vary for the different values of the stratified variable. However, it is assumed that the underlying coefficient of that variable (β) is the same for all values of that variable. The drawback of this method is that the coefficient of the stratified variable cannot be estimated. Therefore, Model 2 presents the results when *Later Stage* is stratified. The Schoenfeld residuals test reveals that the PH assumption is satisfied for all variables and the overall model as well.

The second method involves allowing for variables that do not meet the PH assumption to vary with time. Therefore, these variables are interacted with time. The Schoenfeld residuals test reveals that the PH assumption is satisfied for all variables and the global model as well. Furthermore, figures B1 to B7 (Appendix B) provide the plot for the Schoenfeld residuals over time for each covariate in the model. The figures show that the slope is zero for all variables, which confirms that the PH assumption was met after accounting for time varying coefficients. A Wald test shows that the coefficients of *Later Stage* (both time variant and time invariant coefficients) are statistically different from 0 at the 1% level. Therefore, the second method is preferred for this analysis and the subsequent discussion is based on model 3. Nevertheless, both models provide nearly identical results regarding the effect of board characteristics on hazard of exit.

The results indicate that the coefficient of *Interlock* is positive and significant at the 10% level. This result provides evidence in support for H_1. The estimate indicates that the hazard rate of a successful exit for firms that have at least one interlock with their domestic investors is 1.39 (computed as $e^{0.3322}$) times the hazard rate of exit for firms that do not have an interlock with their domestic investor, keeping other variables fixed. This result is line with Garg's (2013) claim that relative to other firms, startups with board interlocks with their investors are more likely to exit via an M&A or IPO.

Furthermore, the results indicate that the coefficient of *Board Size* is positive and significant at the 1% level. This result provides evidence in support for H_2. The estimate indicates that as the board size increases by one director, the hazard rate of a successful exit increases by 34.98% (computed as $e^{0.3000} - 1$), keeping other variables fixed. This result also resonates with Naoko and Yutaka's (2016) finding that an increase in board size increases the likelihood of VC backed Japanese firms to go public.

Finally, the coefficient of *Tenure* is negative and not significant at the 10% level. Therefore, no evidence is found in support for H_3. A change in average tenure of the board does not lead to a change in the hazard rate of a successful exit, keeping other variables fixed.

The coefficients for the controls *Location*, *Investors,* and *Funding* are positive as expected but not significant at the 10% level. Interestingly, the results show a strong impact of *Later Stage*. The hazard rate of exit for firms that are a later stage of financing is initially 38.10 (computed as $e^{3.6403}$) times the hazard rate of exit for firms that are not at a later stage of financing, keeping other variables fixed. However, the Time Varying Coefficient (TVC) of *Later Stage* indicates that as time increases by 1 year, this hazard ratio reduces by 17.21% (computed as $e^{-0.1889} - 1$). These effects are significant at the 1% level.

Overall, the results in model 3 indicate that H_1 and H_2 are supported while H_3 is not.

6. Robustness Analyses

Table 4

Estimated Coefficients for Hazard of Exit

Variables	(1) Exit (IPOs only)	(2) Exit (M&As only)
<u>Time Invariant Coefficients</u>		
Interlock = 1	0.5616**	-2.0525**
	[0.2778]	[0.9500]
Board Size	0.3025***	0.1942***
	[0.0787]	[0.0300]
Tenure	-0.0117	-0.0358
	[0.0357]	[0.0237]
Investors	0.0636	-0.0053
	[0.0436]	[0.0342]
Funding	0.0005**	0.0041***
	[0.0002]	[0.0011]
Location = 1	0.7484	2.4842**
	[0.7166]	[1.1866]
Later Stage = 1	2.0903***	2.6436***
	[0.4396]	[0.7522]
<u>Time Variant Coefficients (TVC)</u>		
Interlock = 1	-	0.1422***
		[0.0533]
Board Size	0.0054	-
	[0.0054]	
Funding	-	-0.0001***
		[0.0000]
Location = 1	-0.1098**	-0.1023
	[0.0507]	[0.0655]
Later Stage = 1	-	-0.1388***
		[0.0436]
Observations	16,822	16,842
Number of Firms/Clusters	2,704	2,704
Number of Failures	90	171
Time at risk	56,011	56,031
Industry Fixed Effects	Yes	Yes
Stratified	No	No

