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DISCUSSION PAPER

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Big Data and Start-up Performance

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Big Data-based Management Decisions and Start-up Performance

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Abstract

With Big Data (BD) becoming widely available, the question emerges of whether Big Data Analytics (BDA) leads to better managerial decision-making and firm performance not only among incumbents, but also for start-ups. Given their liability of newness and resource constraints, adopting this new technology poses significant risks. Based on a large sample of start-ups in Germany, we study the adoption of BDA among young ventures and analyze its economic impact through various performance measures, such as survival rates, costs, sales, employee growth, and access to financing. Our findings show that BDA adoption indeed is a risky strategy with potentially high rewards. Start-ups using BDA have a lower survival rate, which is closely tied to two interrelated factors: higher operating costs despite their already tight financial resource constraints and higher uncertainty in sales. At the same time, the increased risk of adopting BDA is, conditional on survival, compensated in several ways: Besides increased sales, BDA-adopting ventures show higher employee growth and are more likely to secure Venture Capital (VC) funding. For high-performing BDA-adopting ventures, the positive effects on employee growth are even more pronounced. Given the need for complementary resources, BDA may act as a performance amplifier, yielding higher returns for firms that are better positioned to leverage its potential.

Keywords: Big data, Innovation, Start-ups, Survival, Venture Capital

JEL Classification: D22 , L25 , L26 , O14 , 033

1 Introduction

The relevance of Big Data (BD) and Big Data Analytics (BDA) has increased significantly in recent years. Firms generate data all along the value chain, and the declining costs of computing facilitate the development of innovative data management and analytics (Gandomi & Haider, 2015; Sena, Bhaumik, Sengupta, & Demirbag, 2019).
Both established and young companies have increasingly adopted data analytics methods to improve internal processes, products and services, or customer satisfaction (Bajari, Chernozhukov, Hortaçsu, & Suzuki, 2019; Manyika et al., 2011; Suoniemi, Meyer-Waarden, Munzel, Zablah, & Straub, 2020). Across academic and management literature, BDA is considered to be a 'frontier for innovation, competition, and productivity' (Manyika et al., 2011), a 'big thing in innovation' (Gobble, 2013), or 'the management revolution' (McAfee & Brynjolfsson, 2012). While there seems to be a consensus that BDA is key to current and future economic development and growth (Aghion, Antonin, & Bunel, 2021; Farboodi, Mihet, Philippon, & Veldkamp, 2019), its role for young and emerging companies in building a competitive advantage remains less obvious. Anecdotal evidence illustrates how individual companies successfully incorporate BDA into their existing business models or develop entirely new business ideas. Newcomers such as *OpenAI* or multi-million (or even multi-billion) funded start-ups like *6sense* and *databricks* were extremely successful in building their entire services around BDA. Other start-ups like *Oddbox* or *Autolus* have incorporated BDA into their business models, leveraging data-driven strategies to enhance their services and operations. Unlike other automation technologies that focus on reducing manual labor input, improving speed and quality of production, BDA has the potential to reshape decision-making processes (Müller, Fay, & vom Brocke, 2018; Zuboff, 1985). Particularly, managerial decision-making may profit from BDA and hence, potentially result in a competitive advantage (Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015a; Ghasemaghaei, 2019; Ghasemaghaei, Ebrahimi, & Hassanein, 2018; Janssen, van der Voort, & Wahyudi, 2017; Merendino et al., 2018). In this regard, young firms may particularly benefit given the high degree of uncertainty and the potential lack of experience in certain tasks and decisions.

Considering the high expectations tied to it, the question emerges as to whether BDA can indeed meet them. So far, however, it remains unclear to what extent newly founded ventures can benefit from adopting BDA within their managerial decision-making. Until now, the empirical literature has mainly focused on established organizations rather than young firms. Early research on the antecedents of BDA, such as enterprise resource planning systems (ERP), decision support systems (DSS), and business intelligence (BI), has already established a positive effect on decision-making and firm performance (Elbashir, Collier, & Davern, 2008; Hitt, Wu, & Zhou, 2002; Kohli & Devaraj, 2004). As BDA started to mature, the focus shifted toward data-driven decision-making and exploratory research suggests that data-driven firms are more productive and more profitable (Ghasemaghaei, 2019; McAfee & Brynjolfsson, 2012).

