Data-Driven Venture Capital Funds: A Proven Path to Superior Returns

Chair of Entrepreneurship

Master's thesis

Christian Hennings | 2991175

M.Sc Entrepreneurship and Innovation Management | M.Sc Business Information Systems

TECHNISCHE UNIVERSITÄT DARMSTADT

Christian Hennings
Matriculation number: 2991175
Study program: Business Information Systems + Entrepreneurship and Innovation Management

Master's thesis
Subject: Data-Driven VC: A Proven Path to Superior Returns
Submitted: <Submission date>.
Supervisor: Prof. Dr. Carolin Bock

Prof. Dr. Carolin Bock
Chair of Entrepreneurship
Department of Law and Economics
Technical University of Darmstadt
Hochschulstraße 1
64289 Darmstadt

Declaration on honour

Erklärung zur Abschlussarbeit gemäß § 22 Abs. 7 und § 23 Abs. 7 APB TU Darmstadt

Hiermit versichere ich, Christian Hennings, die vorliegende Master-Thesis gemäß § 22 Abs. 7 APB der TU Darmstadt ohne Hilfe Dritter und nur mit den angegebenen Quellen und Hilfsmitteln angefertigt zu haben. Alle Stellen, die als Quelle dienen und denen Quellen entnommen wurden, sind als solche kenntlich gemacht worden. Diese Arbeit hat in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegen.

Mir ist bekannt, dass im Falle eines Plagiats (§38 Abs.2 APB) ein Täuschungsversuch vorliegt, der dazu führt, dass die Arbeit mit 5,0 bewertet und damit ein Prüfungsversuch verbraucht wird. Abschlussarbeiten dürfen nur einmal wiederholt werden.

Bei der abgegebenen Thesis/Arbeit stimmen die schriftliche und die zur Archivierung eingereichte elektronische Fassung gemäß § 23 Abs. 7 APB überein.

Thesis Statement pursuant to § 22 paragraph 7 and § 23 paragraph 7 of APB TU Darmstadt

I herewith formally declare that I, Christian Hennings, have written the submitted thesis independently pursuant to § 22 paragraph 7 of APB TU Darmstadt. I did not use any outside support except for the quoted literature and other sources mentioned in the paper. I clearly marked and separately listed all of the literature and all of the other sources which I employed when producing this academic work, either literally or in content. This thesis has not been handed in or published before in the same or similar form.

I am aware, that in case of an attempt at deception based on plagiarism (§38 Abs. 2 APB), the thesis would be graded with 5,0 and counted as one failed examination attempt. The thesis may only be repeated once.

In the submitted thesis the written copies and the electronic version for archiving are pursuant to § 23 paragraph 7 of APB identical in content.

Datum / Date: Unterschrift/Signature:

Acknowledgement

I would like to express my sincere gratitude to Level Ventures for their invaluable support in providing the data and assistance that made this research possible. In particular, I thank Dev Dabke for facilitating data access and providing insights into Level Ventures AI and data-driven techniques. Their commitment to transparency and willingness to share their real-world performance data enabled a robust empirical analysis that contributes significantly to the understanding of data-driven strategies in venture capital. I am deeply grateful for their collaboration and the insights they provided throughout this project.

Table of contents

List of figures

List of tables

nitpick: names should be separated by an en-dash, not by an hyphen

List of abbreviations

AI	Artificial Intelligence
AuM	Assets under Management
ETL	Extract, Transform, Load
FoF	Fund of Funds
GPs	General Partners
IPO	Initial Public Offering
IRR	Internal Rate of Return
LPs	Limited Partners
MOIC	Mulitple on Invested Capital
NLP	Natural Language Processing
PE	Private Equity
TVPI	Total Value to Paid-In Capital
VC	Venture Capital
VAC	Value at Cost
XAI	Explainable AI

ML?

1 Introduction

In the era of the 'Fourth Industrial Revolution', characterized by the exponential growth of data and the transformative power of artificial intelligence (AI), traditional industries are undergoing profound shifts (Carter et al., 2020). Venture capital (VC), an industry long reliant on intuition, established networks, and subjective judgment, is no exception (Bygrave & Timmons, 1992; R. S. Harris et al., 2023). This thesis investigates the potential of data-driven and AI-enhanced strategies to revolutionize the VC landscape. It specifically focuses on whether these innovative approaches can generate statistically significant outperformance compared to traditional investment methods. This research is motivated by the growing interest in transformative AI, which has become a 'hot spot for future exploration' within entrepreneurship research. This promises efficiency improvements over prior ways of performing various human tasks, and opening important research opportunities to better understand their transformative impact (R. S. Harris et al., 2023; Lévesque et al., 2020).

why?

add quote, ref Citation in same sentence

either indent or line-break

The global VC landscape has become increasingly competitive, marked by a surge in capital availability and an intensification of the need to identify and secure high-potential ventures (Cumming, 2012; R. S. Harris et al., 2023). This dynamic environment underscores the urgent need for innovation in the VC decision-making process (Callahan & Muegge, 2003). While AI and data-driven systems offer solutions to many of the challenges faced by modern VC funds, their adoption remains limited and often shrouded in secrecy (Eisenhardt & Bourgeois, 1988). Despite this, early research indicates a significant promise in enhancing investment outcomes through the application of the data-driven methods (R. S. Harris et al., 2023; Sorensen & Jagannathan, 2015). This research therefore seeks to contribute to this ongoing debate by providing a comparative analysis of the performance of data-driven VC funds

what does this mean?

old?

Evidence?

too old

against traditional benchmarks, empirically determining whether AI-driven approaches yield measurable advantages (Obschonka & Audretsch, 2020). AI and big data in entrepreneurship mark the beginning of a new era, yet academic understanding of these effects is still lagging behind practical advancements, creating a compelling opportunity for further research in this field (R. S. Harris et al., 2023; Makridakis, 2017; Narayanan et al., 2020; Obschonka & Audretsch, 2020).

what are you citing here?

This study addresses ~~a~~ several hypotheses, aligning with the call for research 'Entrepreneurship ex Machina: Transformative Artificial Intelligence for Theory and Practice' in the Journal Entrepreneurship Theory and Practice (Entrepreneurship Theory and Practice). First, the study finds that data-driven venture capital strategies exhibit statistically significant outperformance compared to a range of venture capital benchmarks and fund ~~of~~ funds benchmarks. Second, it hypothesizes that the Wilcoxon signed-rank test will demonstrate statistically significant outperformance for data-driven investment strategies when compared to all traditional benchmarks (Samuel K.-B & Minkah, 2021). To profoundly investigate this hypothesis, a quantitative methodology has been adopted. This involved a detailed empirical analysis using real-world performance data, made possible through a unique collaboration with Level Ventures, a New York-based fund of funds (FoF) firm. The methodology also includes a thorough assessment of the data assumptions, including independence, normality, and homogeneity of variance, which determines the choice of the statistical test.

explain?,

reword

Test does not go in hypothesis

The structure of this thesis commences (v.c.) with a theoretical foundation, establishing the fundamental principles of venture capital, elaborating on the various phases of financing, and investigating the intrinsic trade-off between risk and return. The subsequent sections delve into the operational framework of VC funds, the decision-making processes within these funds, and the rise of data-driven approaches in the investment landscape. Then follows a thorough analysis of the opportunities and risks associated with implementing data-driven and AI methodologies in VC. The presented framework establishes a rationale for the methodological approach and the empirical investigation. The thesis will then delve into a detailed description of the specific methodology and the statistical techniques used. The results of the empirical study will be presented, offering significant statistical validation for the hypothesis and demonstrating the superior performance of Level Ventures when compared to traditional benchmarks. Finally, the study concludes with a discussion of the findings, an outline of the implications for both research and practice, a future outlook with potential avenues for further investigation and a section on the limitations of the present study. By methodically addressing these fundamental components, this thesis offers insights into the potential of data-driven approaches to transform the VC landscape. By doing so, it addresses a key question of outperformance in this rapidly evolving field of transformative AI for entrepreneurship. This research aims to contribute to the ongoing discussion about the role of AI in the financial sector, and to assist in creating more efficient, and transparent, investment methods.

vague

2 Theoretical Background

This section provides the theoretical foundations necessary to understand the empirical study of data-driven venture capital and its potential to generate superior returns. This thesis will look at the core principles of VC, exploring its definition, characteristics and how it differs from other forms of financing. We will then examine the various stages of VC funding, from the initial seed stage to the eventual exit, highlighting the unique challenges and opportunities that arise at each stage. This chapter also discusses the complex interplay between risk and return inherent in VC investments and identifies the key factors that influence this balance. The structure and operation of a VC fund will be examined, including an exploration of the roles and responsibilities of the various stakeholders involved. Finally, this section outlines the traditional VC decision-making process, providing a reference point against which to assess the impact of data-driven approaches. By establishing these fundamental concepts, we lay the groundwork for a comprehensive understanding of the transformative potential of data and AI within the VC sector (Makridakis, 2017).

what are you citing?

2.1 Definition of Venture Capital

VC, also referred to as "risk capital," is a form of private equity financing allocated to companies in their early growth stages that are not publicly traded (R. Harris et al., 2012; Hege et al., 2009). In contrast to well-established companies, which can access conventional financial resources such as bank loans or bonds, VC-financed companies are typically either early stages or later-stage enterprises (Figure 1) with innovative business models, products, or services (Di Guo & Jiang, 2013). These enterprises are characterized by a high level of risk, but also significant growth potential (Davila et al., 2003).

VC investors, ~~in essence,~~ assume considerable risk in exchange for the potential to achieve returns that surpass the norm, should the enterprise succeed (Cornelius et al., 2009; Schoar & Kaplan, 2005). This phenomenon aligns with the high-risk, high-reward nature of VC, which combines financial investment with strategic guidance (Weidig, 2002a).

In addition to providing capital, venture capitalists frequently assume a crucial role in offering operational and strategic support to their portfolio companies (Achleitner & Lutz, 2004; Ramachandra & Srinivasa, 2016). The portfolio firms tend to specialize in high-growth industries such as technology, biotechnology, or renewable energy, supporting companies that either aim to create new markets or develop innovative products (Ramachandra & Srinivasa, 2016).

Investments made by venture capitalists are typically made with a long-term perspective, with investors exiting their stakes after several years (Cumming, 2012).

Explain what phases are?

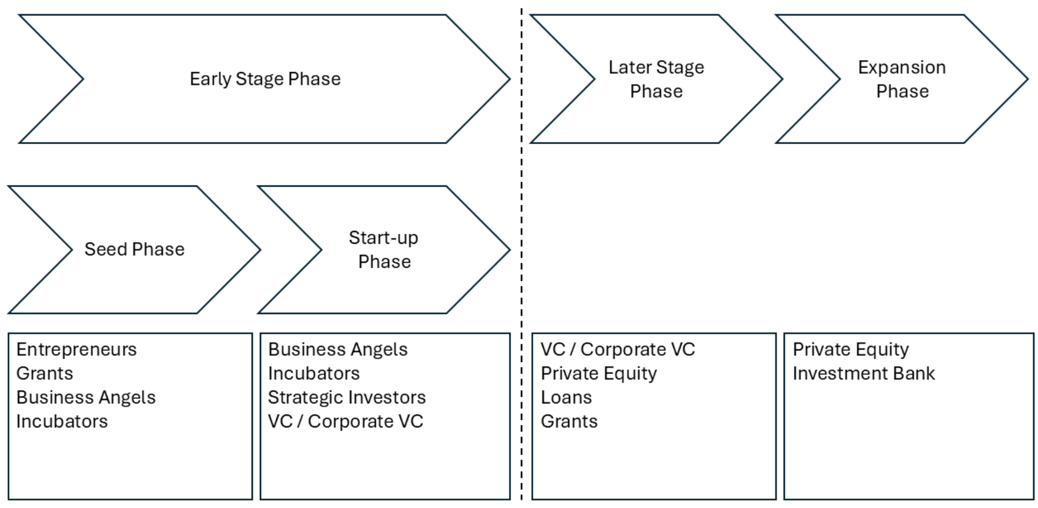

Figure 1: Phases of Investment (Adapted from (Achleitner & Lutz, 2004))

Although VC is a subset of private equity (PE), there are critical differences between the two (Achleitner & Lutz, 2004). Private equity principally concentrates on well-established companies with stable cash flows and proven business models (Wright, 1998). The primary objective of private equity is often to restructure, expand, or prepare the company for a public offering, as seen in Figure 1 (Gompers & Lerner, 2001). PE firms generally invest in mature companies and aim for shorter holding periods, focusing on generating returns through strategic exits such as Initial Public Offerings (IPOs) or acquisitions (Popov & Roosenboom, 2013). In contrast, VCs focuses on high-risk startups, aiming to catalyze their growth and innovation over a long-term partnership (Ramachandra & Srinivasa, 2016).

Nice!

Angel investors, ~~also referred to as business angels,~~ are high-net-worth individuals who provide early stage funding, frequently during the seed phase of a startup (Cavallo et al., 2019). Their investments are typically smaller in comparison to those made by VC funds. In contrast to the VC approach, angel investors invest capital that they personally possess and typically offer less structured strategic support (Cavallo et al., 2019; Thompson, 2008). The role of angel investors is particularly significant in circumstances where a company has not yet reached a stage at which it can attract venture capital (Cavallo et al., 2019; Drover et al., 2017). Despite the potential risks involved, their investments frequently serve as a foundation for subsequent VC financing (Drover et al., 2017; Noone, 2016).

W.C.

In contradistinction to the financing options, VC and PE, debt financing is characterized by the use of borrowed capital that is subject to repayment irrespective of the company's financial performance (Hellmann & Puri, 1999; Timmons & Bygrave, 1986). This is typically facilitated through loans from banking institutions or other financial intermediaries. A notable benefit of debt financing is that it enables business owners to maintain control over their companies (Drover et al., 2017; Hellmann &

Puri, 1999). However, this is accompanied by the responsibility of regular repayment obligations, which can exert pressure on cash flows, particularly during the early stages of a business (Davila et al., 2003; Drover et al., 2017).

a.

This, of course, is not an exhaustive list, but these represent the most relevant financing options for the scope of this work. In contrast, venture capitalists provide funding in exchange for an equity stake in the company, thereby aligning their interests with those of the company (Regan & Tunny, 2008). VC is a financial instrument that is particularly well-suited for companies with high growth potential that are considered too risky for traditional banks, providing loans (Timmons & Bygrave, 1986). This phenomenon is widely observed in innovative sectors such as technology, biotechnology, fintech, and renewable energy, where substantial resources are required for research, development, and scaling (Cumming, 2012; Durrani, 2001). These investments enable startups to rapidly grow and capture market share through innovation (Di Guo & Jiang, 2013; Regan & Tunny, 2008).

VC can be defined as a high-risk high-reward form of financing, predominantly aimed at young and innovative enterprises (Camp & Sexton, 1992; Fried & Hisrich, 1994; R. S. Harris et al., 2023). This attribute positions VC as a pivotal financial instrument in the promotion of innovation and economic growth. However, to fully understand the dynamics of this investment model, it is crucial to examine the different stages of the VC process (Di Guo & Jiang, 2013; Dushnitsky & zur Shapira, 2010). Each stage presents unique challenges and opportunities for both investors and startups, from the initial sourcing of potential deals to the final realization of returns. Therefore, the following section will delve into the different phases of the VC investment process, exploring how these phases shape investment decisions and the overall lifecycle of the VC investment (Agrawal et al., 2016).

2.2 Phases of Venture Capital Financing

VC financing occurs in various stages, corresponding to the developmental phase of the company:

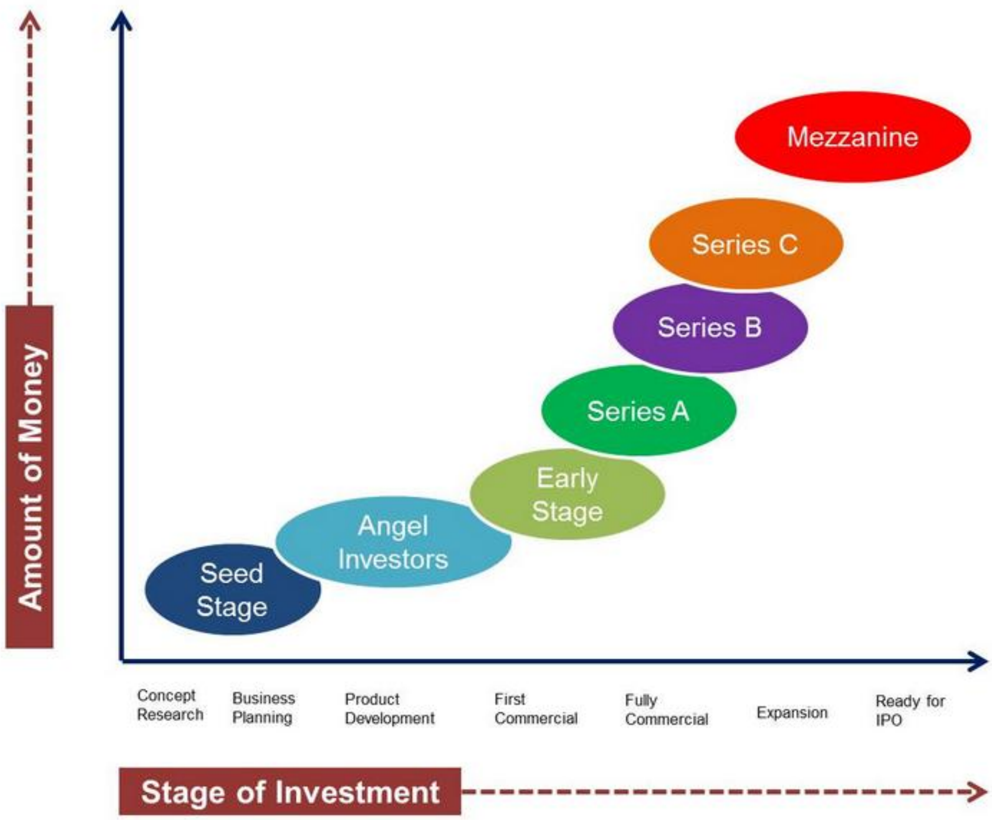

Figure 2: Stages of Investment (Adapted from (Paras Gupta, 2016))

- **Seed Stage / Angel Investors:** These phases are typified by the initial round of financing, which focuses on companies in the idea or concept phase, which require small amounts of funding for preliminary development, such as market research or the creation of prototypes (Molnár & Jáki, 2020; Paras Gupta, 2016). Angel investors or specialized early stage VC funds often provide support at this stage (Molnár & Jáki, 2020).

- **Early Stag**e: Early stage funding bridges the gap between initial seed or angel investment and the larger Series A round. At this point, the company has typically developed its product or service beyond the prototype stage and is starting to see initial market traction (Gompers et al., 2005; Paras Gupta, 2016). Funding at this stage is used to scale early operations, refine the product based on user feedback, build a core team and further validate the business model (Gompers et al., 2005). While still considered a high-risk investment, the early stage represents a significant step forward in de-risking the business, attracting investors who are looking for promising businesses with demonstrable growth potential (Dushnitsky & zur Shapira, 2010; Molnár & Jáki, 2020).
- **Series A:** The objective of the Series A round is to validate the business model and facilitate market entry. At this stage, companies typically have a prototype or initial customer base but need capital to scale their business strategy and expand operations (Molnár & Jáki, 2020; Paras Gupta, 2016). Investments in this round are often several million dollars and are led by institutional VC investors. This stage is crucial for the transition from the startup to the growth phase (Dushnitsky & zur Shapira, 2010; Robinson & Sensoy, 2016).
- **Series B:** The Series B round is focused on scaling the business after market validation. Activities include entering new markets, hiring additional staff, and building production capacity (Gompers et al., 2005; Paras Gupta, 2016). Series B rounds are generally larger than Series A rounds and are intended for companies that have already achieved a certain level of stability and market penetration (Chaplinsky & Gupta-Mukherjee, 2010; Gompers et al., 2005).
- **Series C and later Series:** Subsequent series, such as C and beyond, typically focus on activities such as international expansion, acquiring other companies, or preparing for an IPO or acquisition (Gompers et al., 2005; Gompers & Lerner, 2006). These rounds often involve private equity investors or strategic partners

looking to take the company to the next stage of growth (Gompers & Lerner, 2002; Gorman & Sahlman, 1989; Paras Gupta, 2016).

- **Exit Phase:** This phase involves the realization of investor returns through an Initial Public Offering (IPO) or sale of the company. This phase is crucial for investors as it represents the moment of return on investment (Gompers & Lerner, 1998). A successful exit, whether by IPO or acquisition, serves to highlight the company's success and delivers significant returns to investors (Cumming, 2012).

The beneficiaries of VC are young, technology-driven companies possessing significant growth potential (Cornelius et al., 2009; Gompers & Lerner, 2006). VC funding provides tailored support at the current stage of a company's development, playing an indispensable role in propelling companies towards successive growth milestones (Molnár & Jáki, 2020; Paras Gupta, 2016). The Series A and B phases are particularly crucial, as they provide both the necessary capital and strategic input required to steer companies towards sustainable growth and long-term success (Cavallo et al., 2019). It is critical to understand these distinct phases, as they are intrinsically linked to the inherent risk and return characteristics associated with VC investments (Gompers et al., 2005; Robinson & Sensoy, 2016). This variability across phases necessitates a more detailed examination of the complicated balance between risk and return within VC, which will be explored in the following section (Di Guo & Jiang, 2013; Robinson & Sensoy, 2016).