Note. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. Standard errors, which are clustered at the firm level, are depicted in square brackets. Efron approximation method is used to break ties (Gimmon & Levie, 2021). The dataset contains 17,594 observations; however, 772 and 752 observations in models 1 and 2 respectively relate to observations belonging to a period after the exit was observed. Hence, these cases are dropped automatically. In each model, the TVCs have been interacted with t (linear function of time) to account for the time trend.

Table 4 depicts the results of the cox PH model when the definition of a successful exit varies. In model 1, only IPOs are considered as successful exit events. On other hand, in model 2, only M&As are considered as successful exit events. In each case, a model identical to model 1 in table 3 (see equation 6) is run to identify if the PH assumption was met. All variables for which this assumption is violated are allowed to vary with time. The PH assumption is not met for *Board Size* and *Location* in model 1 while it is not met for *Interlock*, *Funding*, *Location*, and *Later Stage* in model 2. The results in both models are consistent with those found in table 3 with regards to *Board Size* and *Tenure*. This provides further evidence that H_2 is supported while H_3 is not. However, the effect of *Interlock* in table 4 is particularly interesting as the results illustrate heterogeneous effects of *Interlock* on hazard of successful exit.

In model 1, the coefficient of *Interlock* is positive and significant at the 5% level. This result is consistent with the results in table 3. Therefore, H_1 is supported when only IPOs are considered as successful exit events.

On the other hand, in model 2, the time invariant coefficient of *Interlock* is negative and significant at the 5% level. Additionally, the TVC of *Interlock* is positive and significant at the 1% level. This result shows that the hazard rate of exit for firms that have board interlocks with their domestic investors is initially only 0.13 (computed as $e^{-2.0525}$) times the hazard rate of exit for firms that do not have any board interlocks, keeping other variables fixed. However, this hazard ratio increases by 15.28% (computed as $e^{0.1422} - 1$) as time increases by 1 year, keeping other variables fixed. Therefore, H_1 is only partially supported as the effect of *Interlock* is initially negative and increases only over time. Overall, these results lend only partial support for H_1, and the effect of *Interlock* on hazard of exit depends on how a successful exit event is defined.

Several mechanisms help explain this result regarding H_1. In the IPO scenario, the CEO is likely to continue leading the firm while in the M&A scenario, they are likely to lose control and may be subject to more oversight from the acquiror (Broughman & Fried, 2013). A threat to their control over the company may cause them to fend such offers away. Even if the founding team is not concerned about control over the firm after an M&A, they might want to forgo an offer in the hopes of taking the firm public in the future. On the other hand, under certain circumstances, the VC firm may reject an M&A offer if the financial return is not high enough even if the founding firm is interested in accepting the offer. In the case of an IPO, conflicts are less likely to arise as it results in mutually beneficial gains for investees and investors. This result is in line with the expectations of Tripathi and Sharma (2018). The CEO earns the prestige of leading a publicly listed firm while the VC firm obtains a sound financial return. Therefore, the likelihood of a conflict of interest between the VC firm and investee is higher under the M&A scenario relative to the IPO scenario, wherein their interests tend to be aligned (Cumming et al., 2017). However, over time, a board interlock between investors and investees may lead to an alignment of interests and homogeneity in opinions and beliefs (Shepherd & Zacharakis, 2001). With time, the investor-investee relationship strengthens, which facilitates faster conflict resolution and thus, the hazard rate of M&A increases over time for firms that have interlocks relative to firms that do not have any interlocks, keeping other variables fixed.