To explain the performance effects of BDA, the majority of studies draw on the resource-based view (RBV) (Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019; Helfat et al., 2023; Maroufkhani, Wagner, Wan Ismail, Baroto, & Nourani, 2019) and the dynamic capabilities view (DCV), which emphasizes a firm's ability to adapt and reconfigure those resources in changing environments (Chen, Preston, & Swink, 2015; Côrte-Real, Oliveira, & Ruivo, 2017; Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015b; Mikalef, Boura, Lekakos,

& Krogstie, 2019; Mikalef, Krogstie, Pappas, & Pavlou, 2020; Sena et al., 2019). BDA is not conceptualized as a stand-alone tool, but can be seen as a capability that arises from the effective combination of tangible, intangible, and human resources (Ansari & Ghasemaghaei, 2023; Gupta & George, 2016). These complementary resources include IT infrastructure (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Yasmin, Tatoglu, Kilic, Zaim, & Delen, 2020), data-driven management practices (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Ghasemaghaei, 2019; Yasmin et al., 2020) and strategies (Suoniemi et al., 2020; Yu, Jacobs, Chavez, & Feng, 2019), multidisciplinary teams, and BDA skills (Akhtar, Frynas, Mellahi, & Ullah, 2019; Akter et al., 2016; Wang, Kung, Gupta, & Ozdemir, 2019; Yasmin et al., 2020).

While these studies offer valuable insights into specific mechanisms and conceptual elements of the RBV and DCV and how they can lead to a competitive advantage, most rely on cross-sectional designs, interviews, or self-evaluations. Hence, although there are well-established theoretical arguments, we still lack longitudinal, multi-industry analyses that provide broader empirical evidence on the benefits of BDA. Exceptions - although exclusively focusing on established firms - include Ertz, Latrous, Dakhlaoui, and Sun (2025), who analyze 522 publicly listed firms in Canada and the U.S. and find that BDA adoption is positively linked to market value as well as social and environmental performance. In the IT sector, Tambe (2014) and Müller et al. (2018) empirically show that BDA-related investments improve productivity in data-intensive and highly competitive environments, at least partly due to the availability of complementary resources in these sectors. Brynjolfsson, Jin, and McElheran (2021) find that prediction automation[1] increases productivity in U.S. manufacturing firms, but only when complemented by resources such as IT capital, skilled labor, efficient processes, and strong managerial capabilities.

Yet, setting up the necessary complementary resources is costly. As, for example, Tambe (2014) notes, managers must weigh the competitive gains from BDA against the high labor costs of acquiring and maintaining analytic talent. These costs are, given their already tight constraints, especially salient for young firms, potentially reinforcing the incumbent advantage of larger firms (Obschonka & Audretsch, 2020). Although the literature lacks an empirical analysis of the adoption of BDA among young firms (Maroufkhani et al., 2019), we know that general IT adoption among SMEs has historically lagged behind larger firms, especially due to financial constraints (Ghobakhloo, Hong, Sabouri, & Zulkifli, 2012). At the same time, BDA adoption costs also include indirect costs such as productivity disruptions and the organizational burden of transitioning to data-centric systems. These costs and challenges, however, may be more easily overcome by newly founded ventures without entrenched processes (Dubey et al., 2019; Janssen et al., 2017). In comparison to incumbents that are often strapped to a technological status quo, young firms are less path-dependent and, hence, less prone to the 'curse of knowledge' (Henderson, 2006), potentially allowing them to disproportionally benefit from BDA-adoption. This duality - resource scarcity versus adaptability - positions new ventures uniquely: On the one hand, their liability of newness and the resulting resource constraints hamper acquiring complementary skills and technologies essential for successfully adopting BDA. On the other hand, a start-up's very newness, implying low adjustment costs

[1]Prediction automation is a subset of BDA-methods that aims at analyzing historical and current data to predict future or unknown values, events, or probabilities of occurrences.

and the absence of path dependencies, might be a decisive advantage when adopting BDA as part of their business model or as the basis for their (managerial) decision-making processes.