2.3 Balancing Risk and Return in Venture Capital

VC investments are characterized by a difficult balance between high risk and the potential for exceptional returns (Amit et al., 1990; Aven, 2013). Investing in young, innovative companies involves considerable uncertainty, as these companies often operate in emerging markets and rely on unproven technologies (Ewens, 2009). However, the potential for substantial gains, particularly through successful exits such as IPOs or acquisitions, remains a key attraction for VC investors, despite the inherent risks (Ruhnka & Young, 1991).

- **Early Stage Investments (Seed and Series A):** Early stage investments, encompassing Seed and Series A rounds, present a unique risk-reward profile (Korteweg, 2011). While fraught with high uncertainty due to the lack of a proven track record and consistent revenue, these ventures offer the potential for outsized returns (Amit et al., 1990; Aven, 2013). The risk stems from the possibility of failure before achieving a functional prototype or significant market traction (Ruhnka & Young, 1991). However, the attraction lies in the comparatively low entry price for equity. Should the venture succeed, early investors stand to gain substantially, making the risk appealing for those seeking exponential growth (Amit et al., 1990; Ruhnka & Young, 1991). The potential for extraordinary reward, therefore, acts as a counterbalance to the inherent risks of betting on unproven, early stage companies (Reid et al., 1997; Ruhnka & Young, 1991; Werther, 2013).
- **Series B and Later Stages:** As companies progress through Series B and subsequent rounds of funding, the risk to investors decreases (Ruhnka & Young, 1991). At this stage, the company is typically more stable, has the potential to generate revenue and has established market access (Korteweg, 2011). Conversely, the reduced risk is accompanied by higher company valuations,

which limit the potential for outsized returns. As a result, later stage investments embody a lower risk, lower reward dynamic (Aven, 2013).

- **Exit Phase:** The exit phase, achieved through an IPO or acquisition, is the ultimate goal of any VC investor (Aven, 2013). At this stage, the company has typically established a strong market position, and the level of risk and uncertainty is low. However, risks such as market volatility or regulatory uncertainty can still impact the success of an IPO or acquisition and therefore the returns on the investment (Bharat Anant, 2016; Tyebjee & Bruno, 1984; Weidig, 2002a).

Figure 3: Risk Adjusted Expected Returns (Adapted from (Bharat Anant, 2016))

? explain

It is recognized that historically, early stage investment has been shown to offer higher potential returns to investors willing to take on more risk (Amit et al., 1990; Bharat Anant, 2016; R. S. Harris et al., 2023; Mason & Harrison, 2002; Timmons & Bygrave, 1986). This traditional view of risk and return, with its implicit acceptance of high failure rates in early stage investments in exchange for potentially higher returns, was largely based on investment strategies that relied heavily on personal networks, experience and subjective judgement (Reid et al., 1997; Ruhnka & Young, 1991; Weidig, 2002b). However, this traditional model, which was the accepted standard at the time, is now being fundamentally challenged by the emergence of new methodologies that aim to better assess, predict, and mitigate risk in VC (R. S. Harris et al., 2023; Korteweg, 2011; Weidig, 2002b). This paradigm shift opens up a range of potential strategies and opportunities to increase returns in VC while potentially reducing risk (Aven, 2013; Ewens, 2009). It is an important change that new and innovative methodologies are challenging previous assumptions about risk and return in VC (Figure 3) (Amit et al., 1990; Weidig, 2002a). The potential to mitigate risk, improve predictive accuracy, identify emerging trends and reduce cognitive biases will be explored in the remainder of this study, including an analysis of the potential benefits such as reduced bias, increased predictive capacity and a better understanding of current market trends (Aven, 2013; Mason & Harrison, 2002; Timmons & Bygrave, 1986).

2.4 Structure and operation of venture capital

The organizational structure of a VC fund is based on a clearly defined distribution of roles and functions, ensuring effective collaboration between stakeholders while maintaining a balance between risk and return (Dorigo & Schnepf, 1991; Sahlman, 1990). This structure is central to understanding the operational mechanics of the VC model, as it delineates the responsibilities of general partners (GPs), limited partners (LPs), and startup founders within the life cycle of the fund (Aki, 2021; Carlos Nunes et al., 2014).

2.4.1 Stakeholders in the VC Ecosystem

The primary role of LPs is to provide capital to VC funds. These investors are often institutional entities such as pension funds, endowments, corporate funds, and high net worth individuals (Josh Lerner et al., 2007; Sheu & Lin, 2007). While LPs provide significant capital to the fund, they remain passive stakeholders with no direct involvement in the investment strategy or fund management decisions. Their primary interest is achieving attractive returns on their contributions over time (Durrani, 2001; R. S. Harris et al., 2023; Kaplan & Stromberg, 2009).

General partners (GPs) are the active managers of the fund, responsible for implementing the investment strategy and overseeing all operational aspects (Bygrave, 1988). Their role includes identifying and evaluating startups, conducting due diligence, and managing the portfolio of investments. In addition to providing capital, GPs play an advisory role, offering strategic guidance and using their networks to support the growth of portfolio companies (Durrani, 2001; R. S. Harris et al., 2023; Wallmeroth et al., 2018). To align their incentives with those of the limited partners (LPs), general partners often invest a portion of their own capital in the fund. Their compensation is derived from management fees and a profit-sharing mechanism known as carried interest (Metrick & Yasuda, 2010a; Phalippou et al., 2018; Sheu & Lin, 2007).

Founders don't get funds — companies do :)

The recipients of VC funding are ~~the founders of~~ startups. They receive the financial resources needed to develop their ideas, scale their businesses, and bring innovations to the market (Dorigo & Schnepf, 1991; Durrani, 2001). In addition to capital, founders often have access to the expertise and networks of GPs, who actively work with them to drive business growth (Bygrave, 1988; Schwienbacher, 2008). This symbiotic relationship is instrumental in mitigating risk and ensuring the success of startups (Gompers & Lerner, 2006).

2.4.2 Functioning of a Venture Capital Fund

The funding process begins with LPs committing to invest a certain amount of capital in the VC fund over its lifetime (Casebook et al., 2000; Cumming, 2012). This capital is not committed up front but is drawn down incrementally as investments are made. This approach is designed to minimize unused capital and is aligned with the fund's strategic objectives (Callahan & Muegge, 2003; Camp & Sexton, 1992).

GPs are responsible for overseeing the operations of the fund and implementing its investment strategy (Gorman & Sahlman, 1989; Kaplan & Strömberg, 2004). The investment strategy focuses on high-growth, technology-driven companies with the potential to generate significant returns (Cavallo et al., 2019; Davila et al., 2003; Hellmann & Puri, 1999). The GPs seek to optimize the balance between risk and opportunity through a combination of diversification and proactive portfolio management (Bygrave & Timmons, 1992; Casebook et al., 2000; J. Lerner, 1994).

GPs closely monitor portfolio companies and work with founders to address challenges, refine strategies and improve operational efficiency (Cooper et al., 1997; Cumming, 2012). This hands-on approach is essential to mitigate risk and maximize the likelihood of positive outcomes (Kaplan & Strömberg, 2004; Neus & Walz, 2001).

The organizational structure of a VC fund is based on a clear delineation of roles and responsibilities between LPs, who provide capital, and GPs, who manage the fund and invest in startups (Bygrave, 1988; Metrick & Yasuda, 2010b; Neus & Walz, 2001). Through careful risk management and value enhancement strategies, GPs seek to achieve the optimal balance of risk and return for all stakeholders (R. S. Harris et al., 2023; Hellmann & Puri, 1999; Mitra, 2000; Sheu & Lin, 2007; Silver, 1985).

2.4.3 Fund of Funds in Venture Capital

A 'fund of funds' (FoF) in the context of VC adds another layer to this investment structure (Casebook et al., 2000). A fund of funds is a pooled investment fund that invests in other VC funds rather than directly in operating companies (Gompers et al., 2015; Gompers & Lerner, 2001). An FoF therefore acts as both a GP and a LP, creating a two-tier investment model (Cornelius et al., 2009). As an LP, an FoF allocates capital to various VC funds and acts as an investor in other VC (Cumming & Johan, 2013; Phalippou et al., 2018). At the same time, the FoF acts as a GP for its own investors, managing their capital and making investment decisions about which underlying VC funds to select and invest in (Kaplan & Stromberg, 2009; Kaserer & Diller, 2004; Schoar & Kaplan, 2005). This dual role requires an FoF to carefully evaluate not only the startups in which the underlying VCs invest, but also the performance, strategic direction and capabilities of the underlying VCs themselves (Lake & Lake, 1999; Rapp & Olbrich, 2020). As a result, the investment decision-making process of a FoF is more complex than that of a traditional VC fund (Drover et al., 2017; Kaserer & Diller, 2004; Sokołowska, 2016). The FoF has to assess not only the potential of a startup, but also the potential of the VC fund to successfully manage and grow that startup (Cornelius et al., 2009; Schoar & Kaplan, 2005). This two-tier structure introduces both diversification benefits and additional layers of risk management, but also adds complexity to the decision-making process of a FoF (Gupta & van Nieuwerburg, 2021; R. S. Harris et al., 2023; Phalippou et al., 2018; Sokołowska, 2016; Wright, 1998).

2.5 The Venture Capital investment process

Process Stage	Wells (1974)	Tyebjee & Bruno (1984)	Silver (1985)	Hall (1989)
1	Search	Deal origination	Search	Generating deal flow
2		Screening	Initial Screen	Proposal screening
				Proposal assessment
3	Evaluation	Evaluation		Project evaluation
			Due diligence	Due diligence
4		Deal structuring	Deal structuring	Deal structuring
5	Venture board meetings and operations	Post investment activities	Monitor progress	Venture operations
6	Cashing out		Cashing out	Cashing out

Old

Hm..... what's the differen?

Figure 4: Decision Making Process (Adapted from (Hudson & Evans, 2005))

The VC investment process is a methodical and multi-stage decision-making framework used by investors to identify and support promising early stage ventures, while seeking to mitigate the inherent risks associated with these investments (Dorigo & Schnepf, 1991; Tyebjee & Bruno, 1984). Although a variety of models have been proposed to describe this process, including those developed by (Agrawal et al., 2016; Bauer, 2000; Hall, 1989; Silver, 1985; Tyebjee & Bruno, 1984; Wells, 1974) (as illustrated in Figure 5). This thesis adopts a synthesis of these models, adapting and combining pivotal aspects to construct a more comprehensive framework (Eisenhardt & Bourgeois, 1988; Fried & Hisrich, 1994). Given the characteristic, uncertainty and information asymmetries that prevail in the early stage business landscape, the VC investment process requires a progressive, multifaceted approach that emphasizes evaluation and selection at each stage (Wells, 1974; Zacharakis & Shepherd, 2001). The process is often conceptualized as an 'investment funnel' (Bourgeois & Eisenhardt, 1988; Tyebjee & Bruno, 1984), with a broad range of investment opportunities entering in the early stages and a smaller fraction successfully completing each stage (Duan et al., 2019; Eisenhardt & Bourgeois, 1988). This iterative process is designed to gather detailed information and continually refine risk assessments as investment candidates progress through the funnel (Bygrave, 1988; Cornelius et al., 2009). Each stage is carefully structured to contribute to the goal of identifying and selecting opportunities with a high probability of success, thereby maximizing investors' potential for significant financial returns (Bourgeois & Eisenhardt, 1988; Hisrich & Jankowicz, 1990). It is therefore essential to understand the different stages in order to assess the impact of innovative approaches, such as AI, in transforming the decision-making in the investment processes within VC (Fried & Hisrich, 1994; Rapp & Olbrich, 2020; Zacharakis & Shepherd, 2001). The VC investment process consists of eight distinct phases, ranging from the initial observation of a nascent company to its final stage of exit (Lake & Lake, 1999; Phalippou & Gottschalg, 2009).

- **Phase 1: Deal Origination:** The initial phase of the VC investment process, commonly termed 'deal origination' or 'deal sourcing', involves the systematic identification of potential investment prospects (Eisenhardt & Bourgeois, 1988; Wells, 1974). This phase is the basis of the entire VC process, as the quality and quantity of deal flow have been shown to have a significant impact on the investment portfolio (Doumpos & Grigoroudis, 2013). VCs access investment opportunities through a multiplicity of channels, including personal networks of partners and associates, attendance at industry-specific and startup events, and participation in startup competitions (Bourgeois & Eisenhardt, 1988; Rapp & Olbrich, 2020). Furthermore, some VC funds prioritize the establishment of formal and informal relationships with university technology transfer offices, startup incubators, and accelerators to gain early access to promising ventures (Duan et al., 2019; Gompers & Lerner, 2001). The objective of this initial phase is to establish a large and diversified pool of potential investment targets in order to maximize the odds of discovering a venture with substantial growth and return potential (Fried & Hisrich, 1994; Phillips-Wren et al., 2008).

- **Phase 2: Firm-Specific Screen:** Following the identification of potential investment opportunities, a preliminary screening is conducted that focuses on firm-specific parameters (Dew et al., 2009; Rapp & Olbrich, 2020). This stage serves as an initial filter, evaluating whether the candidate startup meets the VC firm's fundamental criteria (Tyebjee & Bruno, 1984; Wells, 1974). VCs typically engage in a thorough examination of several pivotal features, including the potential market size, the feasibility and robustness of the business model, and the expertise and experience of the management team (Bourgeois & Eisenhardt, 1988; J. Lerner, 1994). This screening is intentionally broad and is aimed at eliminating those proposals that fail to meet the fundamental requirements of the investment firm. This stage, therefore, serves to reduce the workload of VCs by avoiding the excessive exploration of unsuitable options (Doumpos & Grigoroudis, 2013; Eisenhardt & Bourgeois, 1988; Tyebjee & Bruno, 1984).
- **Phase 3: Generic Screen:** Following the preliminary, firm-specific screening, the 'generic screen' involves a more comprehensive evaluation of the remaining candidate ventures (Duan et al., 2019; Rapp & Olbrich, 2020; Wells, 1974). This stage is characterized by an emphasis on market analysis and competitive positioning, with the objective of acquiring a more profound understanding of the startup's overall prospects (Bourgeois & Eisenhardt, 1988; Wells, 1974). This evaluation considers, whether the venture is addressing a sufficiently important problem, the market is of adequate size to justify significant investment, and the business model is capable of long-term viability (Knockaert & Clarysse, 2010; Zacharakis & Shepherd, 2001). At this stage, the focus is less on specific operational details and more on the general market and competitive environment

within which the startup is operating (Doumpos & Grigoroudis, 2013; Rapp & Olbrich, 2020).

- **Phase 4: First Phase Evaluation:** During the 'first phase evaluation', the evaluation process is deepened by means of a more rigorous analysis of the quantitative and qualitative aspects of the venture (Doumpos & Grigoroudis, 2013; Zacharakis & Shepherd, 2001). VCs conduct detailed investigations of business plan metrics and assess financial projections, conduct more detailed market analyses, and study the competitive landscape of the industry in question (Dew et al., 2009; Eisenhardt & Bourgeois, 1988). The purpose of this evaluation is to provide a comprehensive view of the venture's viability (Gompers et al., 2015). Often, prospective deals are presented to the VC's Investment Committee – the firm's decision-making body of partners and senior investors – to obtain preliminary feedback (Zacharakis & Shepherd, 2001). These presentations are crucial to refine the evaluation and provide expert guidance for decision making about the future of the opportunity (Gompers et al., 2015; J. Lerner, 1994).
- **Phase 5: Second Phase Evaluation:** The second phase of evaluation is centered around a process of 'due diligence' that involves a comprehensive, in-depth evaluation regarding the candidate venture (J. Lerner, 1994; Wells, 1974). This phase involves investigation and verification of the business, legal, and financial aspects of the company (Fried & Hisrich, 1994). Such a deep assessment can include the auditing of financial records, examination of legal agreements, conversations with customers, interviews with suppliers, and consultations with subject matter experts in the industry (Eisenhardt & Bourgeois, 1988; Hisrich & Jankowicz, 1990). This comprehensive process is undertaken to identify any latent risks or deficiencies in the venture that could potentially impact its success, thereby enabling the VC firm to attain a comprehensive understanding of the investment prospects (Dew et al., 2009; Hudson & Evans, 2005; Wells, 1974).

- **Phase 6: Closing:** The process continues upon the conclusion of due diligence, progressing to the 'closing' phase. This final phase constitutes the completion of all contractual negotiations, and involves the establishment of the equity terms, the valuation of the firm, and the formalization of other contractual clauses (Bourgeois & Eisenhardt, 1988; Bygrave, 1988; J. Lerner, 1994; Sahlman, 1990; Wells, 1974). This phase is of crucial importance in establishing the legal framework governing the agreement between the venture capital fund and the startup company and involves the finalization of legal documentation and the settlement of all monetary transactions (Gompers et al., 2005; Sahlman, 1990; Schwienbacher, 2008; Tyebjee & Bruno, 1984).
- **Phase 7: Post-Investment Activities:** The post-investment phase comprises active engagement and support from the VC firm (Gorman & Sahlman, 1989; Tyebjee & Bruno, 1984). This frequently encompasses the provision of mentorship, access to supplementary resources, strategic counsel, and entry to the VC firm's extensive professional networks (Cornelius et al., 2009; Di Guo & Jiang, 2013; Gompers et al., 2005). The active involvement of VC funds in guiding the development of portfolio companies has been identified as a critical factor in their success (Bygrave, 1988; Cornelius et al., 2009; Tyebjee & Bruno, 1984).
- **Phase 8: Exit:** The final phase in the VC investment process is the exit, where investors are able to monetize the returns on their investments. There are several methods of exit, including a sale of the company via a trade sale, a public offering via IPO, or a share repurchase by the company itself (Metrick & Yasuda, 2010a). A successful exit strategy is pivotal in enabling VC investors to realize significant financial returns, thereby contributing to the VC firm's capacity to secure new funds for future investments (Metrick & Yasuda, 2010b). Consequently, a successful exit strategy represents the ultimate objective of any VC investment (Bygrave, 1988; Di Guo & Jiang, 2013).

2.5.1 Decision-Making vs. Investment Process

It is vital to emphasize that while the VC investment process includes all eight phases outlined above, the primary decision-making process is predominantly situated within the initial five phases: deal origination, firm-specific screening, generic screening, first phase evaluation, and second phase evaluation (due diligence) (Crowdmatrix; Fried & Hisrich, 1994; Lake & Lake, 1999; Tyebjee & Bruno, 1984). These phases entail the detailed analysis, evaluation, and selection of startups, building the core of the investment decision (Carlos Nunes et al., 2014; Tyebjee & Bruno, 1984). The subsequent phases, which include closing, post-investment activities, and exit, are critical parts of the overall investment process (Drover et al., 2017; Tyebjee & Bruno, 1984). However, they fall outside the range of this study's examination of the decision-making framework. The present study's primary focus is therefore an analysis of the impact of data-driven approaches on the early stages of the VC investment process, specifically on the decision-making itself (Dew et al., 2009).

2.6 Data-Driven Venture Capital

Data-driven venture capital signifies a substantial evolution in investment strategy (Carter et al., 2020). This evolution is marked by a transition from the conventional reliance on human intuition, established networks, and prior experience towards methodologies that are inherently data-centric (Carter et al., 2020; Dong & Mcintyre, 2014). This transition is driven by the ambition to enhance the efficiency and objectivity of investment decisions while concurrently reducing the influence of cognitive biases that frequently impact traditional processes (Cockburn et al., 2018; Cooper et al., 1997; Giuggioli & Pellegrini, 2022). At its core, data-driven VC employs quantitative analysis, statistical modelling, and advanced technologies to identify, evaluate, and select investment opportunities (Duan et al., 2019; Koushik et al., 2020; Obschonka & Audretsch, 2020; Sheu & Lin, 2007).

A number of salient characteristics delineate data-driven VCs and differentiate it from its traditional counterparts. Firstly, data-driven VCs utilize substantial and intricate datasets, frequently termed 'big data', to analyze and identify investment opportunities (Carter et al., 2020, 2020; Giuggioli & Pellegrini, 2022; Manyika et al., 2011). This shift enables data-driven VCs to explore beyond existing networks, potentially uncovering latent trends and opportunities. Secondly, data-driven VCs employ advanced technologies, including machine learning (ML) algorithms and artificial intelligence (AI), to analyze patterns within complex datasets and generate predictions and insights that may not be readily apparent through traditional methods (Carter et al., 2020; Chen et al., 2012; Cockburn et al., 2018; Jordan & Mitchell, 2015; Russell & Norvig, 2021; Shan et al., 2022). Finally, these firms incorporate automated processes to analyze a variety of data types, including financial metrics, market information, social media engagement, and consumer behavior data (Makridakis, 2017; Martin, 2012; Wadhwa & Bansal, 2024). This automation is used to ensure more comprehensive and efficient assessments of potential investment targets (Brynjolfsson & McAfee, 2014; Gao & Topp, 2020; Gelernter & Rochester, 1958; Paulus et al., 2019; Rahwan et al., 2019).

A notable distinction emerges between traditional and data-driven VC approaches, particularly in their respective decision-making methodologies (Cockburn et al., 2018; Giuggioli & Pellegrini, 2022). Traditional VCs, for example, rely heavily on personal networks, the completion of due diligence, previous experience, and often subjective evaluations, which can lead to various individual biases (Amit et al., 1990; Dorigo & Schnepf, 1991; Hall, 1989). Conversely, data-driven VCs utilize quantitative data models to assess both potential opportunities and risks, employing statistical and algorithmic analysis to inform investment decisions (Shepherd & Majchrzak, 2022; Sheu & Lin, 2007; Wadhwa & Bansal, 2024). This approach enables data-driven VC to consider a higher number of investments than traditional VC methods (Doumpos & Grigoroudis, 2013). One of the objectives of data-driven VCs is to broaden the range of investments analyzed and to do so at a much more rapid pace than traditional methods (Giuggioli & Pellegrini, 2022; Wadhwa & Bansal, 2024).