Table 5

Estimated Coefficients for Hazard of Exit

Variables	(1) Major Cities Exit	(2) Non-Major Cities Exit
Time Invariant Coefficients		
Interlock = 1	-0.9020	2.5572**
	[0.6129]	[1.2878]
Board Size	0.2808***	0.3999***
	[0.0263]	[0.0545]
Tenure	-0.0134	-0.0774
	[0.0214]	[0.0549]
Investors	-0.0092	0.1085**
	[0.0354]	[0.0483]
Funding	0.0006	0.0003**
	[0.0004]	[0.0002]
Later Stage = 1	3.7416***	1.9723***
	[0.6959]	[0.5239]
Time Variant Coefficients (TVC)		
Interlock = 1	0.0869**	-0.1866**
	[0.0382]	[0.0932]
Later Stage = 1	-0.2113***	-
	[0.0418]	
Observations	12,702	3,368
Number of firms/Clusters	2,091	613
Number of failures	212	49
Time at Risk	42,642	12,617
Industry Fixed Effects	Yes	Yes
Stratified	No	No

Note. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. Standard errors, which are clustered at the firm level, are depicted in square brackets. Efron approximation method is used to break ties (Gimmon & Levie, 2021). In model 1, the dataset contains 13,970 observations; however, 1,268 observations relate to a period after the exit was observed. In model 2, the dataset contains 3,624 observations; however, 256 observations relate to a period after the exit was observed. Hence, these cases are dropped automatically. In each model, the TVCs have been interacted with t (linear function of time) to account for the time trend.

Table 5 depicts the results of the cox PH model when the sample is divided based on the headquarters of investee firms. In model 1, the sample includes only those investees that are headquartered in major Indian cities. In contrast, in model 2, the sample includes only those investees that are not headquartered in major Indian cities. Like in the case of table 4, a model identical to model 1 in table 3 (see equation 6) is run to identify if the PH assumption was met. All variables for which this assumption is violated are allowed to vary with time. The results in both models are consistent with those found in table 3 and 4 with regards to *Board Size* and *Tenure*. This provides further evidence that H_2 is supported while H_3 is not. Like in table 4, the results regarding the effect of *Interlock* on hazard of exit is heterogenous.

In model 1, the time invariant coefficient of *Interlock* is not significantly different from 0 at the 10% level. However, the TVC of *Interlock* is positive and significant at the 5% level. This implies that the hazard rate of exit for firms that have interlocks with their domestic investors is initially not different from the hazard rate of exit for firms that do not have any interlocks, keeping other variables fixed. However, relative to other firms, the hazard rate of exit for firms that have at least one board interlock with their domestic investor increases by 9.07% (computed as $e^{0.0869} - 1$) as time increases by one year, all other variables being equal. This result provides partial support for H_1.

In model 2, the hazard rate of exit for firms that have at least one interlock with their domestic investor is initially 12.89 (computed as $e^{2.5572}$) times the hazard rate of exit for firms that do not have any interlocks with their domestic investors, keeping other variables fixed. However, the TVC of *Interlock* indicates that as time increases by 1 year, this hazard ratio reduces by 17.02% (computed as $e^{-0.1866} - 1$), keeping other variables fixed. These effects are significant at the 5% level. Again, this result provides partial support for H_1.

The explanation behind the impact of *Interlock* in model 2 lies in the roots of signaling theory (Deutsch & Ross, 2003). As explained in section 3, information asymmetry is an inherent feature of VC-Investee relationships. Investors face significant search costs to seek out optimal investment opportunities and incur high monitoring costs to mitigate the moral hazard issue. Furthermore, VC firms exhibit strong geographical bias as they prefer to invest in firms located in well-developed regions (Bassens & Meeteren, 2014; Giot & Schwienbacher, 2007). Hence, when VC firms invest in a firm headquartered in a non-major city, it conveys a positive signal to the market regarding the quality of the investee (Ragozzino & Blevins, 2016). The investee firm may gain traction and receive attractive offers from more investors and potential acquirors. However, over time, this signal may become weak as investors would assess firms on hard information such as revenue and profit growth. Consequently, board interlocks may become less important over time.