Yet, even if adopted successfully, it remains unclear whether BDA is inherently well-suited to the entrepreneurial context. Entrepreneurship is, by definition, decision-making under uncertainty, often relying on intuition, creativity, and informal routines—traits that may conflict with the data-driven, pattern-based logic of BDA systems (Obschonka & Audretsch, 2020). Many small firms operate without formal planning processes or structured management tools, which can further limit the effectiveness of BDA (Ghobakhloo et al., 2012). Studies also suggest that when paired with unsophisticated tools or poor integration, BDA can even worsen decision quality through data misinterpretation or information overload (Ghasemaghaei, 2019). On the other hand, BDA-based management decisions may be highly valuable in volatile and fast-changing environments by enabling early detection of market shifts, enhancing strategic flexibility, and by supporting firms in adjusting resource allocations quickly and effectively (Dubey et al., 2019). Indeed, BDA use has been found to influence business growth more strongly in dynamic environments (Chen et al., 2015). This suggests that, if they succeed in integrating BDA into their typically informal and intuitive decision-making processes, its value could be even greater for newly founded ventures that need to manage uncertainty and volatility on a daily basis. Thus, BDA adoption is complex, resource-intensive, and its returns depend on how well newly founded ventures translate insights into valuable actions. These features make BDA adoption a high-risk, high-potential strategy. In contrast to larger firms for which a positive effect has been established, it is conceptually still unclear whether BDA can truly contribute to a competitive advantage in small and young firms (Maroufkhani et al., 2019).

With our study, we set out to investigate whether newly founded ventures — in the following referred to as start-ups and defined as independent businesses with a maximum age of seven years - can derive economic benefit from the use of BDA or whether the necessary investments and associated risks outweigh the potential advantages, reserving the benefits of BDA to larger, more established firms. We intentionally adopt a broad definition of start-ups that is not restricted by specific sectors, legal forms, founder characteristics, or ex-post performance measures. This inclusive approach reflects our objective to examine these very performance indicators as outcome variables and ensures that the sample is not constrained by predefined firm characteristics. To this end, we use a unique and extensive representative data set of German start-ups observed over the period from 2010 to 2018 that includes information on various founder and firm characteristics, economic performance, as well as financing information. This enables us to extend the existing body of empirical literature on the effect of BDA to younger firms by analyzing both the drivers of BDA adoption and its implications for start-up development across a broad range of indicators. Given the distinct nature of early-stage ventures, we deliberately include performance measures that go beyond those commonly used for established firms. Firm survival, for instance, is one of the most fundamental outcomes in entrepreneurship research (Coad, Frankish, & Storey, 2020; Josefy, Harrison, Sirmon, & Carnes, 2017; Phillips & Kirchhoff, 1989; Soto-Simeone, Sirén, & Antretter, 2020). Financial indicators such as costs and sales provide insight into operational performance, while measures of employee growth reflect the scaling capacity of start-ups (Chatterji, Delecourt, Hasan, & Koning, 2019; Gilbert, McDougall, & Audretsch, 2006). Lastly, similar to market valuation used in research on publicly listed firms (Ertz et al., 2025; Ghasemaghaei, 2019), we analyze a start-up's probability to receive venture capital (VC).

We contribute to the literature by expanding current research on the performance effects and competitive advantage of BDA to start-ups, an area that has been underexplored in previous studies (Maroufkhani et al., 2019). Our analysis includes a wide range of industries, moving beyond the focus on manufacturing and IT sectors in earlier studies. As BDA focuses primarily on decision-making processes rather than the automation of manual labor, its relevance extends across various industries (Zuboff, 1985). We introduce a set of performance measures that are specifically designed to capture the unique characteristics and challenges faced by these early-stage businesses, providing a more accurate assessment of their performance without relying on qualitative self-evaluation of managers or entrepreneurs.