Data analytics and AI are used by data-driven VCs to improve various stages of the decision-making process, drawing from multiple types of data (Chen et al., 2012; Doumpos & Grigoroudis, 2013). Specifically, data-driven VCs utilize startup-specific data, including financial metrics, founder profiles, team composition, and product metrics, market data, and external data sourced from social media, review platforms, and app usage data (Amit et al., 1990; Crevier, 1993; Dorigo & Schnepf, 1991).

A variety of approaches exist for incorporating the expertise and predictive capabilities of artificial intelligence into the decision-making processes of data-driven venture capitalists. These include full human-to-AI delegation, where the VC completely delegates investment decisions to the AI, seeking to maximize objectivity and efficiency by minimizing human influence (Agrawal et al., 2020; Sheu & Lin, 2007; Thomas et al., 2019). Another approach is a hybrid sequential decision-making, which involves alternating between human and AI input, thereby leveraging the benefits of both approaches (Frey & Osborne, 2017; Neus & Walz, 2001). Finally, the model of aggregated human-AI decision making involves collaborative evaluation, combining the knowledge of both AI systems and human experts. (Gelernter & Rochester, 1958; Gharagozloo et al., 2021; Rahwan et al., 2019).

3 Data-Driven AI in the VC Decision-Making Process

The VC investment landscape is a complex arena, characterized by a constant interplay of promising opportunities and significant, often unpredictable challenges (Obschonka & Audretsch, 2020). As the field evolves, the integration of AI into the VC decision-making process presents a significant opportunity (Phillips-Wren, 2014). Especially for capitalizing on the inherent advantages that VC investments can provide, as well as to address and mitigate some of the deeply entrenched risks that have historically burdened the sector (Shepherd & Majchrzak, 2022). This section will provide a detailed exploration of the potential benefits that can arise from incorporating data-driven approaches into VC, as well as an equally detailed analysis of the challenges and risks that accompany this transition (Phillips-Wren, 2014; Phillips-Wren et al., 2008).

3.1 Opportunities: Amplifying the Potential of Venture Capital through AI

VC investments offer the potential for substantial financial returns, but they are also associated with a high degree of risk (Gompers & Lerner, 2006). Beyond the pursuit of individual gains, venture capitalists strategically diversify their investment portfolios to mitigate potential losses (Gompers et al., 2005; Kaplan & Strömberg, 2004; Sokołowska, 2016), drive economic growth by investing in innovative technologies (Hellmann & Puri, 1999) and provide strategic partnerships to portfolio companies (Sapienza, 1992). The fundamental objective of VC is to foster innovation and facilitate transformative ideas (Giuggioli & Pellegrini, 2022; Kortum & Lerner, 2000). However, the VC landscape is confronted with significant challenges (Cockburn et al., 2018; Gelernter & Rochester, 1958). A primary issue is the information asymmetry inherent in the system, wherein startup founders typically possess a greater level of knowledge about their company than potential investors, making it difficult for VCs to accurately assess the risks and potential of any given investment (Akerlof, 1970; Phillips-Wren, 2014). This forces investors to rely on often 'blackbox' generated signals, increasing uncertainty (Sheu & Lin, 2007). The predictive accuracy of traditional VCs is also limited by the fact that startups often operate in rapidly evolving and volatile markets, making it difficult to accurately forecast the future trajectory of an early stage venture (Carter et al., 2020; Chen et al., 2012; Zomaya & Sakr, 2017). This environment of uncertainty often leads to an inverse relationship between the decision-making speed and its overall accuracy (Eisenhardt & Bourgeois, 1988). This dynamic is especially critical for VCs, as the pressure to quickly close deals must be balanced with the necessity of thorough due diligence to mitigate the risk of backing unsuccessful ventures (Dushnitsky & zur Shapira, 2010; Eisenhardt & Bourgeois, 1988; Lévesque et al., 2020; Obschonka & Audretsch, 2020; Shepherd & Majchrzak, 2022). Furthermore, cognitive biases and emotional factors have been demonstrated to influence investment decision-making processes, often causing investors to deviate from a perfectly rational and objective investment decision (Hall, 1989; Kahneman, 2003; Simon, 1955). In circumstances characterized by uncertainty, investors have been observed to utilize heuristics, a process which can cause further biases (Crevier, 1993; Phillips-Wren et al., 2008; Thomas et al., 2019; Tversky & Kahneman, 1974).

Finally, issues related to startup valuations, limited due diligence, and the uncertainty surrounding potential exit strategies can all present further challenges within the VC landscape (Gompers & Lerner, 2001; Kaplan & Strömberg, 2004). It is precisely within this complex and challenging environment that the integration of data-driven methodologies, including AI and advanced analytics, holds significant transformative potential for the VC industry (Carter et al., 2020; Lévesque et al., 2020). Data-driven approaches have the capacity to enhance both the speed and objectivity of the decision-making processes, thus overcoming the limitations of traditional human-centric models (Obschonka & Audretsch, 2020; Phillips-Wren et al., 2008; Russell & Norvig, 2021; Sheu & Lin, 2007). By leveraging data and advanced analytics, tasks such as due diligence and deal sourcing can be significantly optimized, which can also help to reduce the impact of potential biases (Bourgeois & Eisenhardt, 1988; Duan et al., 2019; Pan, 2016). Furthermore, the application of data-driven methods enables the identification of opportunities that may be overlooked by humans in traditional networks, thereby expanding the potential investment universe (Duan et al., 2019; Pan, 2016). The inherent scalability of data analysis and processing allows for the automation of several processes, freeing up valuable time for VC professionals (Bourgeois & Eisenhardt, 1988; Duan et al., 2019; Pan, 2016). The objective is to establish organizational structures where humans and machines can collaborate, combining human expertise with data-driven insights (Florin, 2005; Wadhwa & Bansal, 2024). Data-driven approaches, and in particular AI, also provide entrepreneurs with tools to overcome their limitations, reducing the impact of human bias and allowing for a more level playing field (Cockburn et al., 2018; Obschonka & Audretsch, 2020). The ability to identify subtle patterns and insights within data facilitates more accurate investment predictions and deeper insight into potential future market trends (Sheu & Lin, 2007; Tomy & Pardede, 2018; Wang et al., 2002). Specifically, machine learning algorithms have the capacity to assist both investors and entrepreneurs in determining which factors are most likely to lead to a successful funding round and in allocating capital to those projects with the highest potential for success (Sheu & Lin, 2007; Wang et al., 2002). In essence, data-driven methodologies have the potential to address many of the underlying issues present within the VC industry by generating actionable insights and more robust and efficient decision-making processes (Shepherd & Majchrzak, 2022).

Nice!

3.2 Risks Associated with the Implementation of Data-Driven AI in VC

Whilst data-driven approaches, including AI, present significant opportunities for transforming VC, it is essential to acknowledge the potential risks associated with their implementation (Cockburn et al., 2018; Duan et al., 2019). A primary concern lies in the possibility of biased data, which can result in biased algorithms, regardless of whether AI or other forms of data analysis are employed (Duan et al., 2019; Phillips-Wren, 2014). This can occur when existing human biases are unknowingly reinforced the data-driven systems, thereby creating an illusion of unbiased analysis (Chen et al., 2012; Phillips-Wren et al., 2008). The inherent complexity of many data-driven systems, with their vast number of parameters and self-adaptive learning mechanisms, can also lead to a lack of comprehensibility, thus hindering the effective identification and resolution of problems (Phillips-Wren et al., 2008; Sheu & Lin, 2007). This complexity can create a form of causal ambiguity, where the relative contributions of human and machine inputs become obscured (Shepherd & Majchrzak, 2022). In addition, the importance of human intuition plays a special role in circumstances characterized by increased uncertainty (Obschonka & Audretsch, 2020; Phillips-Wren, 2014; Russell & Norvig, 2021). Specifically, the unpredictable nature of nascent startups can place limitations on the capacity of AI to provide definitive (Pan, 2016). These challenges are not unique to AI; rather, they are relevant to many data-driven and technology-led processes.

very important

The 'black box' nature of many advanced data-driven systems can also make it difficult to identify these biases and can therefore undermine trust in the decisions that are being made by these algorithms (Chen et al., 2012; Shepherd & Majchrzak, 2022). This potential for unintentional bias cannot be disregarded and necessitates a careful and nuanced approach to the implementation of data-driven decision-making (Obschonka & Audretsch, 2020; Shepherd & Majchrzak, 2022).

3.3 Conclusion Opportunities and Risks of Data-driven Venture Capital

?

Despite these risks, technology remains a key aspect of organizational decision-making (Phillips-Wren, 2014). Technology can provide a rational framework for assessing alternatives, while also helping to reduce human biases by providing a clear and structured approach to analyzing data (Crevier, 1993; Dorigo & Schnepf, 1991; Doumpos & Grigoroudis, 2013). Furthermore, technology can assist decision-makers by selecting relevant input data and by supporting the interpretation of outcomes from decision models (Phillips-Wren, 2014; Phillips-Wren et al., 2008; Thomas et al., 2019). The VC industry is characterized as a high-velocity, high-pressure environment (Sheu & Lin, 2007; Zacharakis & Shepherd, 2001) in which investors often rely on intuition for decision-making (Callahan & Muegge, 2003; Hisrich & Jankowicz, 1990). This research investigates the primary challenges of the decision-making process in the industry and examines how data-driven methods, including AI, might address these challenges (Dorigo & Schnepf, 1991; Thomas et al., 2019).

4 Level Ventures Data-Driven and AI-Enhanced Approach

4.1 Overview of Level Ventures Data-Driven and AI Strategies

In order to empirically investigate the potential for outperformance using data-driven strategies in VC, this research has undertaken a detailed quantitative analysis made possible by a collaboration with Level Ventures. Access to Level Ventures real-world performance data provides an invaluable opportunity to bridge the gap between theoretical concepts and empirical validation of data-driven methods in VC. Level Ventures uses artificial intelligence (AI) and data-driven techniques in several key aspects of its investment process, including the classification and selection of promising VC funds. In addition, Level Ventures investment strategy encompasses not only the role of a GP, as described in Chapter 2, but also the role of an LP in VC funds that use a data-driven approach, creating a network of data-driven investment strategies. The aim of this research is to go beyond measuring outperformance to explore the effectiveness of data-driven strategies and whether Level Ventures distinctive investment strategy of focusing on data-driven VC funds is associated with higher returns (Level Ventures, 2025).

4.2 Level Ventures Data-Driven Techniques

Level Ventures has published extensively on its innovative approach to integrating AI into its operations, demonstrating its commitment to transparency and knowledge sharing within the VC community. Their research highlights several key areas where AI plays a crucial role:

1. **Dynamic and neural networks**: Level Ventures uses graph neural networks to model the intricate relationships within the VC ecosystem (Dev Dabke, 2024b). By analyzing the 'dynamic networks' of investors, startups and markets, emerging trends are identified and the potential success of specific funds and investment opportunities are predicted (Level Ventures, 2025). This network-based approach captures the connection of the VC landscape and goes beyond traditional, static methods of analysis (Dev Dabke, 2024b).

2. **Model confidence and jackknife resampling:** To ensure the robustness and reliability of their AI models, Level Ventures uses techniques such as jackknife resampling (Dev Dabke, 2024d). The Jackknife method, a resampling technique, serves to estimate the random error and potential bias of an estimation method (Dev Dabke, 2024d). This helps them assess the stability of their models and quantify the confidence they have in their predictions (Level Ventures, 2025). By systematically evaluating the performance of their models on different subsets of data, they can refine their algorithms and improve the accuracy of their investment decisions (Dev Dabke, 2024d).

3. **Building consensus through Request for Comments:** Level Ventures uses a collaborative approach to AI development inspired by the Request for Comments process used in software engineering. This approach involves circulating proposals for new models or data analysis techniques within the team, with the aim of triggering feedback and building consensus (Level Ventures, 2025). This process ensures that their AI models are rigorously vetted and aligned with the firm's overall investment strategy (Dev Dabke, 2024a).

4. **GPU workloads and infrastructure:** To meet the significant computational demands of their AI models, Level Ventures employs a sophisticated infrastructure that leverages GPU acceleration. They have implemented workflows using Prefect and AWS to manage and optimize their GPU workloads, enabling them to efficiently train and deploy complex machine learning models (Dev Dabke, 2024e).

5. **Fast container builds for ETL:** Level Ventures has optimized its data engineering processes by implementing fast container builds for its extract, transform, load (ETL) pipelines (Level Ventures, 2025). This has enabled them to process large data sets quickly and efficiently, ensuring that their AI models are always trained on the most current and relevant information (Dev Dabke, 2024c).

5 Methodology

In the domain of investment analysis, the concept of 'outperformance' is foundational, serving as a critical measure for evaluating the relative success of investment strategies, particularly within the complex and dynamic environment of VC. In essence, outperformance signifies that an investment strategy has yielded returns that surpass a predetermined reference point or benchmark (Manigart et al., 1994; van Binsbergen et al., 2013). These benchmarks can be expressed in a variety of ways, including broad market indices such as the NASDAQ or S&P 500, or the average performance of VC funds at large (Jelic et al., 2005; Sorensen & Jagannathan, 2015). In this analysis, benchmark data was sourced from Pitchbook, Carta, and Cambridge Associates, as provided by Level Ventures, to provide a comprehensive and industry-relevant comparison. Commonly used metrics for assessing VC performance include Total Value to Paid-In Capital (TVPI), Internal Rate of Return (IRR), and, increasingly, time-series representations of these metrics to analyze performance trends over time (Bauer, 2000; Dushnitsky & zur Shapira, 2010; R. Harris et al., 2012; Hege et al., 2009; Manigart et al., 1994; Phalippou; Sorensen & Jagannathan, 2015). To assess the outperformance, this research uses a calculated approach for a time-series representation of the investment portfolio. This approach is explained as follows:

To assess the performance of VC investments, a method for calculating a time-series performance was employed (Cornelius et al., 2009; Di Guo & Jiang, 2013; Dushnitsky & zur Shapira, 2010; Ewens, 2009; Gompers & Lerner, 1998; Gupta & van Nieuwerburg, 2021; R. Harris et al., 2012; Korteweg, 2011; Metrick & Yasuda, 2010a; Schoar & Kaplan, 2005; Wang et al., 2002). A daily growth factor based on the ratio of Value at Cost (VAC) to Assets under Management (AuM) for active investments is calculated. This is then aggregated quarterly and annually by multiplying the daily growth factors

(Christensen, 1997; Cornelius et al., 2009; R. Harris et al., 2012). While this methodology does not directly calculate the traditional TVPI – which is a single, end-of-fund metric – the aggregated growth factors derived from this approach offer a valuable proxy for TVPI over time (Dushnitsky & zur Shapira, 2010; Ewens, 2009; Gupta & van Nieuwerburg, 2021; R. Harris et al., 2012; Korteweg, 2011; Metrick & Yasuda, 2010a; Schoar & Kaplan, 2005). The VC industry requires specialized metrics that account for the illiquidity and long-term nature of investments (Dushnitsky & zur Shapira, 2010; Korteweg, 2011). The time series TVPI is utilized for this purpose. The quarterly and annual Performance metrics provide a standardized, time-series representation of value creation relative to invested capital (Dushnitsky & zur Shapira, 2010; Gupta & van Nieuwerburg, 2021; Metrick & Yasuda, 2010a, 2010b). Critically, this standardized representation allows a meaningful comparison to benchmarks like quarterly or annual IRR figures reported by the Benchmarks provided by Pitchbook, Carta, and Cambridge Associates, even though the precise calculation methodologies of those benchmarks may vary (Cornelius et al., 2009; Gupta & van Nieuwerburg, 2021; Schoar & Kaplan, 2005; Wright, 1998). Furthermore, the long-term focus is well-suited to this approach, enabling the impact of investment decisions to be observed over extended periods (Bourgeois & Eisenhardt, 1988; Cornelius et al., 2009; Dushnitsky & zur Shapira, 2010; Ewens, 2009; Gupta & van Nieuwerburg, 2021; Schoar & Kaplan, 2005). Therefore, the standardized nature of the calculation creates a reasonable comparison baseline. Although minor variations may exist due to differing benchmark calculations, they do not negate the core finding: the robust statistical significance of Level Ventures outperformance. It is important to recognize that this approach deviates from a direct calculation of TVPI, the method's time-series nature and standardization enable a more flexible and comparative performance assessment (R. Harris et al., 2012; Schoar & Kaplan, 2005; Wang et al., 2002). The creation of quarterly and annual performance metrics facilitates comparisons with the industry benchmarks as highlighted in the analysis of fund-level performance data (Clauset et al., 2007; Gupta & van Nieuwerburg, 2021; R. Harris et al., 2012; Wang et al., 2002). The performance data and calculated adjusted TVPI metrics will then be compared between Level Ventures portfolio and a range of carefully selected benchmarks and evaluated for statistical significance using the Wilcoxon signed-rank and the Mann-Whitney-U test (Nachar, 2008; Wilcoxon, 1945; Wright, 1998). This test is appropriate given the data assumptions that are present in this study and is explained later in this section. The following part of this section provides a detailed justification for the choice of this specific statistical test and outlines the necessary steps taken to ensure the validity of the analysis. An understanding of the factors that drive VC fund performance is critical, including the selection of appropriate analytical methods (Cumming & Johan, 2013; Gupta & van Nieuwerburg, 2021; Schoar & Kaplan, 2005).

5.1 Statistical Methodology Justification

This section details the statistical methods employed to analyze the performance data, particularly focusing on the evaluation of outperformance of data-driven VC strategies as represented by Level Ventures, compared to traditional benchmarks. The nature of VC data requires a careful approach to statistical testing, particularly given its tendency towards non-normality and the presence of extreme values (Dushnitsky & zur Shapira, 2010; Schoar & Kaplan, 2005). To ensure the selection of the most appropriate statistical test and the validity of the analysis, several key assumptions about the data must be assessed before a specific statistical test can be chosen. This includes assessing assumptions about sample independence, normality of distribution, and homogeneity of variance, which dictate whether parametric or non-parametric statistical methods are most suitable. The data cleaning steps must also be undertaken prior to any statistical tests to ensure the validity of the analysis

(Cornelius et al., 2009; Dushnitsky & zur Shapira, 2010; Schoar & Kaplan, 2005). This ensured the accuracy and reliability of the subsequent analysis. The performance data is provided by Level Ventures. The provided dataset included both investments made by Level Ventures as well as benchmark data.

During the initial review of the dataset, few inconsistencies were identified. These inconsistencies were addressed during the data cleaning process to ensure the data's suitability for rigorous statistical analysis. Specific adjustments and the reasoning behind them are outlined below:

- **Negative Investment Durations:** Some records initially showed negative investment durations, which is the time from initial investment to exit. This anomaly could arise from errors in recording the dates or from some other data input problems. Since an investment cannot have a negative duration, these were clearly errors in the dataset. To address this discrepancy, all instances of negative investment durations were adjusted to have an end date of January 3, 2025, which corresponds to the date the data was retrieved. This ensured all investments had a positive time frame.

- **Unrealistic Investment Durations:** Several investment records included instances of unrealistically short durations (e.g., an investment losing 100% of its value in a single day), which is highly unusual, and not in line with what one would expect of VC investments. These are likely due to errors in the provided data. While such outcomes are theoretically possible, in practice it is rare. These entries also significantly distort the overall performance. To resolve this issue, all unrealistically short durations were adjusted to have a duration of 100 days. This ensured that such extreme values would not unduly influence the statistical results while also retaining the information that these investments were unsuccessful.

These data cleaning steps were implemented to ensure the integrity of the dataset and prepare it for valid and reliable statistical analysis. By addressing these issues beforehand, the risk of producing incorrect conclusions in our subsequent analyses was reduced.

In the context of this study, the data provided by Level Ventures was subjected to thorough analysis to ensure consistency of methodology and calculations. This examination confirmed that all calculations were performed on a comparable basis. However, it is important to acknowledge that the used benchmarks, including Pitchbook, Carta, and Cambridge Associates, employ their own distinct calculation methods for metrics such as quarterly returns and IRR. For instance, Pitchbook calculates the quarterly return as the aggregate percentage change in Net Asset Value (NAV), including contributions and distributions, whereas Cambridge Associates determines the since-inception IRR based on cash-on-cash returns and the residual value of the portfolio. These methodological differences may lead to certain variations in the reported performance figures. For instance, Carta states that their IRR is 'net of fees', while Pitchbook only mentions that private capital returns are reported net of fees. This thesis is aware of these methodological differences, but it is crucial to emphasize that these discrepancies are of minor significance within the context of this study. The primary objective of this study is to demonstrate the statistically significant outperformance of Level Ventures relative to the established benchmarks. The observed outperformance is so significant and consistent that it outweighs the potential effects of methodological variation. Consequently, minor methodological deviations in benchmark calculations do not call the overall result into question. Unless otherwise stated, all statistical significance claims in this study are evaluated at a 95% confidence level ($\alpha = 0.05$).

5.2 Assessment of Data Assumptions

Before selecting and applying the specific statistical tests, it was essential to assess several key assumptions about the data. These assumptions include independence, normality, and homogeneity of variance. The data was first analyzed to check if these assumptions were met.