In contrast, board interlocks for investees located in major cities may not convey additional signals to the market due to a high concentration of investments in such cities. Firms with board interlocks do not have an advantage initially over firms with no interlocks as the network influence in initial periods is not strong enough. However, as more information becomes available about these startups, interlocks play an important role in improving exit likelihood as social capital becomes crucial (Alexy et al., 2011). Interlocks may help investees in quickly wrapping up the exit process, such as conducting a pre-IPO due diligence or expediting the IPO approval process, through important political and business connections (Bao et al., 2016; Liu et al., 2020).

7. Limitations and Future Research

This study has several limitations that warrant further attention. The following section highlights how the data used in this paper can be enhanced and how the scope of this study can be extended to improve external validity.

To begin with, board information is not available for 43 domestic investors (out of 404 in the final sample), and it is assumed that these investors did not have board interlocks with their investees. It is possible that some of these investors had board interlocks with investees and availability of this data would have increased confidence in the results obtained. However, no VC database is complete with regards to VC investments in India (and countries outside of the US and Europe in general), and manual work is needed on the part of the researcher to fill gaps (Dai et al., 2012; Kaplan & Lerner, 2017). Further study in this area would require compiling information from multiple databases like Venture Intelligence, Preqin, Tracxn, and T1. Moreover, this study focuses on the role of board interlocks between investees and their domestic investors. This is because board data is not available for foreign firms. Therefore, it would be imperative to compile a list of board members of foreign investors and assign a unique identifier to them (such as the DIN in case of directors of Indian firms) to facilitate the matching process. The resulting dataset can then be used to extend the results of this analysis to assess the impact of board interlocks between investees and all investors.

Additionally, due to lack of data, the effect of several crucial board characteristics such as gender diversity and frequency of board meetings is not considered. Moreover, the background of the founding team, such as previous experience with exits and educational qualifications, is also not considered. Several papers have shown that these characteristics impact the exit likelihood of startups (Guo et al., 2015; Krishna & Subrahmanya, 2019). Finally, VC firms are not distinguished based on their type. Corporate VC firms are generally more interested in gaining access to new technologies by investing in startups while Independent VC firms are driven purely by profit motive (Chemmanur et al., 2014). Hence, further studies in this area must highlight how the inclusion of such characteristics influences the exit likelihood of startups.

Furthermore, this paper considers exit events as an indicator of successful performance of VC backed firms. However, financial performance of firms that have not yet exited is equally important. Several promising startups delay their exits to hone their offerings and obtain higher valuations, especially since PE and VC funding has grown recently (Kerai, 2017; Sahu et al., 2009; Thomas, 2017). For instance, Delhivery, which is one of the most prestigious startups in India, delayed its intention to go public as uncertain market conditions made it unlikely for its target valuation to be achieved on the initially intended IPO listing day (Thathoo, 2022). Therefore, to complement this analysis, the effect of board characteristics on key financial indicators such as revenue growth and profit margins must also be studied.

In relation to the above-mentioned limitation, this study does not consider the valuation premium when the exit event occurs. Experiencing an IPO or an M&A might not provide conclusive evidence regarding a successful exit. For instance, a distressed firm might be taken over by a competitor at a modest valuation. Similarly, the opening price on the IPO listing date may not meet the expectations of investors. Consequently, an in-depth analysis could be conducted by factoring in the exit premium (forecasted firm value upon exit – actual firm value at the exit event).

Moreover, the dataset retrieved from T1 regarding VC investments in India is likely to suffer from survivorship bias (Kaplan & Lerner, 2017; Karsten, 2018). In this sample, only one firm was marked as 'defunct'. Information regarding firms that were unable to make it past their initial funding rounds is unlikely to be available on VC databases. However, it is a common phenomenon that many startups fail, and exclusion of such firms could imply that the sample selected may not be completely random. In future studies, information on such firms would have to be included to ensure that the sample is representative of the population of VC backed firms.