Our results reveal considerable heterogeneity in performance outcomes. Comparing BDA adopters to similar non-adopters, we show that adoption among newly founded ventures comes with a lower survival probability, higher operational costs, mainly due to higher personnel costs, and higher variance in sales. While this first set of findings indicates the costliness and riskiness associated with BDA, adopting BDA also pays off. Conditional on survival, we observe higher sales and employee growth for BDA-adopting ventures. In addition, we take on a strategic entrepreneurship perspective, acknowledging that high-risk tools like BDA may especially provide value to high-performing entrepreneurs. Our findings indicate that the benefits of BDA adoption regarding employee growth are not evenly distributed but are particularly concentrated among firms in the upper performance deciles, suggesting that BDA acts as a performance amplifier, yielding higher returns primarily for those firms already positioned to leverage its potential. Such a high-risk, high-growth pattern naturally appeals to risk-seeking investors (Gompers & Lerner, 2001; Winton & Yerramilli, 2008). In line with this, we find that BDA-adopting companies have a significantly higher likelihood of being linked to financing by VC funds compared to non-adopters. Overall, while BDA represents a significant source of competitive advantage for start-ups, it does come with inherent risks. Our findings confirm the notion of founders at the frontier of innovation who take up higher entrepreneurial risk and a higher probability of failure for the prospect of higher long-term growth if their start-ups survive (Aghion et al., 2021).

2 Big Data Analytics and Firm Performance

Understanding the performance implications of BDA adoption and use in young companies requires re-thinking the mechanisms through which they may benefit, the types of costs they face, and which performance measures can capture these potential effects. While stock market valuations and productivity are useful indicators for larger and established companies (Brynjolfsson et al., 2021; Ertz et al., 2025; Müller et al., 2018; Tambe, 2014), identifying the uses and pitfalls of BDA in newly founded companies requires a different perspective. To determine start-up success in the context of this study, we build on a set of performance measures considered relevant for newly founded ventures. In line with the literature on start-up performance, these include survival after a certain period of time (Coad et al., 2020; Josefy et al., 2017; Phillips & Kirchhoff, 1989; Soto-Simeone et al., 2020), (employment) growth (Chatterji et al., 2019; Gilbert et al., 2006), having secured VC funding (Schlichte, Junge, & Mammen, 2019; Woolley & MacGregor, 2022), and accounting measures such as sales (Chandler & Hanks, 1993; Miller, Washburn, & Glick, 2013) and costs (Grillitsch & Schubert, 2021) that can reveal the drivers of those performance outcomes.[2] These measures differ from those used to evaluate the impact of BDA in established firms, as newly founded ventures are often not (yet) profitable, have a comparably low productivity, and show high volatility in sales and profits as they are in the midst of building new products and services, which requires large upfront investments while facing market uncertainty.

In the following, we build upon insights from the broader management literature and adopt the perspective that performance is inherently multidimensional (Delmar, Davidsson, & Gartner, 2003; Gilbert et al., 2006; Murphy, Trailer, & Hill, 1996; Wiklund & Shepherd, 2005) to develop propositions concerning how a new venture's adoption of BDA influences sales, costs, and performance indicators more pertinent to start-ups.

2.1 Survival probability

Survival probability is one of the most common metrics of start-up performance as it reflects the ability of nascent ventures to persist in a competitive environment (Coad et al., 2020; Josefy et al., 2017; Phillips & Kirchhoff, 1989; Soto-Simeone et al., 2020). Facing unique challenges such as limited (financial) resources, operational inefficiencies, and market uncertainty, the survival of a start-up is a strong indicator of its resilience and ability to adapt and grow (Esteve-Pérez & Mañez-Castillejo, 2008). At the same time, a venture's survival serves as an indirect measure of its effectiveness in leveraging transformative technologies such as BD and BDA. As pointed out above, strong data analytic capabilities can improve a firm's decision-making processes, leading to better resource allocation and strategic planning, both properties that are essential for ensuring sustained growth and, thus, enhance the chances for long-term survival (Sandberg & Hofer, 1987). However, adopting BDA poses significant challenges. Integrating advanced analytics requires substantial investments in the technology itself, the necessary infrastructure, and skilled personnel (Ghasemaghaei et al., 2018; Mikalef et al., 2019), whereby performance effects are often only observed with a time lag (Tambe, 2014). Hence, particularly for newly founded ventures, using BDA can further strain their already