5.2.1 Testing for Normality

A considerable number of conventional statistical tests are predicated on the assumption that the data under investigation adhere to a normal distribution, a requirement that is especially crucial for parametric tests (Fama, 1965). However, financial data, particularly related to VC returns, frequently deviates from this assumption. VC returns, for instance, frequently display characteristics such as skewness (i.e., the asymmetry of the distribution around its mean) and kurtosis (i.e., the 'tailedness' of the distribution compared to the normal distribution). These factors collectively result in significant deviations from normality (Fama, 1965). To formally assess the normality of our dataset, we employed the Shapiro-Wilk test (Fama, 1965). The reason behind this choice is twofold: firstly, its sensitivity to deviations from normality, especially in smaller samples, and secondly, its particular suitability for the types of data distributions found in financial time series (Fama, 1965; Shapiro & Wilk, 1965).

Null Hypothesis (H0): The returns are normally distributed.

Alternative Hypothesis (H1): The returns are not normally distributed.

Confusing notations

Table 1: Shapiro-Wilk Test Statistic

oooh! very close...

Benchmark	***Shapiro-Wilk Test Statistic***	***p-value***	***Normal***
Level Ventures	0.9544	0.0497	✗
VC Fund Index	0.9268	0.0052	✗
US VC	0.9299	0.0067	✗
Europe Developed VC	0.9628	0.1314	✓
China VC	0.8158	0.0000	✗
Pitchbook VC	0.9546	0.0612	✓
Pitchbook FoF	0.8505	0.0000	✗
KfW	0.8965	0.0005	✗

Probably t-distribut.?

The application of the Shapiro-Wilk test yielded p-values that were substantially below the 0.05 significance level for the majority of the return series employed in this study. Specifically, the calculated p-values ranged from a low of 0.0000 for both the China VC and Pitchbook FoF funds, to a high of 0.1314 for the Europe Developed VC benchmark. This finding indicates that the assumption of normality for the majority of the return series data is invalid. This property, when combined with the frequently observed positive skewness in VC returns, renders the assumption of a normal distribution unsuitable (Cumming, 2012; Korteweg, 2011). This finding underscores the necessity to consider departures from a normal distribution in the analysis of fund data. Consequently, given the evident violations of the normality assumption for the majority of the return series, the utilization of parametric statistical tests, which presuppose normally distributed data, was deemed unsuitable for this analysis (Cleves, 1996; Fama, 1965; Shapiro & Wilk, 1965).

Because not all benchmarks exhibited non-normal distributions, a test of homogeneity of variance was also performed to determine whether a nonparametric approach was justifiable for all data sets. The results of this test, which indicated significant heterogeneity of variance, further validated the use of nonparametric methods.

5.2.2 Homogeneity of Variance

Another fundamental assumption inherent to parametric tests is that the variance is homogeneous, the variance of the residuals should be approximately equal across different groups. Violations of this assumption have the potential to compromise the validity of parametric tests (Cleves, 1996). In particular, Levene's test, which is a robust test for assessing variance across different groups, does not assume normality. This renders it appropriate in the context of this research.

Null Hypothesis (H0): The variances are equal across all groups.

Alternative Hypothesis (H1): The variances are not equal across all groups.

Confusing notation

Table 2: Levene Statistic

Benchmark	*Levene Statistic*	*p-value*	*Variance homogenous*
VC Fund Index	12.4274	0.0007	✗
US VC	11.0570	0.0013	✗
Europe Developed VC	8.1464	0.0053	✗
China VC	4.4366	0.0378	✗
Pitchbook VC	15.1950	0.0002	✗
Pitchbook FoF	27.8595	0.0000	✗
KfW	37.9361	0.0000	✗

The results of Levene's test indicated that the assumption of homogeneity of variance was not met across the various benchmarks. Specifically, all of the calculated p-values were found to be below 0.05, with p-values ranging from 0.0000 to 0.0378. Consequently, it was determined that the data exhibited substantial variances, thereby further emphasizing the necessity for non-parametric tests that are not contingent on equal variances. This finding further supports the rationale for using nonparametric statistical techniques (Cleves, 1996; Levene, 1960; Wilcoxon, 1945).

5.2.3 Independence of Samples

A fundamental requirement for any statistical test that compares distinct groups is the assumption that the samples being compared are independent of each other. If this assumption is violated, it can significantly impact the accuracy of the test results, and can lead to incorrect conclusions (Spearman, 1904). To ensure the validity of the statistical analysis, the independence of the different benchmarks used in this study explicitly assessed (Spearman, 1904; Wilcoxon, 1945). The non-parametric Spearman's rank correlation test was chosen to perform this check since the data is not normally distributed (Cleves, 1996; Spearman, 1904). Spearman's rank correlation measures the monotonic relationship between two variables, which shows how two variables tend to increase or decrease together (Spearman, 1904). Any Correlation < 0.5 is considered as small and < 0.3 as weak. In this study, we aimed to identify potential correlations between the returns of the various VC benchmarks and the Level Ventures portfolio returns.

Confusing notation

Null Hypothesis (H0): There is no monotonic relationship between the ranks of the returns of the Level Ventures portfolio and the ranks of the returns of the benchmark.

Alternative Hypothesis (H1): There is a positive monotonic relationship between the ranks of the returns of the Level Ventures portfolio and the ranks of the returns of the benchmark.

Table 3: Spearman Correlation Statistic

Benchmark	***Spearman Correlation***	***p-value***	***Dependent***
VC Fund Index	0.2319	0.1128	✗
US VC	0.2114	0.1493	✗
Europe Developed VC	0.2815	0.0526	✗
China VC	0.1927	0.1893	✗
Pitchbook VC	0.2047	0.1628	✗
Pitchbook FoF	0.1813	0.2175	✗
KfW	-0.1422	0.3350	✗

I'm surprised...

The results of the Spearman correlation test yielded correlation coefficients ranging from a low of -0.1422 to a high of 0.2815 across the benchmark comparisons. Given that all p-values are greater than 0.05, it can be concluded that they are not dependent. However, this does not imply that they are independent. These correlation coefficients, all relatively close to zero, indicate a weak monotonic correlation between benchmark returns. While statistical tests can only assess dependence, our analysis reveals Spearman correlation values consistently below 0.3, suggesting a weak relationship. This, while not definitively proving independence, suggests a sufficiently weak dependence (Spearman, 1904). To ensure the robustness of our findings, both the Wilcoxon signed-rank test, suitable for paired data, and the

Mann-Whitney U test, suitable for independent data, were employed (Spearman, 1904; Wilcoxon, 1945).

5.2.4 Justification of Wilcoxon Signed-Rank and Mann-Whitney U Tests

The selection of an appropriate statistical test is critical for the validity of any analysis. The Wilcoxon signed-rank test is a widely applied non-parametric method for comparing paired samples, making it a natural candidate for this analysis; therefore, its underlying assumptions require careful consideration. The Wilcoxon Signed-Rank test is a non-parametric test designed to compare two related samples, while the Mann-Whitney U test is used to compare two independent groups (Nachar, 2008; Wilcoxon, 1945). Given the documented non-normality of the return data for the benchmarks and the heterogeneous variance across all groups, the Wilcoxon signed-rank test was initially considered the most appropriate statistical method for this study, given its suitability for paired data. However, given the indeterminate result of the Spearman's correlation test, the Mann-Whitney U test, which assumes independence, was also employed to provide a more comprehensive analysis (Nachar, 2008).

Ok

The Wilcoxon signed-rank test does not require data following a specific distribution and is robust against unequal variances, which makes it particularly well-suited for the type of return data frequently found in VC (Dushnitsky & zur Shapira, 2010; Wilcoxon, 1945). This is consistent with its application in other studies analyzing financial performance, particularly when dealing with non-normal distributions (Carlos Nunes et al., 2014; Cornelius et al., 2009; Cumming & Johan, 2008; Di Guo & Jiang, 2013; Dushnitsky & zur Shapira, 2010; Hege et al., 2009; Jelic et al., 2005; Schwienbacher, 2008; Universität Zürich; Wang et al., 2002). The fundamental requirements for employing this test are that the data must be at least ordinal scaled, and that the samples are paired (Universität Zürich; Wilcoxon, 1945). For the Mann-Whitney U test to be applicable, the data must also be at least ordinal scaled, and the samples must be independent.

The following section delineates the key requirements for the Wilcoxon signed-rank test and how they are met in this analysis.

- **Ordinal Scaling:** The data that is the subject of analysis must be of an ordinal nature, implying that it is capable of being arranged in a hierarchical structure. Interval-scaled data is a suitable example of such data, as it is possible to rank all interval-scaled data, in addition to the data demonstrating a consistent scale for the differences between values (Stevens et al.). Performance data in finance, including the VC returns analyzed here, are typically interval-scaled and therefore meet this criterion, a requirement also satisfied for the application of the Mann-Whitney-U test (Nachar, 2008; Phalippou; Razafitombo, 2011; Universität Zürich).
- **Paired Samples:** The samples must be paired. This is reflected in the necessity to compare the returns with paired values of a related benchmark within the same calendar quarter. This ensures a direct comparison of performance under similar market conditions, eliminating potential biases in the data used for this research (Gompers & Lerner, 1998; Razafitombo, 2011; Universität Zürich).

The following section delineates the key requirements for the Mann-Whitney-U test and how they are met in this analysis.

- **Ordinal Scaling:** Is displayed and described with the Wilcoxon signed rank test.
- **Independence:** The Mann-Whitney U test assumes that two groups are independent. While the Spearman correlation analysis suggests a relatively weak correlation between Level Ventures and other benchmarks, which have a high score in the test, this could be considered independent groups. Specifically, the

Spearman correlation coefficients are consistently below 0.3, indicating a weak monotonic relationship, and the null hypothesis of independence could not be rejected, supporting the assumption of independent samples for the Mann-Whitney U test.

In conclusion, the statistical methods employed in this research were carefully selected to ensure the validity and accuracy of the findings. The VC return data indicates violations of the assumptions of normality and homoscedasticity. These characteristics, commonly observed in financial time series data (Cumming, 2006; Cumming & Johan, 2008; Dushnitsky & zur Shapira, 2010; Gupta & van Nieuwerburg, 2021), render traditional parametric tests inappropriate for examination of the research hypothesis. The application of this tests aligns with established practices in financial research, particularly when assessing outperformance in situations where data do not meet the assumptions of parametric tests (Bollen & Busse, 2005; Gupta & van Nieuwerburg, 2021; Nandini, 2015). The selection of these statistical techniques was driven by the objective of conducting a robust and reliable analysis of the data, thereby ensuring that the conclusions drawn in this study are supported by methodological approaches tailored to the specific distributional and structural characteristics of the return data under investigation (Gupta & van Nieuwerburg, 2021).

5.3 Hypothesis

In consideration of the data characteristics, the methodology employed, and the prior results, the following testable hypothesis will be specifically examined within this empirical study:

OK

Hypothesis 1 (H1): Data-driven venture capital strategies, represented by Level Ventures, outperform venture capital benchmarks and fund of funds benchmarks.

The statistical analysis will employ the metrics previously discussed to measure the absolute and relative performance of the Level Ventures portfolio, alongside all the benchmarks. This methodological approach is expected to facilitate a robust and rigorous analysis of different strategies, with a particular emphasis on the empirical effects of data-driven approaches. The results of the hypothesis test and statistical analysis will provide valuable empirical evidence regarding the potential of data-driven decision-making in the VC domain. The conclusions drawn will aim to demonstrate the statistical significance of these findings. Regardless of whether a paired (Wilcoxon) or independent (Mann-Whitney U) statistical test is applied, the empirical results consistently demonstrate the statistically significant outperformance of Level Ventures relative to the selected benchmarks (Nachar, 2008; Wilcoxon, 1945).

5.4 Statistically Significant Outperformance of Level Ventures

5.4.1 Wilcoxon-Test

The empirical analysis conducted in this study provides substantial evidence that data-driven VC strategies, as exemplified by the Level Ventures portfolio, demonstrate statistically significant outperformance compared to a diverse array of benchmarks. These analyses validate the hypothesis of this study. Beyond the statistical significance, the Level Ventures portfolio demonstrated higher median and average returns compared to the benchmarks (R. S. Harris et al., 2023). Specifically, the observed returns for Level Ventures, while seemingly high in absolute terms, are plausible when compared to their internal benchmark and historical performance, as supported by their TVPI and MOIC metrics. These internal metrics, which reflect Level Ventures unique investment strategy and portfolio construction, offer a valuable context for understanding the magnitude and sustainability of the observed outperformance.

Table 4: Outperformance of Level Ventures (Wilcoxon signed-rank Test)

Benchmark	***Average Quarterly Outperformance***	***Wilcoxon Test-Statistic***	***p-value***	***Effect Size***
VC Fund Index	17.34 %	1148	5.27E-12	2.1718
US VC	17.35 %	1150	3.80E-12	2.1569
Europe Developed VC	17.02 %	1151	3.21E-12	2.1436
China VC	16.83 %	1104	1.30E-09	2.1111
Pitchbook VC	17.65 %	1157	1.09E-12	2.1895
Pitchbook FoF	17.83 %	1161	4.87E-13	2. 1821
KfW	18.39 %	1156	1.32E-12	2.2176

What about upper quartile?,

Given the number of benchmark comparisons made in this study, it is imperative to address the possibility of Type I error (false positives) resulting from multiple hypothesis testing. To mitigate this risk, the Bonferroni correction was implemented, leveraging the Union Bound inequality (Abdi, 2007, pp. 5–7). The Union Bound states that the probability of at least one of several events occurring is less than or equal to the sum of the probabilities of each individual event. In the context of multiple hypothesis testing, this implies that the probability of observing at least one statistically significant result by chance increases with the number of tests performed (Abdi, 2007, p. 5). The Bonferroni correction directly addresses this by adjusting the significance level (α) for each individual test. In the context of seven benchmark comparisons, the significance level ($\alpha = 0.05$) was divided by the number of tests ($n = 7$), resulting in a Bonferroni-corrected significance level of approximately 0.0071. A subsequent review of this adjusted threshold and the resulting p-values shows that all p-values are well below the Bonferroni-corrected significance level. Consequently, even when implementing the Bonferroni correction, which employs the conservative Union Bound principle to regulate multiple comparisons, the statistically significant outperformance of Level Ventures relative to the benchmarks persists (Abdi, 2007). This corroborates the validity of the findings and further mitigates the risk of false results due to chance (Abdi, 2007).

5.4.2 Mann-Whitney U Test

To further validate the outperformance and account for the ambiguity regarding sample independence left by the inconclusive result of the Spearman correlation test, the Mann-Whitney U test was also conducted. Given the weak dependence suggested by the Spearman results, an independent test provides additional insights. The Mann-Whitney U test, which assumes independent samples, consistently demonstrates significant outperformance of data-driven VC strategies, as exemplified by the Level Ventures portfolio, compared to a variety of established benchmarks (Nachar, 2008). The test statistics range from a minimum of 2013 (China VC) to a maximum of 2086 (KfW), indicating a substantial deviation from the null hypothesis of no difference in distributions. The p-values, all between 1.88E-11 and 3.95E-12, are well below the conventional significance level of α = 0.05. The test strengthens the analysis further. The table is as follows:

Table 5: Outperformance of Level Ventures (Mann-Whitney-U Test)

Benchmark	***Average Quarterly Outperformance***	***Mann-Whitney-U Statistic***	***p-value***	***Effect Size***
VC Fund Index	17.34 %	2055	1.88E-11	2.1718
US VC	17.35 %	2045	3.078E-11	2.1569
Europe Developed VC	17.02 %	2035	5.001E-11	2.1436
China VC	16.83 %	2013	1 .44E-10	2.1111
Pitchbook VC	17.65 %	2067	1.03E-11	2.1895
Pitchbook FoF	17.83 %	2062	1.33E-11	2. 1821
KfW	18.39 %	2086	3.95E-12	2.2176

Given the multiple comparisons made in the study, we use the Bonferroni correction which directly addresses this by adjusting the significance level (α) for each individual test. In the context of seven benchmark comparisons, the significance level ($\alpha = 0.05$) was divided by the number of tests ($n = 7$), resulting in a Bonferroni-corrected significance level of approximately 0.0071. A subsequent review of this adjusted threshold and the resulting p-values shows that all p-values are well below the Bonferroni-corrected significance level. Even after applying the Bonferroni correction, the achieved p-values remain significantly below the adjusted threshold, further solidifying that Level Ventures outperformance is not a result of chance (Abdi, 2007).

Regardless of whether a paired (Wilcoxon) or independent (Mann-Whitney U) statistical test is applied, the empirical results consistently demonstrate the statistically significant outperformance of Level Ventures relative to the selected benchmarks.

5.5 Absolute Outperformance of Level Ventures

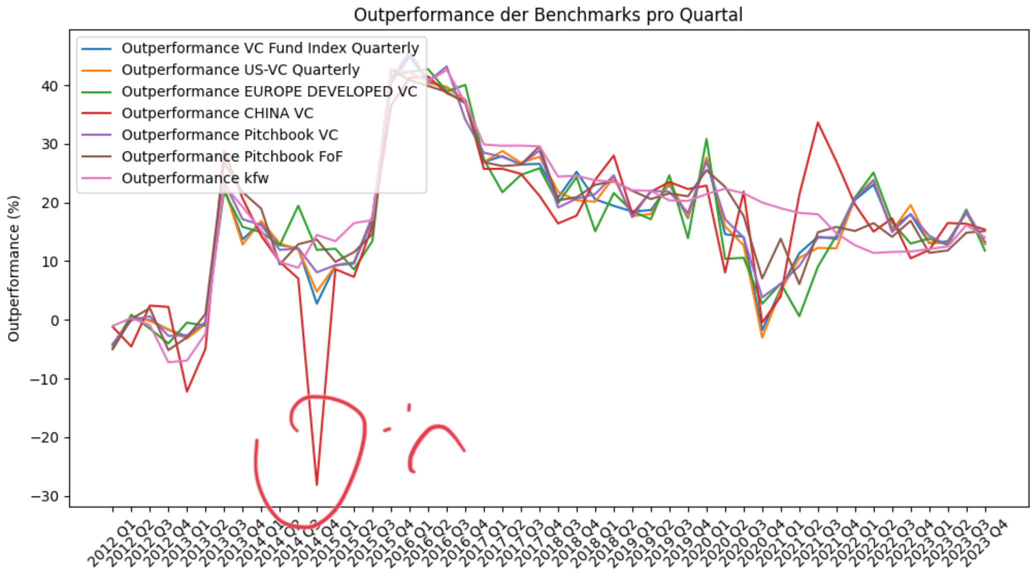

Figure 5: Outperformance of Level Ventures

The Level Ventures portfolio exhibited a consistent pattern of absolute outperformance relative to all selected benchmarks. This analysis was conducted using data from Q1 2012 onwards, ensuring a robust and comprehensive examination of performance. The mean quarterly outperformance percentages ranging from a low of 16.83% when compared to the China VC benchmark, to a high of 18.39% when compared to the KfW benchmark. It is critical to acknowledge that the performance figures from Level Ventures at the inception of the analysis period (early 2012) exhibit a pattern of lower performance. This phenomenon is predominantly attributable to the fact that, during that period, the portfolio contained a limited number of investments, as the data collected in this study pertains exclusively to the year 2012 and later. Consequently, the initial performance is significantly influenced by the composition of early investments. However, as the portfolio undergoes diversification and the duration of investments increases, the performance becomes more stable and reflects the overall strategy of the portfolio (Davila et al., 2003; Gompers & Lerner, 2001). These substantial positive differences in absolute returns lend support to the notion that a data-driven approach to VC can provide a notable advantage over more traditional methods. The findings indicate the potential for data-driven strategies to enhance returns and underscore the value that this approach can create in the VC space. The relative consistency of these findings across a range of diverse benchmarks lends further support to the robustness of these results and underscores a notable potential advantage for the Level Ventures strategy over more traditional approaches.

5.6 Test Results and Statistical Significance

The core statistical analysis was conducted using the Wilcoxon signed-rank and the Mann-Whitney-U test, a method that has been demonstrated to be particularly effective in the analysis of data characterized by non-normal distributions and heavy-tailed characteristics (Nachar, 2008; Wilcoxon, 1945). To address the uncertainty regarding the independence of the samples as indicated by the Spearman correlation results, a Mann-Whitney U test was additionally conducted, yielding findings consistent with the Wilcoxon test and reinforcing the observed patterns of outperformance. The test consistently yielded highly statistically significant results, with p-values falling below the predetermined threshold of $\alpha = 0.05$ and reaching $\alpha < 0.001$ for all benchmark comparisons. The Wilcoxon test statistic demonstrated a range of 1104 when evaluated against the China VC benchmark and 1161 when evaluated against the Pitchbook FoF benchmark. Notably, this result attained a significance level of less than 0.001, a notable achievement in statistical analysis. These figures indicate a strong and consistent pattern of outperformance across all benchmarks, with Level Ventures demonstrating superior returns in each instance. All tests yielded statistically significant p-values, with all benchmark comparisons yielding p-values less than 0.001, indicating an extremely low probability that the observed outperformance occurred due to random chance. The findings provide a robust statistical foundation for concluding that the observed outperformance is unlikely to be the result of outliers. The effect sizes, which are a measure of the magnitude of the difference between the two groups, ranged from 2.1111 to 2.2176 across all comparisons, demonstrating a large and practically meaningful level of outperformance across all benchmarks. In each instance, Level Ventures also demonstrated higher medians when compared to the medians of all of the benchmarks, demonstrating higher returns for Level Ventures across all tests.

5.7 Summary of Figures

The graphs (see Figures 6 through 12 in the Appendix) visually represent the performance of Level Ventures compared to each benchmark and are consistent with the findings outlined above.