Finally, the VC landscape in India has gained extensive traction only in the last few years. About 56% of the firms in the sample used in this paper received their first VC investment in 2016 or later (see Table A2 in Appendix A). In contrast, the VC environment is well-established in USA and Europe (Mustafa, 2019). Given that VC ecosystem was underdeveloped during much of the sample period, the impact of board characteristics could be minimal as exit of firms may have been purely driven by their financial performance and earnings potential. A more developed VC environment implies that firms that can establish strong connections with investors quickly may obtain preferential treatment and hence, may exit faster relative to firms with limited connections. Therefore, studying the effect of board characteristics on exit likelihood would be even more crucial in the future as the importance of building connections through board interlocks may be even more pronounced.

8. Conclusion and Discussion

Notwithstanding the above-mentioned limitations, this paper adds to the literature regarding the importance of governance in VC backed firms. The results indicate that board size and board interlocks have a positive and significant impact on exit likelihood of startups while average tenure of directors does not impact their exit likelihood. Further robustness analyses reveal that while the impact of board size is consistent across different models and sub-samples, the impact of board interlocks is heterogenous and varies over time. For instance, firms with interlocks have a higher hazard rate of going public relative to firms without interlocks. On the other hand, firms with interlocks have a lower hazard rate of being involved in an M&A initially relative to firms without interlocks. However, this hazard rate improves over time.

These findings present several implications for founders of startups. Although founders prefer maintaining maximum control over their startups, they must consider increasing the size of their board if their ambition is to experience a successful exit. A larger board size increases the legitimacy of a firm from the perspective of market participants. Furthermore, a larger board size can help firms maintain their edge as more directors can evaluate strategic plans objectively and recommend steps to maximize their efficacy. These recommendations resonate with Wasserman's (2008) and Naoko and Yutaka's (2016) findings. Additionally, board interlocks with investors are crucial for startups that have the ambition of going public or being involved in an M&A. This is because these outside directors provide signals to the market regarding the quality of the startup, enhance knowledge of startups regarding unfamiliar processes involved in IPOs and M&As, and help startups establish influential connections. However, CEOs must also consider the fit with outside directors regarding their ideologies as differences in opinions may lead to conflicts, which could delay exit. This finding is especially critical in the case of M&A's as inside and outside directors may value factors such as prestige, investment return, and autonomy differently.

These findings also yield several implications for VC investors. VC firms can improve the exit likelihood of their investees by taking up board positions in them and helping them build networks and make the right strategic choices. Taking up an active role in guiding their investees implies that VC firms must optimize their portfolio size to ensure that sufficient time is allocated to each investee. Finally, the investment criteria used by VC firms for their investment decisions include background of the founding team, market characteristics, and product innovativeness, amongst others (Kollmann & Kuckertz, 2010). In accordance, VC firms could also use board size as an additional criterion to assess potential investees as it may indicate the willingness of the founding team to give up control and to expedite the exit process.

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Appendix A
Data Description

Step	Name	Explanation	Remaining number of investees
1	ThomsonOne VentureXpert Database	Indian firms that received their first VC investment on or after 1/1/2001 until 31/12/2021	3324
2	Missing CIN numbers	Those firms that had a missing CIN value are deleted as it would not be possible to identify their board characteristics	3127
3	Missing DIN numbers	Those firms that had a CIN value but no information on board characteristics are deleted. Board data is then merged with the T1 dataset	3073
4	Investment Value - Zero	Firms that had at least one investment round of USD 0 are deleted	2800
5	Unrealistic Exit Duration	Those firms that had an exit date before their first VC investment date are deleted	2791
6	Age > 25 Years	Those investees that were incorporated more than 25 years before their first investment are deleted	2704
7	Merge Exit Data	Information regarding exits is merged with the T1 dataset	2704

Table A1. Steps involved in Dataset Construction

Breakdown of Firms

Panel A. Industry

TRBC Economic Sector	Number of Firms	% of Total Firms
Academic & Educational Services	76	2.81%
Basic Materials	31	1.15%
Consumer Cyclicals	326	12.06%
Consumer Non-Cyclicals	236	8.73%
Energy	23	0.85%
Financials	161	5.95%
Government Activity	1	0.04%
Healthcare	226	8.36%
Industrials	330	12.20%
Real Estate	22	0.81%
Technology	1,251	46.26%
Utilities	21	0.78%
Total	**2704**	**100.00%**