[2] Other possible measures of start-up performance that are found in the literature but not used here are the growth in market share (Gilbert et al., 2006), the (total) amount of VC funds raised (Yua, 2020), or a successful exit (Croce, Guerini, & Ughetto, 2018; Gaulé, 2018). Also, self-reported subjective measures can be found in the relevant literature (see e.g., Ruiz-Jiménez, Ruiz-Arroyo, & del Mar Fuentes-Fuentes, 2021).

limited (financial) resources with a direct impact on firm survival (Stucki, 2014). In addition, the complexity and rapid evolution of BDA technologies may outpace the learning curve of young and small businesses, leading to implementation pitfalls and strategic misalignments (Gupta & George, 2016) that might even worsen decision-making quality (Ghasemaghaei, 2019).

While adopting BDA can generally drive gains, it may also exacerbate inherent entrepreneurial risks. These risks manifest in high operational uncertainties and increased vulnerability to competitive pressures (Fosso Wamba et al., 2015b). For newly founded ventures, adopting BDA is, thus, expected to ultimately result in a lower probability of survival:

Proposition 1 *Start-ups adopting BDA are associated with higher entrepreneurial risk, reflected by a lower probability of survival.*

2.2 Costs

A major determinant of a start-up's survival probability is its cost structure, especially as start-ups usually face tight financial constraints. Adopting novel technology often requires a significant upfront investment and, at least initially, higher operating costs (Grillitsch & Schubert, 2021). This holds particularly true for the use of BDA: To have a positive impact on firm performance, BDA needs to be paired with complementary resources and capabilities (Gupta & George, 2016; Mikalef et al., 2019; Wamba et al., 2017). Adopting BDA requires building up costly (IT-)infrastructure (Akter et al., 2016; Brynjolfsson et al., 2021) and hiring highly skilled personnel (Akter et al., 2016; Tambe, 2014). To enhance human decision-making, BDA needs to be linked to (data-related) human capital (Helfat et al., 2023). Given the scarcity of skilled data-related workforce (Carioli, Czarnitzki, & Fernández, 2024), adopting BDA is likely accompanied by high labor costs. We expect to observe this negative impact of BDA-adoption on the cost structure of newly founded ventures:

Proposition 2 *The adoption of BDA is associated with higher costs. This increase is particularly driven by the need for human capital, translating into higher personnel costs.*

2.3 Sales

Despite the high (upfront) costs, BDA may provide businesses with enhanced capabilities in data-driven decision-making, operational efficiencies, and market responsiveness, all of which are critical for generating revenue (Akter et al., 2016; Andres, Niebel, & Sack, 2024; Brynjolfsson et al., 2021; Ghasemaghaei, 2019; Yasmin et al., 2020). Generally, the same also applies to newly founded ventures, and adopting BDA thus manifests in an increase in sales volume - a common proxy for performance that, despite some limitations, is also used for new ventures (Brush & Vanderwerf, 1992; Chandler & Hanks, 1993; Coad, Frankish, Roberts, & Storey, 2016). Hence, for start-ups that manage to survive the first adoption phase, BDA is likely to have a positive impact on sales:

Proposition 3.1 *The adoption of BDA is associated with higher sales volume.*

As outlined above, the adoption process can strain limited resources and may not pay off immediately, thus, we expect considerable heterogeneity in performance returns. Newly founded ventures with high revenues, i.e., already favorable capabilities and a strong position to leverage data effectively, may benefit disproportionately from adopting BDA. This aligns with the findings of Coad, Segarra, and Teruel (2016) in the context of innovation activities, where young firms at the upper quantiles of the growth rate distribution derive greater performance gains from R&D investments. In the case of BDA, this superior performance is likely due to the successful start-ups' additional resources and ability to leverage advanced analytics for strategic insights and better managerial decision-making, thus gaining a competitive edge in market responsiveness and customer engagement (Akter et al., 2016). Circumnavigating the trade-off between scarce financial resources to invest in and the benefits of new technologies, high-performing start-ups that successfully implement BDA can harness the advantage of their still low adjustment costs. Consequently, particularly start-ups in the upper quantiles of the sales distribution can realize significant benefits from adopting BDA, highlighting its conditional advantages in entrepreneurial contexts:

Proposition 3.2 *High-performing BDA-adopting ventures outperform high-performing non-BDA-adopting ventures with respect to sales volume.*

In addition to heterogeneity and sales volatility between firms, we also expect the dynamic nature of BDA-driven strategies to contribute to heightened within-firm volatility as firms navigate the complexities of data integration and analytics-driven decision-making (Chen et al., 2015). By modeling both inter- and intra-firm variance, we are able to disentangle different dimensions of entrepreneurial risk. Prior research has established sales volatility as a strong predictor for new venture survival, with ventures showing unstable sales trajectories facing substantially higher exit rates than those experiencing smooth sales growth (Coad, Daunfeldt, & Halvarsson, 2022; Lundmark, Coad, Frankish, & Storey, 2020). Hence, while we assume BDA adoption is associated to some extent with higher sales, we particularly anticipate it to induce significantly higher risks. These risks are not only reflected in reduced survival probabilities but are, prior to (involuntary) exit, also expected to manifest in greater sales volatility among BDA-adopting start-ups:

Proposition 3.3 *The adoption of BDA is associated with higher sales volatility.*

2.4 Employee Growth

In contrast to conventional performance measures, employee growth is a more common and perhaps more relevant measure of success in the context of newly founded ventures (Chatterji et al., 2019; Gilbert et al., 2006; Lange, Mollov, Pearlmutter, Singh, & Bygrave, 2007; Nielsen, 2015). Davila, Foster, and Gupta (2003) argue that employee growth is especially useful as a proxy for venture performance, as it is easily accessible and updated more often and regularly. In contrast to that, a venture's valuation, for example, occurs in irregular intervals as part of funding rounds.[3]

[3]Further examples that suggest the use of employee growth as a measure for new venture performance are Feeser and Willard (1990), Chandler and Hanks (1993), or Reid and Smith (2000).

In general, it is found that enterprises that adopt BDA not only achieve greater operational efficiencies but also experience significant employee growth (Wamba et al., 2017). If successfully adopted, the advantages of BDA translate into improved business processes and better strategic planning, which are crucial for scaling operations and expanding the workforce. The data-driven insights obtained through BDA allow these companies to identify and capitalize on new business opportunities, optimize talent management, and enhance employee productivity. As a result, these ventures tend to have a more optimistic outlook and higher long-term expectations for sales and profits, enabling them to expand their workforce in the present:

Proposition 4.1 *The adoption of BDA is associated with higher employee growth.*

Again, similar to Coad, Segarra, and Teruel (2016) and in line with prior studies that highlight the need for (BDA related) human capital for a successful BDA adotion (compare e.g. Akhtar et al., 2019; Akter et al., 2016; Wang et al., 2019; Yasmin et al., 2020), this effect is expected to be even more pronounced for already high-performing ventures in the upper quantiles of the growth distribution that are able to successfully adopt BDA:

Proposition 4.2 *Higher employee growth manifests itself particularly among the subset of high-performing ventures.*

2.5 VC funding

Besides employee growth, another common measure of the performance of newly-founded ventures is their attractiveness to investors. Comparable to the effect of adopting BDA on the market value of publicly listed enterprises (Ertz et al., 2025; Ghasemaghaei, 2019; Hitt et al., 2002), investigating VC funding allows us to infer the expected future market value of start-ups that implement BDA.[4] This is based on the idea that VC investors discount start-ups' future performance, thus serving as a testimony of their potential (future) market values. This measure allows us to account for risk adjustments and the value of intangible assets.