- **Quarterly Outperformance Chart:** As illustrated in Figure 5, the quarterly outperformance of Level Ventures relative to the combined benchmarks is evident. This chart demonstrates the consistency of the outperformance over time, showing that the outperformance is not due to individual instances of extreme performance. The figure indicates that the outperformance is persistent and not confined to one or two periods in time.

- **Histograms of Performance**: Figures 6 through 12 present histograms that compare the distribution of returns for the Level Ventures portfolio with that of seven chosen benchmarks. These histograms visually demonstrate the higher median returns for Level Ventures and also show the degree of variation in performance. It is evident that the distributions of Level Ventures are noticeably shifted to the right of the benchmarks in all instances, which further underscores the pronounced outperformance achieved by Level Ventures.

5.8 Evaluation of Hypothesis

Hypothesis 1 (H1): Data-driven venture capital strategies, represented by Level Ventures, outperform venture capital benchmarks and fund of funds benchmarks.

Evaluation: Supported. As demonstrated by the Level Ventures portfolio, data-driven venture capital strategies exhibit statistically significant outperformance compared to a range of venture capital benchmarks and fund of funds benchmarks (see Figure 5). The consistent, statistically significant results across all benchmarks, and the high average outperformance figures, demonstrate that Level Ventures consistently outperforms the traditional benchmarks, thus supporting the first hypothesis. The application of both the Wilcoxon signed-rank test and Mann-Whitney-U test, considering the non-normal distribution of venture capital data and the probable Pareto distribution for individual VC fund performance, validates the suitability of this non-parametric approach. The consistent significance observed across all benchmark comparisons affirms the appropriateness of using the Wilcoxon and Mann-Whitney U tests.

Level Ventures demonstrates statistically significant outperformance across all selected benchmarks, supported by consistent and robust results and substantial effect sizes. This compelling combination of statistical significance and meaningful impact suggests Level Ventures consistently exceeds benchmark expectations. The findings of the study provide clear statistical validation for the core hypothesis, thus strongly supporting the thesis that data-driven methods can improve VC investment returns.

6 The Role of AI and Data-Driven Methodologies in Outperformance

This study has provided robust evidence that data-driven VC strategies demonstrate statistically significant outperformance against a variety of benchmarks. Statistical analysis confirms Level Ventures consistently generates higher returns relative to benchmarks, supported by visual evidence of outperformance. This outperformance is statistically significant and consistent across all benchmarks evaluated, indicating a robust effect. The subsequent discussion will explore the potential underlying factors and mechanisms contributing to this observed advantage.

- **Potentially improved deal sourcing and selection:** Traditional VC funds often rely heavily on established networks and personal contacts to source investment opportunities. In contrast, Level Ventures uses AI to analyze a significantly broader universe of potential deals. This could include using machine learning algorithms to analyze through vast amounts of data from multiple sources, identifying promising startups and emerging trends that traditional methods might miss (Carter et al., 2020). By expanding the scope of deal sourcing, Level Ventures is able to access a wider range of opportunities, potentially leading to a higher probability of investing in high-potential companies (Shepherd & Majchrzak, 2022). It is therefore possible that the wider range of investment opportunities has enabled Level Ventures to select investments that are more likely to succeed (Pan, 2016).
- **Potentially more comprehensive and objective due diligence:** Traditional due diligence is often a time-consuming process that is susceptible to human biases and information processing limitations (Doumpos & Grigoroudis, 2013; Makridakis, 2017). Level Ventures leverages AI to automate and significantly enhance this critical process. By utilizing quantitative data and algorithmic analysis, Level

Ventures potentially reduces biases, which often influence human decision-making in traditional VC (Giuggioli & Pellegrini, 2022; Kahneman, 2003; Obschonka & Audretsch, 2020). This results in more objective evaluations and potentially better investment choices. Additionally, the employment of AI and data-driven tools has the potential to streamline the investment process, enabling faster and more comprehensive due diligence, deal sourcing, and portfolio management (Giuggioli & Pellegrini, 2022; Gompers et al., 2015). This enhanced efficiency allows Level Ventures to analyze a larger volume of opportunities and make more informed decisions. For example, natural language processing (NLP) analyzes unstructured data from news articles, social media platforms, and other sources to assess brand reputation, investor sentiment, and market positioning, providing a more rounded analysis (Cockburn et al., 2018; Duan et al., 2019). This helps mitigate the risk associated with subjective assessments and enables a more evidence-based approach (Korteweg, 2011). As a result, a more objective assessment of potential investments is more likely to reduce the risk of selecting underperforming investments (Shepherd & Majchrzak, 2022).

- **Potential for predictive analytics and proactive risk mitigation:** The use of advanced machine learning algorithms potentially enables Level Ventures to identify complex patterns within available data sets that are not readily apparent using traditional methods (Weidig, 2002b). This data analysis allows Level Ventures to predict the potential success of various startups with greater accuracy and proactively identify key risk factors (Korteweg, 2011; Ruhnka & Young, 1991). This improved pattern recognition capability allows machine learning algorithms to uncover latent opportunities and make more precise predictions about a startup's potential (Aven, 2013; Jordan & Mitchell, 2015). This ability to predict potential outcomes could enable Level Ventures to make more strategic investment decisions, potentially resulting in optimized returns for the level of risk taken (Amit et al., 1990). In contrast, more traditional methods may fail to identify risks that are readily apparent in machine-analyzed data (Korteweg, 2011; Weidig, 2002a).

- **The potential for dynamic portfolio management:** Traditional portfolio management often involves periodic reviews and adjustments. Level Ventures uses AI to continuously monitor its portfolio companies and the broader VC landscape (Obschonka & Audretsch, 2020; Schwienbacher, 2008). This real-time data analysis could enable rapid adjustments to portfolio composition based on changes in market conditions, company performance and overall risk profile (Manyika et al., 2011; Taddy, 2019). This dynamic management approach could enable Level Ventures to take advantage of emerging opportunities while mitigating potential threats (Chen et al., 2012; Duan et al., 2019; Manyika et al., 2011). The ability to quickly adapt to market changes by using AI to constantly monitor and make decisions may allow Level Ventures to outperform benchmarks that only periodically adjust (Obschonka & Audretsch, 2020; Tomy & Pardede, 2018; Zomaya & Sakr, 2017).
- **Potential network effects of a data-driven ecosystem:** Level Ventures distinctive strategy of investing in other data-driven VC funds potentially creates a powerful network effect (Chen et al., 2012; Duan et al., 2019; Zomaya & Sakr, 2017). The collective intelligence and data insights generated by this network can enhance the effectiveness of each individual fund, as knowledge and insights can be shared across the network (Shan et al., 2022). This collaboration could provide access to a wider range of perspectives and information, allowing for better identification and capitalization on emerging market trends (Duan et al., 2019; Obschonka & Audretsch, 2020). The combined knowledge and data-driven

processes of these linked funds could potentially create a robust competitive advantage over traditional approaches or isolated fund of funds (Tomy & Pardede, 2018).

In addition to these factors, it is also possible that the use of AI may reduce the risk associated with early stage investments (Ruhnka & Young, 1991). In the context of pre-seed and seed investments, where risk is typically higher due to the uncertainty surrounding new ventures, this risk reduction may also contribute to higher risk-adjusted returns for the Level Ventures portfolio (Bharat Anant, 2016; Werther, 2013). It is therefore possible that the risk associated with these ventures may be lower than what would be expected from other pre-seed and seed investments (Reid et al., 1997; Werther, 2013).

These mechanisms, all underpinned by a rigorous data-driven approach and the use of AI technologies, may collectively contribute to Level Ventures outperformance relative to traditional methods (Cockburn et al., 2018; Duan et al., 2019). By using these methods, it can be concluded that Level Ventures may have an advantage over more traditional benchmarks and that this particular strategy, as tested in this study, may generate higher returns than the benchmarks selected for this study (Carter et al., 2020; Makridakis, 2017). The results of this study have shown a correlation between data-driven approaches and better performance and this can be further explored in future research.

7 Conclusion

This thesis investigated the efficacy of data-driven and AI-enhanced strategies in the venture capital (VC) arena, specifically examining their ability to generate outperformance relative to traditional investment methodologies. Through meticulous empirical analysis conducted in close collaboration with Level Ventures, a New York-based fund of funds (FoF), this research has provided robust evidence that data-driven approaches can indeed lead to statistically significant and consistently superior investment outcomes.

The key findings of this study clearly demonstrates the outperformance of the Level Ventures portfolio against a wide range of benchmarks, including both traditional venture capital indices and funds of funds. This was achieved through the strict application of the Wilcoxon signed-rank and the Mann-Whitney-U test, non-parametric statistical methods specifically chosen to account for the non-normal distribution and potential for Pareto distribution characteristics inherent in venture capital return data. The consistently low p-values derived from the tests, combined with substantial effect sizes, provide compelling statistical validation that the observed outperformance is not simply the result of chance. These statistical results are further supported by consistently positive average quarterly outperformance percentages and visual representations in the form of histograms and quarterly performance charts, all of which reinforce the conclusion that the Level Ventures portfolio consistently outperforms traditional investment benchmarks.

The study's findings underscore that data-driven approaches using AI and advanced analytics are not just incremental improvements but represent a fundamental shift in how venture capital investments are identified, evaluated and managed (Giuggioli & Pellegrini, 2022; R. S. Harris et al., 2023; Makridakis, 2017). Mechanisms likely to contribute to this outperformance include a more expansive and efficient deal sourcing process, potentially accessing opportunities beyond the reach of traditional networks (Doumpos & Grigoroudis, 2013; Duan et al., 2019; R. S. Harris et al., 2023). In addition, the use of AI in the due diligence process has been shown to promote a more objective evaluation of potential investments, mitigating the cognitive biases that often plague traditional VC decision-making (Carter et al., 2020; Duan et al., 2019). The application of predictive analytics derived from machine learning algorithms can enable Level Ventures to proactively assess and manage risk, identifying and decreasing potential pitfalls before they can significantly impact returns (R. S. Harris et al., 2023; Shepherd & Majchrzak, 2022; Thomas et al., 2019; Wadhwa & Bansal, 2024). The ability to dynamically adjust portfolio allocations based on real-time data and market insights, rather than relying on periodic reviews, is a further advantage (Giuggioli & Pellegrini, 2022). Finally, the network effects generated by Level Ventures approach to investing in other data-driven venture capital funds also creates a system where knowledge and insights are shared, potentially amplifying the impact of data-driven methodologies (Gelernter & Rochester, 1958; R. S. Harris et al., 2023; Shepherd & Majchrzak, 2022; Thomas et al., 2019).

These findings definitively validate the core hypothesis of this research: data-driven VC strategies, as represented by Level Ventures, achieve statistically significant outperformance relative to conventional benchmarks. The cumulative evidence points to a significant advantage associated with a data-driven approach to VC, highlighting the potential for AI to generate superior returns and transform the industry's investment approach (Phillips-Wren et al., 2008; Shepherd & Majchrzak, 2022). This is also achieved by potentially reducing the risk associated with early stage investing, which in turn increases the overall return on investment (Aven, 2013; R. S. Harris et al., 2023; Werther, 2013).

In conclusion, this thesis provides robust empirical evidence for the effectiveness of data-driven and AI-enhanced methodologies in venture capital. The findings underscore that such methodologies are not just incremental improvements but rather represent a fundamental shift that can deliver measurable and statistically significant improvements in investment returns compared to more traditional approaches. This suggests that a data-driven approach may represent a superior investment model in the venture capital landscape (Cockburn et al., 2018; Duan et al., 2019; Gelernter & Rochester, 1958; Giuggioli & Pellegrini, 2022; R. S. Harris et al., 2023; Makridakis, 2017; Obschonka & Audretsch, 2020; Pan, 2016).

7.1 Implications for Research and Practice

The findings of this study carry substantial implications for both the academic research community and the practical application of investment strategies within the venture capital industry.

Implications for Research:

This research contributes to the growing body of literature on the impact of AI and data analytics on the financial industry, specifically within the VC sector. It provides empirical evidence supporting the theoretical advantages of data-driven decision-making, demonstrating its potential to generate superior returns. Furthermore, this research calls for further exploration into the long-term performance and risk profiles of data-driven VC strategies, with further exploration of how these strategies perform across different market cycles and economic conditions. This research also provides the basis for further investigation of the specific causal factors that lead to this outperformance and highlights the importance of further research in this area.

Implications for Practice:

The findings suggest that traditional VC funds may benefit from incorporating data-driven tools and techniques into their investment processes to enhance efficiency, reduce bias, and improve decision-making. LPs seeking superior returns may consider allocating a portion of their portfolio to data-driven VC funds or FoFs. The study emphasizes the significance of transparency and explainability in AI-driven investment models to cultivate trust and comprehension among stakeholders. Practitioners should be aware of the potential risks associated with AI, such as data biases and the 'black box' nature of some algorithms and implement measures to mitigate these risks.

In conclusion, this thesis provides robust empirical evidence supporting the efficacy of data-driven and AI-enhanced methodologies in VC. The results underscore that such methods are not merely incremental improvements but rather present a fundamental shift that can yield measurable and statistically significant improvements in investment returns when compared to more traditional approaches.

7.2 Future Outlook

The future of VC is poised to become increasingly data-driven. Building on the mechanisms of outperformance identified in the discussion, and the need to further validate these mechanisms, future research should prioritize a more granular understanding of the factors driving the observed results, specifically exploring the following key trends:

- **Deconstructing the Impact of Unstructured Data:** Future studies should focus on deconstructing the impact of utilizing unstructured data sources. This includes a detailed investigation of how specific types of unstructured data, such as social media sentiment, news articles, or patent filings, contribute to enhanced deal sourcing and due diligence. Moreover, further research is required to assess the effectiveness of various NLP techniques in extracting valuable and actionable insights from this information. A comparative analysis of the different methods may prove to be a valuable area of study.
- **The Need for Granular Explainable AI:** The further development of Explainable AI (XAI) models in the VC space is essential, but further study is needed to determine whether they are truly effective in explaining the logic behind data-driven investment decisions. This includes developing methods that can help users not only understand the reasoning behind decisions, but also to evaluate whether these decisions are robust and valid, providing a deeper level of confidence and greater transparency for all stakeholders. This is particularly relevant for understanding the causal pathways of outperformance and should be a key consideration in future model building.
- **Dynamic Benchmarking and the Control of External Variables:** The development of truly dynamic benchmarking methodologies is required in order to adequately control for the effect of external factors on VC fund returns. This includes the creation of more robust benchmarks that can adjust to changing market conditions, economic cycles, and macroeconomic shifts. Such a study will be needed in order to accurately ascertain whether the outperformance is a result of the data driven approach, or other factors. Further investigation is required to develop methods that can control these externalities and produce a more valid

understanding of whether the data-driven method has truly produced the outperformance.

- **Causal Investigation of AI on Early Stage Investing:** Further and more detailed investigation into the specific impact of AI on very early stage startup identification and investment strategies will be required. This includes an analysis of the extent to which AI can not only improve returns, but can also reduce risk, and improve the overall reliability of investment in this area of VC. The specific causal pathways by which AI achieves these improvements must be determined, in order to better understand the effects of AI in VC.
- **The Detailed Examination of Network Effects:** Additional research is necessary to better understand how network effects within data-driven ecosystems contribute to the overall performance of individual funds. This should include a detailed investigation into how the sharing of knowledge, insights, data, and other resources impacts the decision-making process and the overall investment performance. This also includes developing and using methods that allow for the isolation and assessment of the contribution of this specific effect and its precise causal impact.
- **Deconstructing Predictive Power:** Rigorous testing is required in order to assess the reliability of AI-based predictions in the VC context. This should include studies which evaluate the extent to which AI can accurately forecast the success of startups, and whether these methods can truly outperform more traditional methods of analysis. A better understanding of where and how these models work best is essential for future use.

- **The Efficacy of AI Enhanced Due Diligence:** While data-driven approaches may reduce bias, further investigation into this is also required. This research must specifically determine whether, and how, AI can reduce cognitive biases and other issues associated with more traditional due diligence methods, and whether this results in higher risk-adjusted returns. A comparison of the effect and reliability of these methods must be undertaken in order to ascertain their true value.

very ¡important!

In the future, it is imperative to persist in the improvement of risk assessment and mitigation strategies. Next research efforts should investigate the potential of data-driven approaches to quantify the multifaceted risks inherent in venture investments more accurately. These risks encompass market volatility, technological obsolescence, and risk related to team performance. This includes the exploration of the development of sophisticated risk models that incorporate a wider range of data sources and analytical techniques. The aim of this development is to provide a more comprehensive and dynamic view of potential investment risks. Additionally, the evaluation of the efficacy of risk mitigation strategies employed by data-driven VC funds, such as diversification, active portfolio management, and staged funding, in reducing overall portfolio risk and enhancing long-term returns, is imperative.

The future of data-driven VC research lies in exploring the nuanced ways in which AI and expanding data availability are reshaping investment practices. Beyond broad performance metrics, future studies should prioritize investigating the impact of specific data-driven strategies on each distinct phase of the VC investment lifecycle. For instance, future theses could focus on developing frameworks for assessing how different data sources (e.g., patent databases, alternative credit data) influence specific due diligence tasks like technological viability or credit risk assessment. Furthermore, research should explore the causal pathways through which specific data-driven interventions, such as AI-powered lead scoring systems, affect investment outcomes. This could involve using causal inference techniques to understand how these interventions impact deal flow, due diligence efficiency, and ultimately, investment returns. Research must also move beyond simply observing correlations, seeking to understand the underlying mechanisms through which data-driven approaches generate value. By focusing on these granular analyses and causal investigations, future research can unlock actionable insights into the most effective components of data-driven VC, guiding both researchers and practitioners in developing more refined and successful investment strategies.

7.3 Limitations:

It is essential to acknowledge the limitations of this study to provide a balanced perspective on the findings and to guide future research. Several factors may influence the generalizability and interpretation of the results. The analysis is primarily based on data from a single data-driven FoF, Level Ventures. While the results are compelling and statistically significant, the dependence on a single source may limit the generalizability of the findings to the broader universe of data-driven VC strategies, as different approaches, strategies and data may result in varying outcomes. The study is also limited by the data available. The potential for bias also exists within the study, due to issues with data collection, processing, and analysis, and also through algorithmic bias that is built into the AI. While efforts were made to clean and pre-process the data, the possibility of errors, inconsistencies, and missing information remains. This limitation in data also limits the depth of analysis that can be undertaken, and the study has also only provided a limited time-frame of data, therefore limiting its long-term applicability. While our analysis suggests a lack of statistically significant dependence between the tested datasets ($p > 0.05$ in the Spearman correlation tests), it is crucial to acknowledge that this does not definitively prove independence. Residual correlations or dependencies below the detection

true

Also: catastrophic statistical analysis, and proper values vs. ground truth threshold of our chosen statistical test may still exist, potentially influencing the robustness of conclusions drawn from tests relying on the assumption of independence. While this period is sufficient to demonstrate statistical significance, further analysis is needed to establish the long-term consistency of the observed effects, particularly through various market cycles and macroeconomic conditions. The study has shown a strong correlation between data-driven methods and superior performance, the precise causal mechanisms through which these results are achieved are not fully established, and it is challenging to fully isolate the impact of individual factors. Further, it is not possible to definitively state that the outperformance is due to the data-driven approach, or some other external factor. The study also primarily relies on quantitative financial performance metrics and has not included a detailed examination of the qualitative aspects of the study, which could influence the overall findings. he Wilcoxon signed-rank test was chosen to suit the distribution characteristics of the data; however, to address concerns regarding sample independence, a Mann-Whitney U test was also conducted. While other statistical methods might yield different perspectives, this study primarily focused on these two complementary approaches. The unique approach of Level Ventures, as a fund of funds specializing in data-driven VC funds, may not be fully representative of all data-driven strategies, and the data is primarily related to VC investments within particular market geographies, meaning the performance of data-driven VC strategies may differ in other markets. The Coverage of some AI models, often referred to as the 'black box' nature, can create challenges in understanding and trusting their decision-making processes and the study has not addressed the optimal balance between human and machine intelligence in VC. These limitations underscore the need for caution in generalizing the findings of this study and also serve as critical avenues for future research. By acknowledging these limitations, this study can provide a more balanced and nuanced contribution to the existing body of knowledge on data-driven VC.

8 Appendix

8.1 Quarterly Performances

Units? Is this IRR?