Panel B. First Investment Year

Year	Number of Firms	% of Total Firms
2001	35	1.29%
2002	18	0.67%
2003	21	0.78%
2004	22	0.81%
2005	24	0.89%
2006	74	2.74%
2007	83	3.07%
2008	96	3.55%
2009	62	2.29%
2010	83	3.07%
2011	109	4.03%
2012	150	5.55%
2013	102	3.77%
2014	96	3.55%
2015	197	7.29%
2016	140	5.18%
2017	115	4.25%
2018	169	6.25%
2019	220	8.14%
2020	319	11.80%
2021	569	21.04%
Total	**2704**	**100.00%**

Table A2. Breakdown of Firms

Breakdown of Exits

Panel A. Industry

TRBC Economic Sector	Number of Firms	% of Total Exits
Academic & Educational Services	3	1.15%
Services	0	0.00%
Basic Materials	3	1.15%
Consumer Cyclicals	38	14.56%
Consumer Non-Cyclicals	13	4.98%
Energy	5	1.92%
Financials	21	8.05%
Government Activity	0	0.00%
Healthcare	18	6.90%
Industrials	39	14.94%
Real Estate	2	0.77%
Technology	114	43.68%
Utilities	5	1.92%
Total	**261**	**100.00%**

Panel B. Exit Year

Year	Number of Firms	% of Total Exits
2001-2004	0	0.00%
2005	8	3.07%
2006	8	3.07%
2007	10	3.83%
2008	6	2.30%
2009	8	3.07%
2010	13	4.98%
2011	7	2.68%
2012	10	3.83%
2013	16	6.13%
2014	24	9.20%
2015	23	8.81%
2016	10	3.83%
2017	16	6.13%
2018	16	6.13%
2019	23	8.81%
2020	17	6.51%
2021	46	17.62%
Total	**261**	**100.00%**

Table A3. Breakdown of Successful Exits

Appendix B
Verification of the PH Assumption

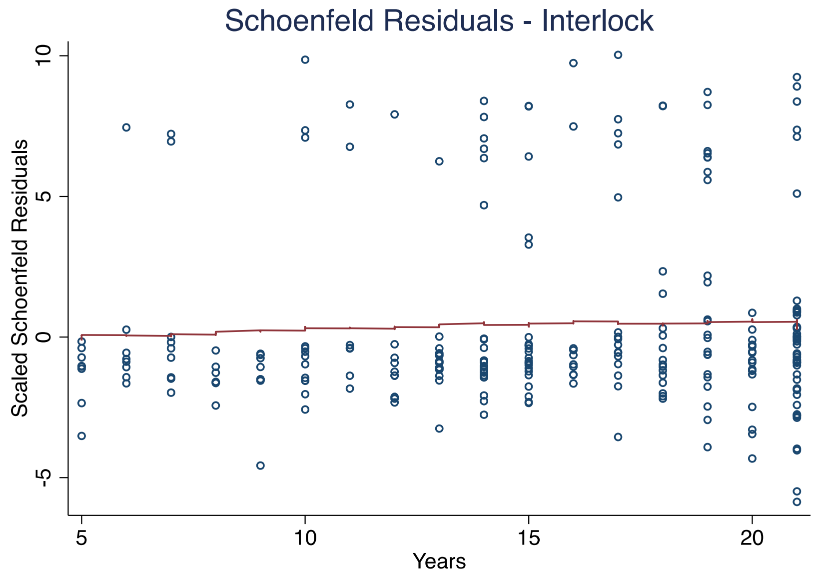

Figure B1. Schoenfeld Residuals plot for *Interlock*
Note. This plot is based on model 3 in table 3