Table 6: Quarterly Performances Level Ventures and Benchmarks

Quarter	*Level Ventures*	*VC Fund Index*	*US-VC*	*European Developed VC*	*China VC*	*Pitchbook VC*	*Pitchbook FoF*	*KfW*
Q1 2012	0.00	4.28	4.47	4.88	1.19	4.09	5.02	1.04
Q2 2012	1.35	0.96	0.7	0.48	5.9	1.44	1.19	1.04
Q3 2012	0.44	0.5	0.62	1.93	-1.99	-0.18	-1.56	1.32
Q4 2013	-0.74	0.94	0.88	3.29	-2.95	1.99	4.42	6.49
Q1 2013	-0.58	2.22	2.61	-0.1	11.67	2.08	2.42	6.38
Q2 2013	3.90	4.51	4.63	4.91	8.83	4.29	2.89	6.27
Q3 2013	29.55	6.99	6.85	7.67	0.73	6	2.7	6.54
Q4 2014	25.82	12.12	12.98	9.98	5.13	8.66	4.05	6.57
Q1 2014	21.46	4.83	4.6	6.51	7.13	5.29	2.49	6.20
Q2 2014	16.07	3.31	3.05	3.35	6.18	4.15	6.63	6.22
Q3 2014	14.78	2.59	2.78	-4.67	7.74	2.59	1.89	5.89
Q4 2015	15.39	12.63	10.57	3.47	43.53	7.29	1.7	0.91
Q1 2015	13.74	4.43	4.5	1.62	5.11	4.41	3.85	0.33
Q2 2015	16.68	7.07	6.89	8.08	9.35	6.91	5.15	0.17
Q3 2015	17.05	-0.08	-0.54	3.58	0.92	-0.63	2.42	0.06
Q4 2016	42.66	2.27	1.77	1.05	6.11	2.17	0.01	-0.03
Q1 2016	42.33	-2.59	-3.5	0.05	1.05	-3.34	1.47	0.09
Q2 2016	40.95	0.27	0.58	-1.79	-0.54	0.29	1.07	0.29
Q3 2016	43.10	3.46	3.38	4.14	4.45	-0.11	4.24	0.49
Q4 2017	37.55	0.05	0.11	-2.51	0.26	3.41	0.63	0.48
Q1 2017	30.29	3.36	3.37	2.93	4.55	1.79	3.4	0.39
Q2 2017	30.14	2.24	1.36	8.39	4.39	2.36	3.92	0.46
Q3 2017	30.31	3.82	3.52	5.59	5.42	3.8	3.86	0.60
Q4 2018	30.70	4.11	2.9	4.86	9.56	1.84	1.11	1.12
Q3 2018	25.87	5.02	4.04	5.98	9.43	6.72	5.48	1.44
Q4 2018	26.34	1.10	5.97	2.01	8.57	5.68	5.45	1.77
Q1 2018	25.74	5.2	5.6	10.65	1.87	4.3	2.71	1.96
Q2 2019	25.73	6.29	1.42	4.11	-2.27	1.09	2.12	2.17
Q1 2019	24.22	5.76	6.54	5.71	6.18	6.74	2.22	2.12
Q2 2019	24.52	5.81	6.49	7.38	2.69	2.49	3.93	2.54
Q3 2019	23.39	0.27	-0.06	-1.25	-0.11	1.57	1.84	3.03
Q4 2020	23.81	6.45	6.18	9.89	1.52	5.57	2.75	3.53
Q1 2020	24.92	-2.63	-2.75	-5.93	2.03	-2.13	-0.6	3.49
Q2 2020	25.90	11.29	9.95	15.5	17.83	8.75	3.22	3.55
Q3 2020	25.57	11.43	12.89	14.99	3.7	11.56	7.86	4.00
Q4 2021	24.24	26.03	27.27	21.5	24.71	20.41	17.18	4.23

Q1 2021	23.51	18.19	18.5	17.31	19.51	17.35	9.67	4.48
Q2 2021	22.75	11.39	12.19	22.14	1.44	13.55	16.67	4.52
Q3 2021	22.56	8.39	10.29	13.5	-11.09	8.55	7.63	4.55
Q4 2022	19.75	5.95	7.55	5.37	-7.25	5.66	3.9	4.98
Q1 2022	16.84	-3.6	-3.97	-4.02	-2.85	-3.81	1.69	4.12
Q2 2022	14.34	-8.72	-9.53	-10.77	-0.7	-9.4	-2.15	2.94
Q3 2022	12.82	-2.78	-2.39	-3.85	-4.49	-2.14	-1.34	1.25
Q4 2023	12.78	-5.24	-6.79	-0.22	2.29	-5.24	-4.1	1.14
Q1 2023	12.27	-0.8	-0.91	-1.6	0.36	-2.07	0.85	0.21
Q2 2023	12.60	-0.79	-0.47	-0.16	-3.91	-0.13	0.78	0.09
Q3 2023	15.85	-2.36	-2.54	-2.96	-0.53	-2.72	1	-0.31
Q4 2024	13.42	0.3	0.55	1.62	-1.97	0.08	-1.72	-0.64
Q1 2024	12.97	1.4	2.28	-0.99	-1.44	2.68	3.98	-1.39

8.2 Charts

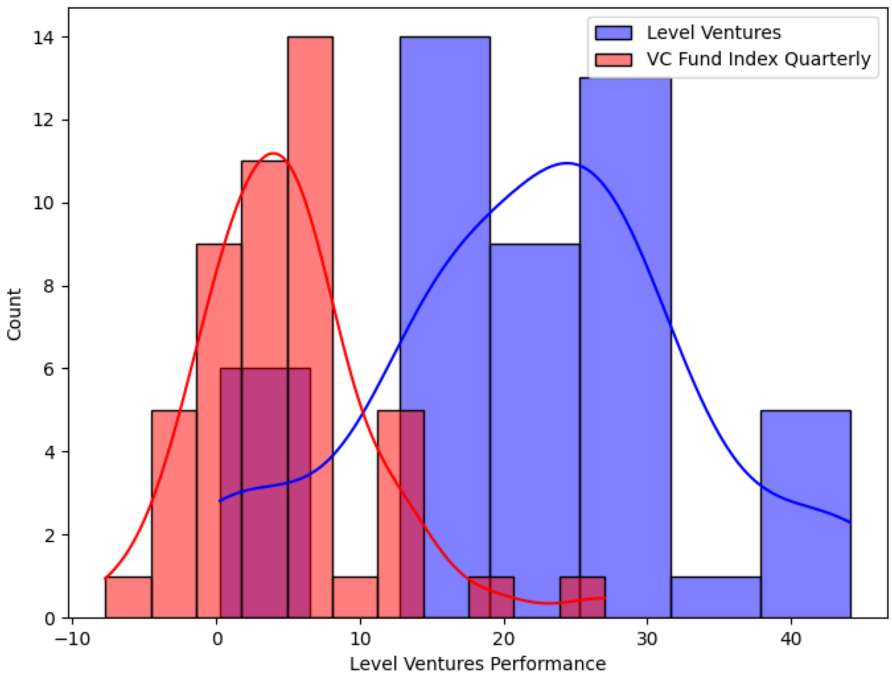

Figure 6: Histogram of Level Ventures vs. VC Fund Index Quarterly

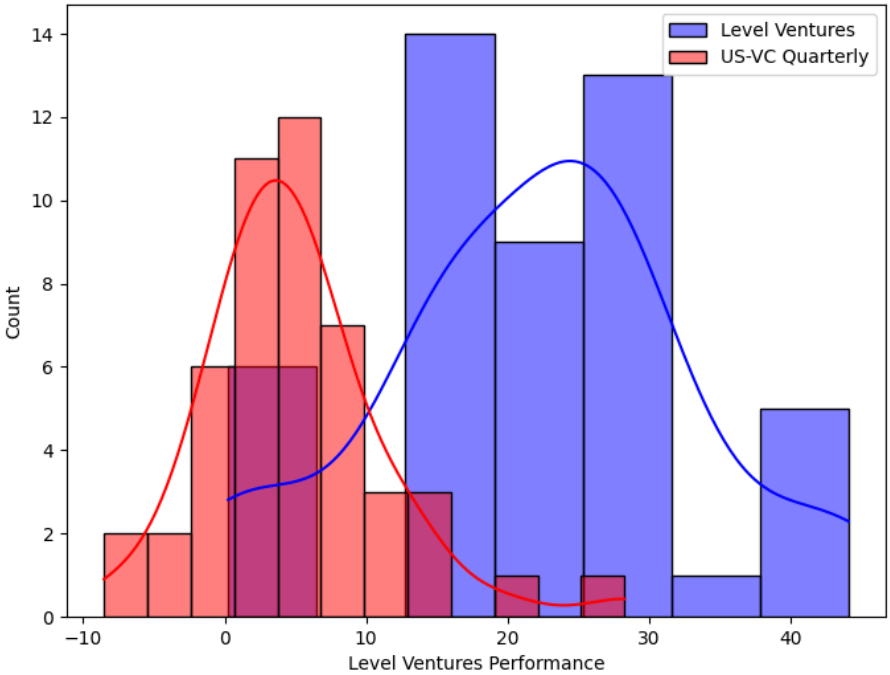

Figure 7: Histogram of Level Ventures vs. US-VC Quarterly

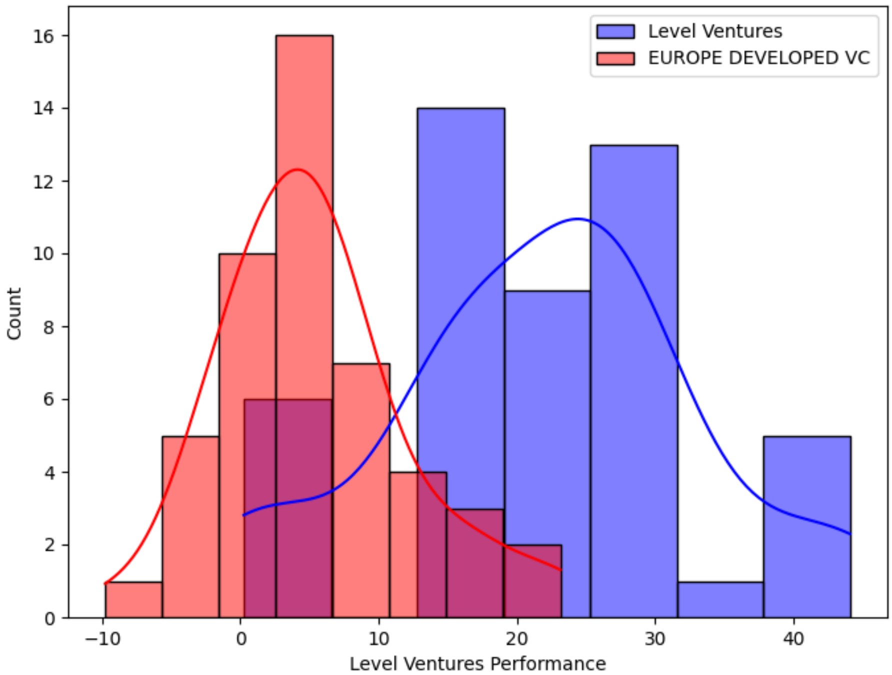

Figure 8: Histogram of Level Ventures vs. Europe Developed VC

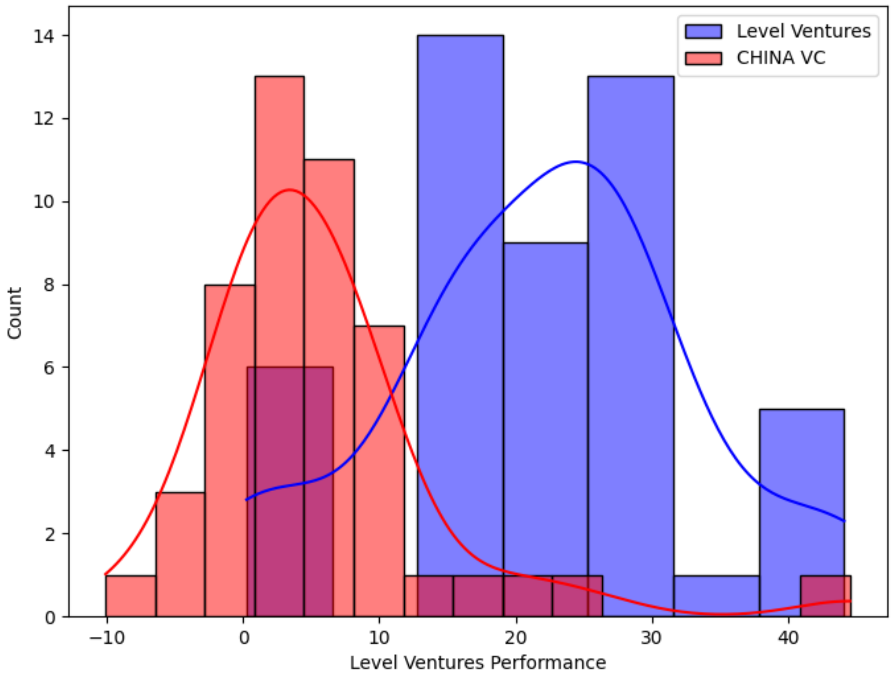

Figure 9: Histogram of Level Ventures vs. China VC

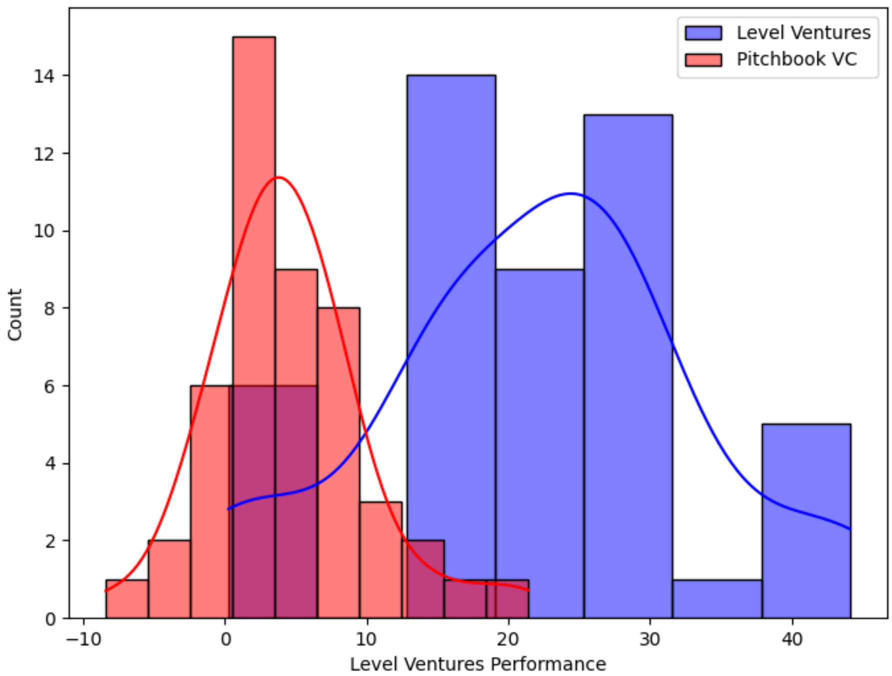

Figure 10: Histogram of Level Ventures vs. Pitchbook VC

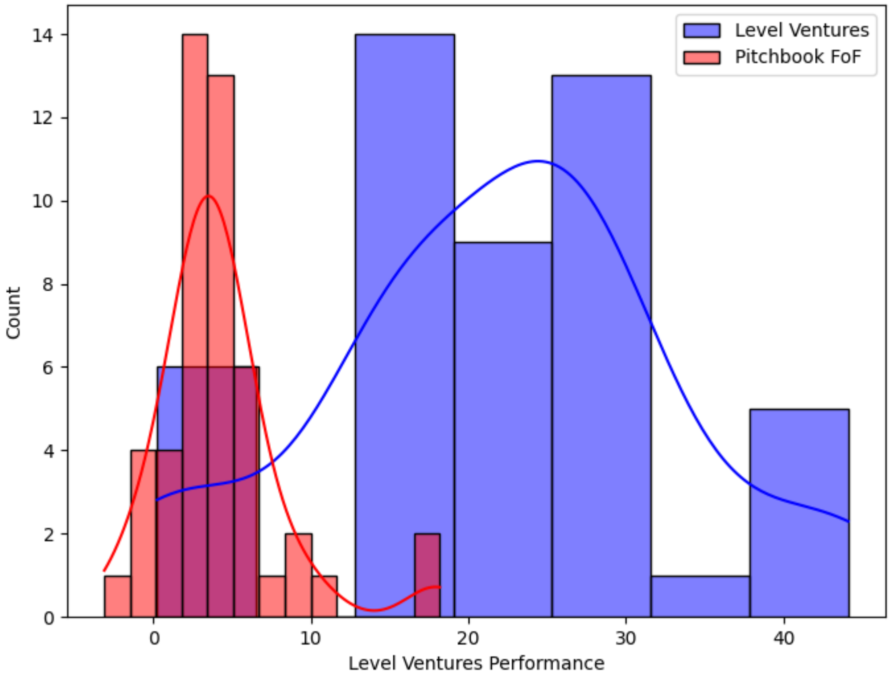

Figure 10: Histogram of Level Ventures vs. Pitchbook FoF

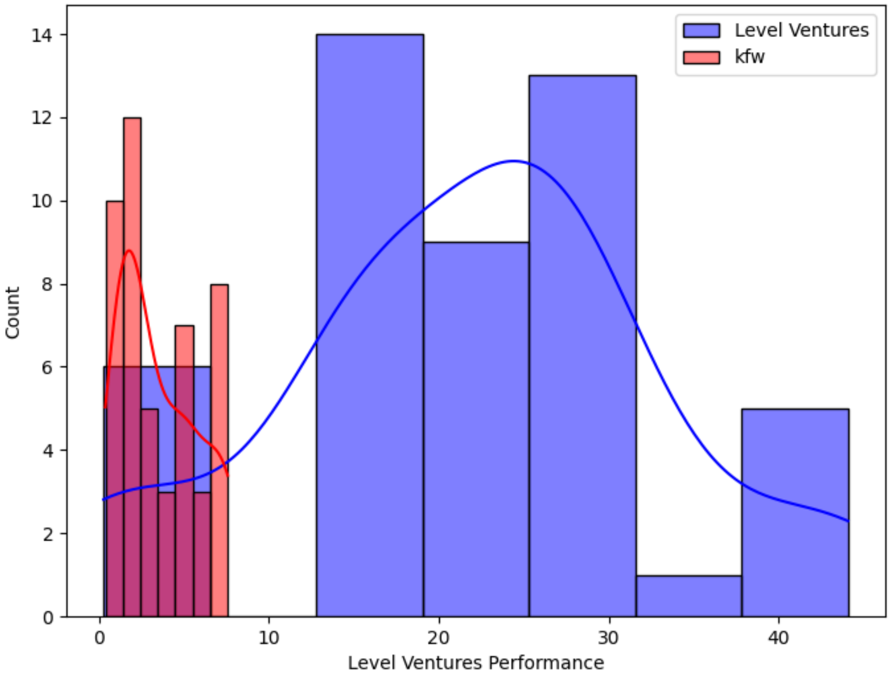

Figure 11: Histogram of Level Ventures vs. KfW

8.3 Final Code:

8.3.1 Calculation of Performance:

Code Performance Calculation.txt

```
Import pandas as pd
import numpy as np
import os
import shutil
from datetime import datetime

#excel_file_path = 'C:\\Users\\henni\\Dropbox\\1_Christian\\Master-
thesis\\Level Ventures\\Daten\\level underlying\\level-under-
lyin.xlsx'
excel_file_path = 'C:\\Users\\henni\\Dropbox\\1_Christian\\Master-
thesis\\Level Ventures\\Daten\\KFW\\kfw.xlsx'
data = pd.read_excel(excel_file_path)

data['company_value_date'] = pd.to_datetime(data['com-
pany_value_date'], errors='coerce')
data['max_announced_on'] = pd.to_datetime(data['max_announced_on'],
errors='coerce')

start_date = data['max_announced_on'].min() - pd.Timedelta(days=1)
end_date =  data['company_value_date'].max()
date_range = pd.date_range(start_date, end_date)

daily_performance = pd.DataFrame(index=date_range, columns=['Growth
Factor', 'Growth Factor_multiple'])
daily_performance[['Growth Factor_multiple']] = 1.0
daily_performance[['Growth Factor']] = 0.0

data['AuM'] = data['raised_amount_usd'] * data['ownership']

for current_date in date_range:
    active_investments = data[
        (data['max_announced_on'] <= current_date) &
        (data['company_value_date'] >= current_date)
    ].copy()

    cumulative_performance_for_day = 0.0
    for index, row in active_investments.iterrows():
        if current_date > row['max_announced_on']:
```

```
            total_aum = active_investments['AuM'].sum()
            if total_aum != 0:
              daily_return = (row['vac'] / total_aum) / row['In-
vestment Duration']
            else:
              daily_return = 0
            cumulative_performance_for_day += daily_return


    daily_performance.at[current_date, 'Growth Factor'] = cumula-
tive_performance_for_day
    daily_performance.at[current_date, 'Growth Factor_multiple'] =
cumulative_performance_for_day + 1

# --- Quartals- und Jahresaggregation mit Multiplikation ---
# 1. Quartale
daily_performance['Quarter'] = pd.DatetimeIndex(daily_perfor-
mance.index).to_period('Q')
quarterly_growth = daily_performance.groupby('Quarter')['Growth Fac-
tor_multiple'].prod()
quarterly_performance = (quarterly_growth - 1) * 100

# 2. Jahre
daily_performance['Year'] = pd.DatetimeIndex(daily_performance.in-
dex).year
annual_growth = daily_performance.groupby('Year')['Growth Fac-
tor_multiple'].prod()
annual_performance = (annual_growth - 1) * 100

quarterly_output = pd.DataFrame({'Quarterly Performance (%)': quar-
terly_performance, 'Growth Factor_multiple': quarterly_growth})
annual_output = pd.DataFrame({'Annual Performance (%)': annual_per-
formance, 'Growth Factor_multiple': annual_growth})

output_folder = os.path.dirname(excel_file_path)
current_time = datetime.now().strftime('%Y-%m-%d_%H-%M-%S')
excel_file_name = f'combined_performance_{current_time}.xlsx'
excel_file_path = os.path.join(output_folder, excel_file_name)

if os.path.exists(excel_file_path):
    archive_folder = os.path.join(output_folder, 'Archiv')
    if not os.path.exists(archive_folder):
        os.makedirs(archive_folder)

    archived_file_path = os.path.join(archive_folder, ex-
cel_file_name)
    shutil.move(excel_file_path, archived_file_path)
```

```
    print(f"Die Datei existierte bereits und wurde nach '{ar-
chive_folder}' verschoben.")

writer = pd.ExcelWriter(excel_file_path, engine='xlsxwriter')

quarterly_output.to_excel(writer, sheet_name='Quarterly Perfor-
mance', index=True)
annual_output.to_excel(writer, sheet_name='Annual Performance', in-
dex=True)
daily_performance.to_excel(writer, sheet_name='Daily Performance',
index=True)

writer.close()

print('Fertig! Alle Daten wurden in die Excel-Datei exportiert.')
```

8.3.2 Code for statistical analysis:

Code Statistical Analysis.txt

```
import pandas as pd
import numpy as np
import os
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from scipy.stats import wilcoxon, mannwhitneyu, shapiro, levene,
spearmanr, iqr

# Datei und Daten einlesen
file_path = 'C:\\Users\\henni\\Dropbox\\1_Christian\\Masterthe-
sis\\Level Ventures\\Combined_data - Copy.xlsm'
data = pd.read_excel(file_path, sheet_name='Quartarly', header=3)
output_folder = 'C:\\Users\\henni\\Dropbox\\1_Christian\\Masterthe-
sis\\Level Ventures\\output_images'
```

```
os.makedirs(output_folder, exist_ok=True)
output_file = 'C:\\Users\\henni\\Dropbox\\1_Christian\\Masterthe-
sis\\Level Ventures\\output_analysis.xlsx'

# Relevante Spalten auswählen
columns_with_performance = data.iloc[52:100, [0, 3, 9, 14, 19, 24,
29, 34, 39]]
columns_with_performance.columns = ['Quarter', 'Level Ventures Per-
formance', 'VC Fund Index Quarterly', 'US-VC Quarterly',
                                    'EUROPE DEVELOPED VC', 'CHINA
VC', 'Pitchbook VC',
                                    'Pitchbook FoF', 'kfw']

# NaN-Werte entfernen
columns_with_performance_clean = columns_with_perfor-
mance.dropna(subset=columns_with_performance.columns[1:])
columns_with_performance_clean.iloc[:, 1:] += 1  # 1 addieren für
Wachstumsfaktor

columns = ['Spearman Correlation', 'p-value (Spearman)', 'Shapiro-
Wilk Test Statistic', 'p-value (Shapiro)',
           'Levene Test Statistic', 'p-value (Levene)', 'Outliers
(IQR)', 'Wilcoxon Test Statistic', 'p-value (Wilcoxon)',
           'Mann-Whitney U Test Statistic', 'p-value (Mann-Whitney
U)', 'Effect Size (r)', 'Fazit']
benchmarks = ['VC Fund Index Quarterly', 'US-VC Quarterly', 'EUROPE
DEVELOPED VC', 'CHINA VC', 'Pitchbook VC',
              'Pitchbook FoF', 'kfw', 'Interpretation']

# DataFrame mit Benchmarks und den entsprechenden Testspalten
results_df = pd.DataFrame(index=columns, columns=benchmarks)
# Performancedaten extrahieren
performance_data = columns_with_performance_clean[['Quarter', 'Level
Ventures Performance', 'VC Fund Index Quarterly', 'US-VC Quarterly',
                                                   'EUROPE DEVELOPED
VC', 'CHINA VC', 'Pitchbook VC', 'Pitchbook FoF', 'kfw']]

# Bereinigung: Nicht-negative Werte behalten
performance_data_clean = performance_data
performance_data_outperformance = data.iloc

performance_data_outperformance = data.iloc[52:100, [0, 42, 43, 44,
45, 46, 47, 48]]

performance_data_outperformance.columns = [
    'Quarter',
    'Outperformance VC Fund Index Quarterly',
    'Outperformance US-VC Quarterly',
```

```python
    'Outperformance EUROPE DEVELOPED VC',
    'Outperformance CHINA VC',
    'Outperformance Pitchbook VC',
    'Outperformance Pitchbook FoF',
    'Outperformance kfw'
]

plt.figure(figsize=(12, 6))
for column in performance_data_outperformance.columns[1:]:  # Spalte
'Quarter' ausschließen
    plt.plot(performance_data_outperformance['Quarter'], perfor-
mance_data_outperformance[column], label=column)


# Achsenbeschriftungen und Titel
plt.title("Outperformance der Benchmarks pro Quartal")
plt.xlabel("Quartal")
plt.ylabel("Outperformance (%)")
plt.xticks(rotation=45)
plt.legend(loc='upper left')
image_path = os.path.join(output_folder, f"outperformance_{col-
umn}.png")
plt.savefig(image_path)

# 1. **Unabhängigkeitsprüfung (Spearman-Korrelation)**
for column in performance_data_clean.columns[2:]:
    corr, p_corr = spearmanr(performance_data_clean['Level Ventures
Performance'], performance_data_clean[column])
    results_df.loc['Spearman Correlation', column] = corr
    results_df.loc['p-value (Spearman)', column] = p_corr


# 2. **Normalverteilung testen (Shapiro-Wilk)**
for column in performance_data_clean.columns[1:]:
    stat, p_shapiro = shapiro(performance_data_clean[column])
    results_df.loc['Shapiro-Wilk Test Statistic', column] = stat
    results_df.loc['p-value (Shapiro)', column] = p_shapiro
    results_df.loc['Spearman Correlation', 'Interpretation'] =
'>0,05 normalverteilt, ansonsten nicht'



# 3. **Varianzhomogenität (Levene-Test)**
for column in performance_data_clean.columns[2:]:
    stat, p_levene = levene(performance_data_clean['Level Ventures
Performance'], performance_data_clean[column])
    results_df.loc['Levene Test Statistic', column] = stat
    results_df.loc['p-value (Levene)', column] = p_levene
```

```
    results_df.loc['p-value (Levene)', 'Interpretation'] = '>0,05
unterschiedliche Varianzen, ansonsten nicht'


# 4. **Ausreißeranalyse**
for column in performance_data_clean.columns[1:]:
    q1, q3 = np.percentile(performance_data_clean[column], [25, 75])
    iqr_value = iqr(performance_data_clean[column])
    lower_bound, upper_bound = q1 - 1.5 * iqr_value, q3 + 1.5 *
iqr_value
    outliers = performance_data_clean[(performance_data_clean[col-
umn] < lower_bound) | (performance_data_clean[column] > up-
per_bound)]
    results_df.loc['Outliers (IQR)', column] = len(outliers)

# 5. **Wilcoxon-Test und Mann-Whitney-U-Test**
for column in performance_data_clean.columns[2:]:
    level_ventures_performance = performance_data_clean['Level Ven-
tures Performance']
    benchmark_performance = performance_data_clean[column]

    # Wilcoxon-Test (für gepaarte Daten)
    try:
        stat_w, p_wilcoxon = wilcoxon(level_ventures_performance,
benchmark_performance, alternative='greater')
        results_df.loc['Wilcoxon Test Statistic', column] = stat_w
        results_df.loc['p-value (Wilcoxon)', column] = p_wilcoxon
    except ValueError:
        results_df.loc['Wilcoxon Test Statistic', column] = None
        results_df.loc['p-value (Wilcoxon)', column] = None

    # Mann-Whitney-U-Test (für unabhängige Stichproben)
    stat_u, p_mwu = mannwhitneyu(level_ventures_performance, bench-
mark_performance, alternative='greater')
    results_df.loc['Mann-Whitney U Test Statistic', column] = stat_u
    results_df.loc['p-value (Mann-Whitney U)', column] = p_mwu

    # Effektstärke berechnen
    n = len(level_ventures_performance)
    z = (stat_u - n * (n + 1) / 4) / np.sqrt(n * (n + 1) * (2 * n +
1) / 24)
    r = abs(z) / np.sqrt(n)
    results_df.loc['Effect Size (r)', column] = r
    """
    # Interpretation der Effektstärke
    if abs(r) < 0.1:
        print("Effektstärke: vernachlässigbar")
    elif abs(r) < 0.3:
```

```
        print("Effektstärke: klein")
    elif abs(r) < 0.5:
        print("Effektstärke: mittel")
    else:
        print("Effektstärke: groß")
    """
    # Ergebnisbewertung
    alpha = 0.05
    if p_mwu < alpha:
        results_df.loc['Fazit', column] = f"Signifikant: 'Level Ven-
tures' überperformt '{column}'."

    else:
        results_df.loc['Fazit', column] = f"Keine signifikante Out-
performance für '{column}'."


# 6. **Grafische Analysen**
for column in performance_data_clean.columns[2:]:
    plt.figure(figsize=(8, 6))
    sns.histplot(performance_data_clean['Level Ventures Perfor-
mance'], label='Level Ventures', kde=True, color='blue')
    sns.histplot(performance_data_clean[column], label=column,
kde=True, color='red')
    plt.legend()
    plt.title(f"Histogramm von Level Ventures vs. {column}")
    #speichern
    image_path = os.path.join(output_folder, f"histogramm_{col-
umn}.png")
    plt.savefig(image_path)

    sm.qqplot_2samples(performance_data_clean['Level Ventures Per-
formance'], performance_data_clean[column], line='s')
    plt.title(f"QQ-Plot: Level Ventures vs. {column}")
    #speichern
    image_path = os.path.join(output_folder, f"qqplot_{column}.png")
    plt.savefig(image_path)

output_path = 'C:\\Users\\henni\\Dropbox\\1_Christian\\Masterthe-
sis\\Level Ventures\\output_images\\test_results.xlsx'
results_df.to_excel(output_path, index=True)

with pd.ExcelWriter(output_path, engine='xlsxwriter') as writer:
    results_df.to_excel(writer, index=True, sheet_name='Results')

    workbook = writer.book
    worksheet = writer.sheets['Results']
```

```
    for i, column in enumerate(results_df.columns):
        max_length = max(results_df[column].astype(str).ap-
ply(len).max(), len(column))
        worksheet.set_column(i, i, max_length)

print("\n**Analyse abgeschlossen!**")
```

9 References

Abdi, H. (2007). The Bonferonni and Šidák Corrections for Multiple Comparisons. *Encyclopedia of Measurement and Statistics*, *3*, 1–9. https://personal.utdallas.edu/~herve/Abdi-Bonferroni2007-pretty.pdf

Achleitner, A.-K., & Lutz, E. (2004). *Venture Valuation - Bewertung von Wachstumsunternehmen : klassische und neue Bewertungsverfahren mit Beispielen und Übungsaufgaben*. Schäffer-Poeschel.

Agrawal, A., Andrews, R., Arora, A., Aulet, B., Azoulay, P., Bresnahan, T., Catalini, C., Chavda, A., Cook, D., Ching, K., Cockburn, I., Cohen, W., Dougherty, J., Ederer, F., Eisenmann, T., Fehder, D., Fitzgerald, E., Furman, J., Gambardella, A., . . . Sull, D. (2016). The Foundations of Entrepreneurial Strategy. https://consensus.app/papers/the-foundations-of-entrepreneurial-strategy-agrawal-andrews/069787ea3b165570bc3f78630015033f/

Agrawal, A., Gans, J., & Stern, S. (2020). Enabling Entrepreneurial Choice. *IO: Productivity.* Advance online publication. https://doi.org/10.2139/ssrn.3592509

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500. https://doi.org/10.2307/1879431

Aki, E. (2021). Venture capital and government involvement from a qualitative systematic literature review perspective. *Acta Oeconomica.* Advance online publication. https://doi.org/10.1556/032.2021.00044

Amit, R., Glosten, L., & Muller, E. (1990). Entrepreneurial Ability, Venture Investments, and Risk Sharing. *Management Science*, *36*(10), 1232–1245. http://www.jstor.org/stable/2632662

Aven, T. (2013). On the meaning of a black swan in a risk context. *Safety Science*, *57*, 44–51. https://doi.org/10.1016/J.SSCI.2013.01.016

Bauer, P. (2000). Multiple comparisons - theory and methods. Jason C. Hsu, Chapman & Hall, London, 1996. No. of pages: xiv+277. Price: 35. ISBN 0-412-9828-1. *Statistics in Medicine - STAT MED*, *19*, 1951. https://doi.org/10.1002/1097-0258(20000730)19:143.0.CO;2-W

Bharat Anant. (2016). *Evaluating the Risk — Reward Relationship Across Funding Rounds*. https://medium.com/@bharatanant/evaluating-the-risk-reward-relationship-across-funding-rounds-5c951f21236b

Bollen, N., & Busse, J. (2005). Short-Term Persistence in Mutual Fund Performance. *Review of Financial Studies*, *18.* https://doi.org/10.1093/rfs/hhi007

Bourgeois, L., & Eisenhardt, K. (1988). Strategic decision processes in high velocity environments: four cases in the microcomputer industry. *Management Science*, *34*, 816–835. https://doi.org/10.1287/MNSC.34.7.816

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: work, progress, and prosperity in a time of brilliant technologies, 1st Edition, 1–306. https://consensus.app/papers/the-second-machine-age-work-progress-and-prosperity-in-a-brynjolfsson-mcafee/99d0881732a057dabbed7b6a86bbd468/

Bygrave, W. (1988). The structure of the investment networks of venture capital firms. *Journal of Business Venturing*, *3*, 137–157. https://doi.org/10.1016/0883-9026(88)90023-7

Bygrave, W., & Timmons, J. (1992). Venture capital at the crossroads. https://consensus.app/papers/venture-capital-at-the-crossroads-bygrave-timmons/92e775e546c259bc95ad521b62dddddc/

Callahan, J., & Muegge, S. (2003). Venture Capital's Role in Innovation: Issues, Research and Stakeholder Interests, 641–663. https://doi.org/10.1016/B978-008044198-6/50044-9

Camp, S., & Sexton, D. (1992). Trends in Venture Capital Investment: Implications for High-Technology Firms. *Journal of Small Business Management*, *30*, 11. https://consensus.app/papers/trends-in-venture-capital-investment-implications-for-camp-sexton/4f498344949c5f65a1c4f539aff03622/

Carlos Nunes, J., Gomes Santana Félix, E., & Pacheco Pires, C. (2014). Which criteria matter most in the evaluation of venture capital investments? *Journal of Small Business and Enterprise Development*, *21*(3), 505–527. https://doi.org/10.1108/JSBED-10-2013-0165

Carter, S., Chalmers, D., & MacKenzie, N. (2020). Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution. *Entrepreneurship Theory and Practice*, *45*, 1–9. https://doi.org/10.1177/1042258720934581

Casebook, A., Lerner, J [Josh], Hardymon, F., & Leamon, A. (2000). Venture Capital and Private Equity: A Casebook. https://consensus.app/papers/venture-capital-and-private-equity-a-casebook-casebook-lerner/10e6f8ff1dc350eb82d95242538358fd/

Cavallo, A., Ghezzi, A., Dell'Era, C., & Pellizzoni, E. (2019). Fostering Digital Entrepreneurship from startup to scaleup: The role of Venture Capital funds and Angel Groups. *Technological Forecasting and Social Change*, *145.* https://doi.org/10.1016/j.techfore.2019.04.022

Chaplinsky, S., & Gupta-Mukherjee, S. (2010). The Form of Exit in Venture Capital: Implications of the Rise of M&A Exits. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.1571881

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, *36*(4), 1165–1188. https://doi.org/10.2307/41703503

Christensen, R. (1997). Multiple Comparisons: Theory and Methods. *Technometrics*, *39*, 232–233. https://doi.org/10.1080/00401706.1997.10485097

Clauset, A., Shalizi, C., & Newman, M. (2007). Power-Law Distributions in Empirical Data. *SIAM Rev*, *51*, 661–703. https://doi.org/10.1137/070710111

Cleves, M. (1996). Robust tests for the equality of variances. *Stata Technical Bulletin*, *5*.

Cockburn, I., Henderson, R., & Stern, S. (2018). The Impact of Artificial Intelligence on Innovation. *IRPN: Innovation & Cyberlaw & Policy (Topic).* Advance online publication. https://doi.org/10.3386/W24449

Cooper, A., Gimeno-Gascón, F., & Woo, C. (1997). Initial Human and Financial Capital as Predictors of New Venture Performance. Advance online publication. https://doi.org/10.3905/jpe.1997.409668

Cornelius, P., Juttmann, K., & Veer, R. de (2009). Industry Cycles and the Performance of Buyout Funds. *The Journal of Private Equity*, *12*(4), 14–21. http://www.jstor.org/stable/43503614

Crevier, D. (1993). Ai: The Tumultuous History Of The Search For Artificial Intelligence. Advance online publication. https://doi.org/10.5860/choice.31-1555

Crowdmatrix. *An Investor's Guide to Venture Capital*. https://sandbox.crowdmatrix.co/venture-capital-guide

Cumming, D. (2006). The Determinants of Venture Capital Portfolio Size: Empirical Evidence. *The Journal of Business*, *79*, 1083–1126. https://doi.org/10.2139/ssrn.261747

Cumming, D. (2012). The Oxford Handbook of Venture Capital. Advance online publication. https://doi.org/10.1093/OXFORDHB/9780195391596.001.0001

Cumming, D., & Johan, S [Sofia] (2008). Preplanned exit strategies in venture capital. *European Economic Review*, *52*(7), 1209–1241. https://EconPapers.repec.org/RePEc:eee:eecrev:v:52:y:2008:i:7:p:1209-1241

Cumming, D., & Johan, S [S.] (2013). Venture Capital and Private Equity Contracting. *Research Papers in Economics.* Advance online publication. https://doi.org/10.1016/c2012-0-06081-4

Davila, A., Foster, G., & Gupta, M. (2003). Venture Capital and the Growth Strategy of Startup Firms. *Journal of Business Venturing*, *18*, 689–708. https://doi.org/10.1016/S0883-9026(02)00127-1

Dev Dabke. (2024a). *Building consensus through RFCs*. https://levelvc.com/building-consensus-through-rfcs/

Dev Dabke. (2024b). *Dynamic Networks and Machine Learning*. https://levelvc.com/dynamic-networks-and-neural-networks/

Dev Dabke. (2024c). *Fast container builds*. https://levelvc.com/fast-container-builds-for-etl/

Dev Dabke. (2024d). *Jackknife+ and Model Confidence*. https://levelvc.com/jackknife-and-model-confidence/

Dev Dabke. (2024e). *Running GPU workflows with Prefect and AWS*. https://levelvc.com/running-gpu-workloads-with-prefect-and-aws/

Dew, N., Read, S., Sarasvathy, S., & Wiltbank, R. (2009). Effectual versus Predictive Logics in Entrepreneurial Decision Making: Differences between Experts and Novices. *Journal of Business Venturing*, *24*, 287–309. https://doi.org/10.1016/j.jbusvent.2008.02.002

Di Guo, & Jiang, K. (2013). Venture capital investment and the performance of entrepreneurial firms: Evidence from China. *Journal of Corporate Finance*, *22*, 375–395. https://doi.org/10.1016/j.jcorpfin.2013.07.001

Dong, X., & Mcintyre, S. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. *Quantitative Finance*, *14.* https://doi.org/10.1080/14697688.2014.946440

Dorigo, M., & Schnepf, U. (1991). Organisation of robot behaviour through genetic learning processes. *Fifth International Conference on Advanced Robotics 'Robots in Unstructured Environments*, 1456–1460. https://doi.org/10.1109/ICAR.1991.240535

Doumpos, M., & Grigoroudis, E. (2013). Multicriteria Decision Aid and Artificial Intelligence. *Multicriteria Decision Aid and Artificial Intelligence.* Advance online publication. https://doi.org/10.1002/9781118522516

Drover, W., Busenitz, L., Matusik, S., Townsend, D., Anglin, A., & Dushnitsky, G. (2017). A Review and Road Map of Entrepreneurial Equity Financing Research: Venture Capital, Corporate Venture Capital, Angel Investment, Crowdfunding, and Accelerators. *Journal of Management*, *43*, 1820–1853. https://doi.org/10.1177/0149206317690584

Duan, Y., Edwards, J., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data - evolution, challenges and research agenda. *Int. J. Inf. Manag.*, *48*, 63–71. https://doi.org/10.1016/J.IJINFOMGT.2019.01.021

Durrani, M. (2001). Venture capital financing in India: a study of venture capitalist's valuation, structuring, and monitoring practices. https://consensus.app/papers/venture-capital-financing-in-india-a-study-of-venture-durrani/1adf82b2595559d5865aa263c79b2b6a/

Dushnitsky, G., & zur Shapira (2010). Entrepreneurial finance meets organizational reality: comparing investment practices and performance of corporate and independent venture capitalists. *Strategic Management Journal*, *31*(9), 990–1017. https://doi.org/10.1002/smj.851

Eisenhardt, K. M., & Bourgeois, L. J. (1988). Politics of Strategic Decision Making in High-Velocity Environments: Toward a Midrange Theory. *The Academy of Management Journal*, *31*(4), 737–770. https://doi.org/10.2307/256337

Entrepreneurship Theory and Practice. *Entrepreneurship ex Machina: TRANSFORMATIVE ARTIFICIAL INTELLIGENCE FOR THEORY AND PRACTICE*. https://www.entrepreneurship-ex-machina.org/wp-content/uploads/2024/03/ETP-Special-Issue-CFP-AI-and-Entrepreneurship.pdf

Ewens, M. (2009). A New Model of Venture Capital Risk and Return. *Social Science Research Network.* Advance online publication. https://doi.org/10.2139/SSRN.1356322

Fama, E. (1965). *The Behaviour of Stock Market Prices. Journal of Business*. Journal of Business.

Florin, J. (2005). Is venture capital worth it? Effects on firm performance and founder returns. *Journal of Business Venturing*, *20*, 113–135. https://doi.org/10.1016/J.JBUSVENT.2003.12.006

Frey, C., & Osborne, M. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/J.TECHFORE.2016.08.019

Fried, V. H., & Hisrich, R. D. (1994). Toward a Model of Venture Capital Investment Decision Making. *Financial Management*, *23*, 28–37.