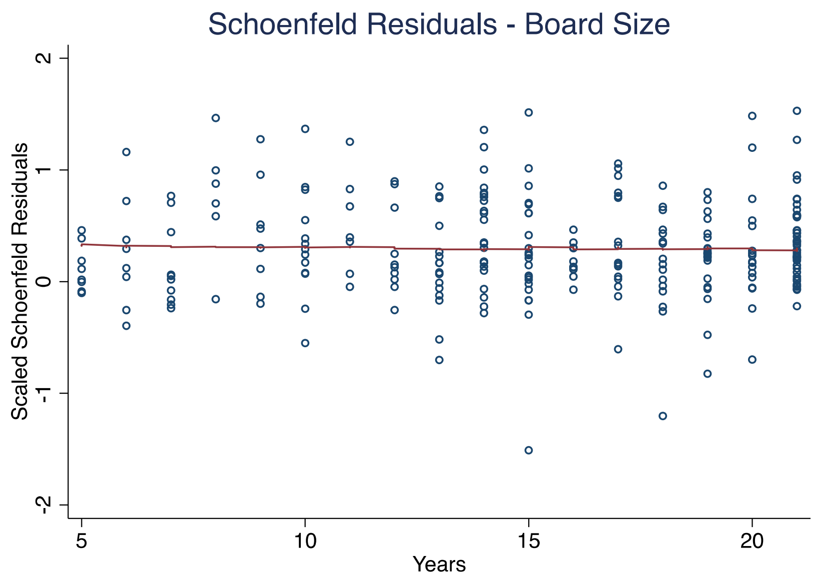

Figure B2. Schoenfeld Residuals plot for *Board Size*
Note. This plot is based on model 3 in table 3

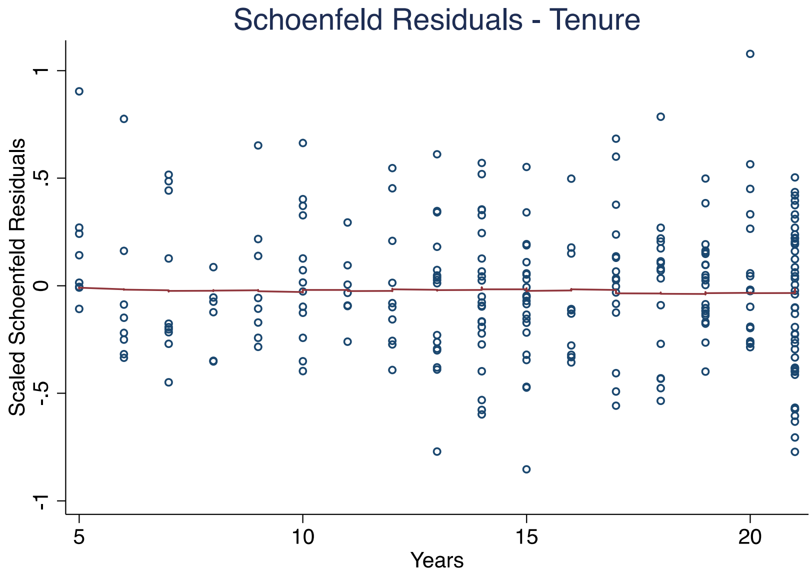

Figure B3. Schoenfeld Residuals plot for *Tenure*
Note. This plot is based on model 3 in table 3

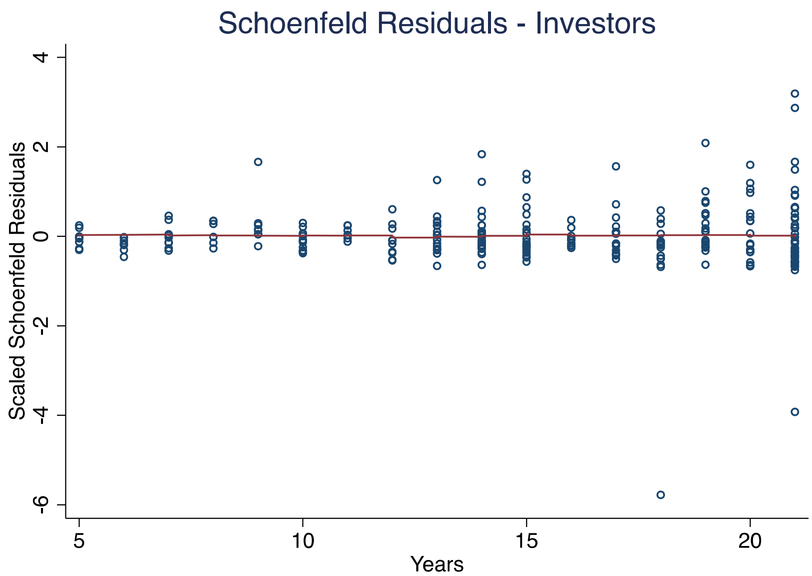

Figure B4. Schoenfeld Residuals plot for *Investors*
Note. This plot is based on model 3 in table 3

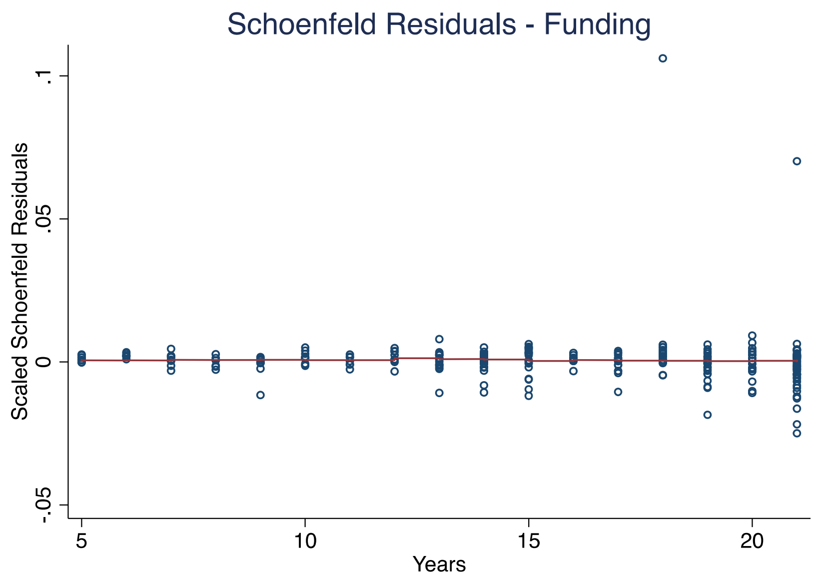

Figure B5. Schoenfeld Residuals plot for *Funding*
Note. This plot is based on model 3 in table 3

Figure B6. Schoenfeld Residuals plot for *Location*
Note. This plot is based on model 3 in table 3

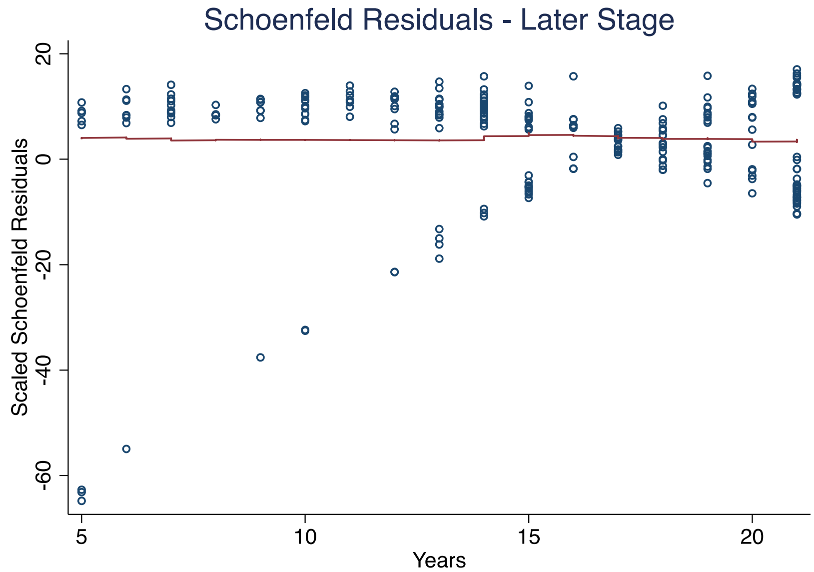

Figure B7. Schoenfeld Residuals plot for *Later Stage*
Note. This plot is based on model 3 in table 3