Gao, Y [Yuan], & Topp, E. (2020). Machine Behavior Development and Analysis using Reinforcement Learning. https://consensus.app/papers/machine-behavior-development-and-analysis-using-gao-topp/2610555a00fc551bb860e2bbd52cac21/

Gelernter, H., & Rochester, N. (1958). Intelligent Behavior in Problem-Solving Machines. *Il Nuovo Cimento (1955-1965)*, *13*, 474–493. https://doi.org/10.1147/rd.24.0336

Gharagozloo, M., Amrani, A., Wittingstall, K., Hamilton-Wright, A., & Gris, D. (2021). Machine Learning in Modeling of Mouse Behavior. *Frontiers in Neuroscience*, *15.* https://doi.org/10.3389/fnins.2021.700253

Giuggioli, G., & Pellegrini, M. (2022). Artificial intelligence as an enabler for entrepreneurs: a systematic literature review and an agenda for future research. *International Journal of Entrepreneurial Behavior & Research.* Advance online publication. https://doi.org/10.1108/ijebr-05-2021-0426

Gompers, P., Kaplan, S [S.], & Mukharlyamov, V. (2015). What Do Private Equity Firms Say They Do? *Mutual Funds*, 314–339. https://doi.org/10.2139/ssrn.2447605

Gompers, P., Kovner, A., Lerner, J [Josh], & Scharfstein, D. (2005). Venture Capital Investment Cycles: The Impact of Public Markets. *Organizations & Markets EJournal*, 1–23. https://doi.org/10.2139/ssrn.724225

Gompers, P., & Lerner, J [Josh] (1998). Venture Capital Distributions: Short-Run and Long-Run Reactions. *The Journal of Finance*, *53*(6), 2161–2183. https://doi.org/10.1111/0022-1082.00086

Gompers, P., & Lerner, J [J.] (2001). The Venture Capital Revolution. *Journal of Economic Perspectives*, *15*, 145–168. https://doi.org/10.1257/JEP.15.2.145

Gompers, P., & Lerner, J [Josh] (2002). The Money of Invention: How Venture Capital Creates New Wealth. *Ubiquity*, *2002.* https://doi.org/10.1145/763903.763904

Gompers, P., & Lerner, J [J.] (2006). The Venture Capital Cycle, 2nd Edition, *1*. https://consensus.app/papers/the-venture-capital-cycle-2nd-edition-gompers-lerner/5f267126f9eb51e6b5911293442d5e44/

Gorman, M., & Sahlman, W. (1989). What do venture capitalists do. *Journal of Business Venturing*, *4*, 231–248. https://doi.org/10.1016/0883-9026(89)90014-1

Gupta, A., & van Nieuwerburg, S. (2021). Valuing Private Equity Investments Strip by Strip. *The Journal of Finance*, *76*(6), 3255–3307. https://doi.org/10.1111/jofi.13073

Hall, R. (1989). The Management of Intellectual Assets: A New Corporate Perspective. *Journal of General Management*, *15*(1), 53–68. https://doi.org/10.1177/030630708901500104

Harris, R., Jenkinson, T., & Kaplan, S. (2012). Private Equity Performance: What Do We Know? *Entrepreneurship & Finance EJournal*, 1851–1882. https://consensus.app/papers/private-equity-performance-what-do-we-know-harris-jenkinson/bf2911e32cd75e30af354b2cf821ddd9/

Harris, R. S., Jenkinson, T., Kaplan, S. N., & Stucke, R. (2023). Has persistence persisted in private equity? Evidence from buyout and venture capital funds. *Journal of Corporate Finance*, *81.* https://doi.org/10.1016/j.jcorpfin.2023.102361

Hege, U., Palomino, F., & Schwienbacher, A. (2009). Venture Capital Performance: The Disparity Between Europe and the United States. *Finance*, *Vol. 30*(1), 7–50. https://doi.org/10.3917/fina.301.0007

Hellmann, T., & Puri, M. (1999). The Interaction between Product Market and Financing Strategy: The Role of Venture Capital. *Corporate Finance: Governance*, 959-584. https://doi.org/10.2139/ssrn.173655

Hisrich, R., & Jankowicz, A. (1990). Intuition in venture capital decisions: An exploratory study using a new technique. *Journal of Business Venturing*, *5*, 49–62. https://doi.org/10.1016/0883-9026(90)90026-P

Hudson, E., & Evans, M. (2005). A Review of Research into Venture Capitalists' Decision Making: Implications for Entrepreneurs, Venture Capitalists and Researchers. *Journal of Economic and Social Policy*, *10*.

Jelic, R., Saadouni, B., & Wright, M [Mike] (2005). Performance of Private to Public MBOs: The Role of Venture Capital. *Journal of Business Finance & Accounting*, *32*(3-4), 643–682. https://doi.org/10.1111/j.0306-686X.2005.00608.x

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Kahneman, D. (2003). Maps of Bounded Rationality: Psychology for Behavioral Economics. *The American Economic Review*, *93*(5), 1449–1475. http://www.jstor.org/stable/3132137

Kaplan, S., & Stromberg, P. (2009). Leveraged buyouts and private equity. *Journal of Economic Perspectives*, *23*, 121–146. https://doi.org/10.1257/jep.23.1.121

Kaplan, S., & Strömberg, P. (2004). Characteristics, Contracts, and Actions: Evidence From Venture Capitalist Analyses. *The Journal of Finance*, *59*, 2177–2210. https://doi.org/10.1111/j.1540-6261.2004.00696.x

Kaserer, C., & Diller, C. (2004). European Private Equity Funds - a Cash Flow Based Performance Analysis. *Financial Accounting EJournal.* Advance online publication. https://doi.org/10.2139/ssrn.547142

Knockaert, M., & Clarysse, B. (2010). The Extent and Nature of Heterogeneity of Venture Capital Selection Behavior in New Technology-Based Firms. *R&D Management*, *40*, 307–335. https://doi.org/10.1111/j.1467-9310.2010.00607.x

Korteweg, A. (2011). Risk and Return Characteristics of Venture Capital-Backed Entrepreneurial Companies. *Review of Financial Studies*, *23*, 3738–3772. https://doi.org/10.2139/ssrn.1108610

Kortum, S., & Lerner, J [Josh] (2000). Assessing the Contribution of Venture Capital to Innovation. *RAND Journal of Economics*, *31*, 674–692. https://doi.org/10.2307/2696354

Koushik, A., Manoj, M., & Nezamuddin, N. (2020). Machine learning applications in activity-travel behaviour research: a review. *Transport Reviews*, *40*, 288–311. https://doi.org/10.1080/01441647.2019.1704307

Lake, R [R.], & Lake, R [Ronald] (1999). Private Equity and Venture Capital: A Practical Guide for Investors and Practitioners. https://consensus.app/papers/private-equity-and-venture-capital-a-practical-guide-for-lake-lake/8e30d3928e74548da4810b91efd7d819/

Lerner, J [J.] (1994). VENTURE CAPITALISTS AND THE DECISION TO GO PUBLIC. *Journal of Financial Economics*, *35*, 293–316. https://doi.org/10.1016/0304-405X(94)90035-3

Lerner, J [Josh], Schoar, A., & Wongsunwai, W. (2007). Smart Institutions, Foolish Choices: The Limited Partner Performance Puzzle. *Journal of Finance*, *62*, 731–764. https://doi.org/10.2139/ssrn.657482

Level Ventures. (2025). *Research*. https://levelvc.com/research/

Levene, H. (1960). *Robust Tests for Equality of Variances*. Stanford University Press.

Lévesque, M., Obschonka, M., & Nambisan, S. (2020). Pursuing Impactful Entrepreneurship Research Using Artificial Intelligence. *Entrepreneurship Theory and Practice*, *46*(4), 803–832. https://doi.org/10.1177/1042258720927369

Makridakis, S. (2017). Forecasting the Impact of Artificial Intelligence (AI). *Foresight: The International Journal of Applied Forecasting*, 7–13, 47-50. https://consensus.app/papers/forecasting-the-impact-of-artificial-intelligence-ai-makridakis/530c10db83ac5161bb1401a79587e6cb/

Manigart, S., Joos, P., & Vos, D. de (1994). The Performance of Publicly Traded European Venture Capital Companies. *The Journal of Entrepreneurial Finance.* Advance online publication. https://doi.org/10.57229/2373-1761.1147

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. (2011). *Big data: The next frontier for innovation, competition, and productivity.*

Martin, I. (2012). On the Valuation of Long-Dated Assets. *Journal of Political Economy*, *120*(2), 346–358. https://doi.org/10.1086/666527

Mason, C., & Harrison, R. (2002). Is It Worth It? The Rates of Return from Informal Venture Capital Investments. *Journal of Business Venturing*, *17*, 211–236. https://doi.org/10.1016/S0883-9026(00)00060-4

Metrick, A., & Yasuda, A. (2010a). The Economics of Private Equity Funds. *The Review of Financial Studies*, *23*(6), 2303–2341. https://doi.org/10.1093/rfs/hhq020

Metrick, A., & Yasuda, A. (2010b). Venture Capital & the Finance of Innovation.

Mitra, D. (2000). The Venture Capital Industry in India. *Journal of Small Business Management*, *38*, 67. https://consensus.app/papers/the-venture-capital-industry-in-india-mitra/bce6a746936c5f8d86e866afcdfd58e6/

Molnár, E., & Jáki, E. (2020). What qualities do government-owned venture capital investors seek in a new venture? A comparison of investment criteria across pre-seed, seed, and expansion stage startups. *Vezetéstudomány - Budapest Management Review*, *51.* https://doi.org/10.14267/VEZTUD.2020.11.06

Nachar, N. (2008). The Mann-Whitney U: A Test for Assessing Whether Two Independent Samples Come from the Same Distribution. *Tutorials in Quantitative Methods for Psychology*, *4.* https://doi.org/10.20982/tqmp.04.1.p013

Nandini, G. (2015). An Empirical Study on the Performance of Selected Mutual Fund Schemes In India.

Narayanan, A., Desai, F., Stewart, T., Duncan, S., & Mackay, L. (2020). Application of Raw Accelerometer Data and Machine-Learning Techniques to Characterize Human Movement Behavior: A Systematic Scoping Review. *Journal of Physical Activity & Health*, 1–24. https://doi.org/10.1123/jpah.2019-0088

Neus, W., & Walz, U. (2001). Exit timing of venture capitalists in the course of an initial public offering. *Journal of Financial Intermediation*, *14*, 253–277. https://doi.org/10.1016/j.jfi.2004.02.003

Noone, C. (2016). THE VARIOUS SOURCES OF VENTURE CAPITAL AVAILABLE TO SMALL BUSINESS CONCERNS. https://consensus.app/papers/the-various-sources-of-venture-capital-available-to-small-noone/3b4cde63250d5d85888b7fabc5dedc25/

Obschonka, M., & Audretsch, D. (2020). Artificial Intelligence and Big Data in Entrepreneurship: A New Era Has Begun. *Small Business Economics*, *55.* https://doi.org/10.1007/s11187-019-00202-4

Pan, Y. (2016). Heading toward Artificial Intelligence 2.0. *Engineering*, *2*, 409–413. https://doi.org/10.1016/J.ENG.2016.04.018

Paras Gupta. (2016). *Fundraising Stages for Startup*. https://carocked.wordpress.com/2016/06/26/fundraising-stages-for-startup/

Paulus, M., Kuplicki, R., & Yeh, H.-W. (2019). Machine Learning and Brain Imaging: Opportunities and Challenges. *Trends in Neurosciences*, *42*, 659–661. https://doi.org/10.1016/j.tins.2019.07.007

Phalippou, L. The Hazards of Using IRR to Measure Performance: The Case of Private Equity.

Phalippou, L., & Gottschalg, O. (2009). The Performance of Private Equity Funds. *The Review of Financial Studies*, *22*(4), 1747–1776. https://doi.org/10.1093/rfs/hhn014

Phalippou, L., Rauch, C., & Umber, M. (2018). Private Equity Portfolio Company Fees. *Journal of Financial Economics*, *129.* https://doi.org/10.1016/j.jfineco.2018.05.010

Phillips-Wren, G. (2014). Intelligent Systems to Support Human Decision Making, 1297–1309. https://doi.org/10.4018/978-1-4666-5202-6.CH119

Phillips-Wren, G., Ichalkaranje, N., & Jain, L. (2008). Intelligent Decision Making: An AI-Based Approach, *97.* https://doi.org/10.1007/978-3-540-76829-6

Popov, A., & Roosenboom, P. (2013). Venture capital and new business creation. *Journal of Banking and Finance*, *37*, 207–224. https://doi.org/10.1016/J.JBANKFIN.2013.08.010

Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., Crandall, J., Christakis, N., Couzin, I., Jackson, M., Jennings, N., Kamar, E., Kloumann, I., Larochelle, H., Lazer, D., Mcelreath, R., Mislove, A., Parkes, D., Pentland, A., . . . Wellman, M. (2019). Machine behaviour. *Nature*, *568*, 53–56. https://doi.org/10.1038/s41586-019-1138-y

Ramachandra, & Srinivasa (2016). Venture Capital – A Tool in Promoting Entrepreneurship. *Adhyayan: A Journal of Management Sciences*, *2*, 60–72. https://doi.org/10.21567/adhyayan.v2i1.10235

Rapp, D., & Olbrich, M. (2020). On entrepreneurial decision logics under conditions of uncertainty: an attempt to advance the current debate. *Journal of Innovation and Entrepreneurship*, *9*, 1–9. https://doi.org/10.1186/s13731-020-00131-7

Razafitombo, H. (2011). A Statistical Analysis of Mutual Fund Performance Measures: The Relevance of IR, Betas and Sharpe Ratios. *The Journal of Index Investing*, *1.* https://doi.org/10.3905/jii.2010.1.2.089

Regan, D., & Tunny, G. (2008). Venture Capital in Australia. *Economic Round-up*, 1–13.

Reid, G., Terry, N., & Smith, J. (1997). Risk Management in Venture Capital Investor-Investee Relations. *European Journal of Finance*, *3*, 27–47. https://doi.org/10.1080/135184797337525

Robinson, D. T., & Sensoy, B. A. (2016). Cyclicality, performance measurement, and cash flow liquidity in private equity. *Journal of Financial Economics*, *122*(3), 521–543. https://doi.org/10.1016/j.jfineco.2016.09.008

Ruhnka, J., & Young, J. (1991). Some hypotheses about risk in venture capital investing. *Journal of Business Venturing*, *6*, 115–133. https://doi.org/10.1016/0883-9026(91)90014-5

Russell, S., & Norvig, P. (2021). *Artificial Intelligence, Global Edition : A Modern Approach*. Pearson Deutschland. https://elibrary.pearson.de/book/99.150005/9781292401171

Sahlman, W. A. (1990). The structure and governance of venture-capital organizations. *Journal of Financial Economics*, *27*(2), 473–521. https://doi.org/10.1016/0304-405X(90)90065-8

Samuel K.-B, D., & Minkah, R. (2021). Assessing the Performance of the Discrete Generalised Pareto Distribution in Modelling Non-Life Insurance Claims. *Journal of Probability and Statistics*, *2021*, 1–8. https://doi.org/10.1155/2021/5518583

Sapienza, H. J. (1992). When do venture capitalists add value? *Journal of Business Venturing*, *7*(1), 9–27. https://doi.org/10.1016/0883-9026(92)90032-M

Schoar, A., & Kaplan, S. (2005). Private Equity Performance: Returns, Persistence, and Capital Flows. *Journal of Finance*, *60*, 1791–1823. https://doi.org/10.1111/j.1540-6261.2005.00780.x

Schwienbacher, A. (2008). Venture capital investment practices in Europe and the United States. *Financial Markets and Portfolio Management*, *22*(3), 195–217. https://doi.org/10.1007/s11408-008-0080-z

Shan, B., Liu, X., Gao, Y [Yang], & Lu, X. (2022). Big Data in Entrepreneurship. *Journal of Organizational and End User Computing.* Advance online publication. https://doi.org/10.4018/joeuc.310551

Shapiro, S. S., & Wilk, M. B. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika*, *52*(3/4), 591–611. https://doi.org/10.2307/2333709

Shepherd, D., & Majchrzak, A. (2022). Machines Augmenting Entrepreneurs: Opportunities (and Threats) at the Nexus of Artificial Intelligence and Entrepreneurship. *Journal of Business Venturing*, *37*, 162. https://doi.org/10.1016/j.jbusvent.2022.106227

Sheu, D.-F., & Lin, H. (2007). Impact of Venture Capital on Board Composition and Ownership Structure of Companies: An Empirical Study. *The International Journal of Management*, *24*, 573. https://consensus.app/papers/impact-of-venture-capital-on-board-composition-and-sheu-lin/856e858792665c85bce121e40d0173d0/

Silver (Ed.) (1985). *Venture capital : the complete guide for investors*.

Simon, H. A. (1955). A Behavioral Model of Rational Choice. *Quarterly Journal of Economics*, *69*, 99–118.

Sokołowska, E. (2016). Funds of Funds. In (pp. 81–93). https://doi.org/10.1007/978-3-319-13215-0_4

Sorensen, M., & Jagannathan, R. (2015). The Public Market Equivalent and Private Equity Performance. *Financial Analysts Journal*, *71*(4), 43–50. https://doi.org/10.2469/faj.v71.n4.4

Spearman, C. (1904). The proof and measurement of association between two things. *The American Journal of Psychology*, *15*(1), 72–101. https://doi.org/10.2307/1412159

Stevens, S. S., Meyerhoff, H. A., Davis, W., & Bacto-Agar, I. On the Theory of Scales of Measurement. *Science*, *103 2684*, 677–680.

Taddy, M. (2019). *Business Data Science: Combining Machine Learning and Economics to Optimize, Automate, and Accelerate Business Decisions* (1st Edition).

McGraw-Hill Education. https://www.accessengineeringlibrary.com/content/book/9781260452778

Thomas, P., Da Silva, B. C., Barto, A., Giguere, S., Brun, Y., & Brunskill, E. (2019). Preventing undesirable behavior of intelligent machines. *Science*, *366*, 1004–1999. https://doi.org/10.1126/science.aag3311

Thompson, R. (2008). Venture Capital Definitions and Approaches. In (pp. 50–62). https://doi.org/10.1057/9780230594067_4

Timmons, J. A., & Bygrave, W. D. (1986). Venture capital's role in financing innovation for economic growth. *Journal of Business Venturing*, *1*(2), 161–176. https://EconPapers.repec.org/RePEc:eee:jbvent:v:1:y:1986:i:2:p:161-176

Tomy, S., & Pardede, E. (2018). From Uncertainties to Successful Start Ups: A Data Analytic Approach to Predict Success in Technological Entrepreneurship. *Sustainability*, *10*, 602. https://doi.org/10.3390/SU10030602

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Tyebjee, T., & Bruno, A. (1984). A Model of Venture Capitalist Investment Activity. *Management Science*, *30*, 1051–1066. https://doi.org/10.1287/MNSC.30.9.1051

Universität Zürich. *Wilcoxon-Test*. https://www.methodenberatung.uzh.ch/de/datenanalyse_spss/unterschiede/zentral/wilkoxon.html

van Binsbergen, J., Hueskes, W., Koijen, R., & Vrugt, E. (2013). Equity yields. *Journal of Financial Economics*, *110*(3), 503–519. https://doi.org/10.1016/j.jfineco.2013.08.017

Wadhwa, R., & Bansal, R. (2024). Unleashing the Role of Artificial Intelligence on Entrepreneurship. *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)*, 364–371. https://doi.org/10.1109/CCICT62777.2024.00066

Wallmeroth, J., Wirtz, P., & Groh, A. P. (2018). Venture Capital, Angel Financing, and Crowdfunding of Entrepreneurial Ventures: A Literature Review. Advance online publication. https://doi.org/10.1561/0300000066

Wang, K., Wang, C. K., & Lu, Q. (2002). Differences in Performance of Independent and Finance-Affiliated Venture Capital Firms. *Journal of Financial Research*, *25*(1), 59–80. https://doi.org/10.1111/1475-6803.00004

Weidig, T. (2002a). Risk Model for Venture Capital Funds. *Capital Markets: Asset Pricing & Valuation EJournal.* Advance online publication. https://doi.org/10.2139/ssrn.365881

Weidig, T. (2002b). Towards a Risk Model for Venture Capital Funds: Liquidity and Performance Forecasting. *Capital Markets: Asset Pricing & Valuation EJournal.* Advance online publication. https://doi.org/10.2139/ssrn.353562

Wells, W. A. (1974). *Venture capital decision-making* [S.l.].

Werther, G. (2013). When Black Swans Aren't: On Better Recognition, Assessment, and Forecasting of Large Scale, Large Impact, and Rare Event Change. *Risk Management EJournal.* Advance online publication. https://doi.org/10.1111/rmir.12000

Wilcoxon, F. (1945). Individual Comparisons by Ranking Methods. *Biometrics Bulletin*, *1*(6), 80–83. https://doi.org/10.2307/3001968

Wright, M [M.] (1998). Venture Capital and Private Equity: A Review and Synthesis. *Journal of Business Finance & Accounting*, *25*, 521–570. https://doi.org/10.1111/1468-5957.00201

Zacharakis, A., & Shepherd, D. (2001). The Nature of Information and Overconfidence on Venture Capitalists' Decision Making. *Journal of Business Venturing*, *16*, 311–332. https://doi.org/10.1016/S0883-9026(99)00052-X

Zomaya, A., & Sakr, S. (2017). Handbook of big data technologies. *Handbook of Big Data Technologies.* Advance online publication. https://doi.org/10.1007/978-3-319-49340-4