In the last decades, VC has become an increasingly important source of financing for start-ups in the U.S. (Lerner & Nanda, 2020) but also in Europe (Berger & Hottenrott, 2021; Bertoni, Colombo, & Quas, 2015).[5] Whereas traditional lenders like banks do not profit from any upside potential of an investment in a start-up but bear the entire inherent risk, VC investors can monetize the higher performance of their equity investments in case of an exit event. Thus, they are willing to take on the additional risk associated with newly founded ventures. Before allocating funds to risky endeavors, they usually conduct a thorough examination of the targeted venture. There exists an extensive body of literature on how VC investors screen and evaluate start-ups. Selection factors include intellectual property, technological capability, the products or services, the management team, and the market and industry outlook (Gompers, Gornall, Kaplan, & Strebulaev, 2020; Hellmann & Puri, 2000;

[4] Since newly founded ventures are usually privately owned and not publicly listed, data on the valuation by the stock market is unavailable.

[5] Although the VC market in Europe is much smaller, it is receiving increasing attention from policymakers, for example, as part of the European Commission's EU 2020 strategy or the Green New Deal (Berger & Hottenrott, 2021; Wallace, 2020).

Kaplan & Strömberg, 2004).[6] Assuming, conditional on firm survival, that BDA adoption will eventually lead to a competitive advantage, these start-ups are a primary target for VC investors:

Proposition 5 *Due to the potential for higher rewards, BDA-adopting ventures attract risk-seeking investors and are therefore more likely to secure VC funding.*

Together, these propositions serve as the theoretical basis for the subsequent empirical investigations. They will guide our analyses based on a unique and comprehensive data set on start-ups founded in Germany. The goal is to better understand the adoption of new tools, such as BDA, and how, or in the first place, whether they can generate value in newly-founded ventures.

[6] As these are all factors that seem to match with the characteristics of (new) ventures that, in line with prior empirical literature, are most likely to successfully introduce BDA, we explicitly account for this selection bias within our empirical analyses.

3 Data and Methodology

3.1 Data Sources

The analyses draw from two data sources. The main source is the IAB/ ZEW Start-up Panel. The panel comprises a large, representative sample of start-ups in Germany and tracks the founding process, business activities, and the development of newly founded companies with the help of annual computer-aided telephone interviews (CATI). The questionnaire additionally collects a large set of founder- and company-specific characteristics. The survey sample of start-ups is drawn as a stratified random sample from the Mannheim Enterprise Panel (ZEW-MUP), which represents the entire universe of companies operating in Germany and is recorded by Creditreform, the largest credit rating agency in Germany. Using the data of Crefitreform allows us to include all types of young ventures, independent of their legal form or obligation to register with the official German Handelsregister. The sample is stratified by founding year and industry.[7] High-technology sectors are slightly oversampled. The panel targets these firms, as start-ups from high-technology industries are expected to play a particularly significant role in driving innovation, structural change, and job creation (Audretsch, Link, Sauer, & Siegel, 2016; Fudickar & Hottenrott, 2019; Schneider & Veugelers, 2010). Table A.1 in the Appendix shows the distribution of firms across sectors. When entering the IAB/ ZEW Start-up Panel, the surveyed companies are not older than three years and remain in the sample until a maximum age of seven years. The collected information thus captures the first phase of the firms' life cycle for a large and representative sample of German start-ups.[8] We link this data to the ZEW-MUP, to track start-up survival based on information provided by Creditreform that allows us to observe firm exits, mergers, and acquisitions (M&A) and insolvencies until the end of 2023. Thus, the resulting data set includes unique and comprehensive information covering founder and start-up characteristics, business activities, information about the start-ups' financing structure, and the ventures' market exits. It consists of a total of 3,395 firms, resulting in 12,261 firm-year observations for which we have full information. The start-ups were founded between 2010 and 2015, with more than half of the firms being founded later than 2013. They are relatively small ventures with, on average, 5 employees.

3.2 BDA Adoption

In 2017, the IAB/ ZEW Start-up Panel included several new questions addressing the topic of digitization and BDA usage, the latter being our main variable of interest. We thus restrict our sample to firms answering this BDA question.[9] During the survey interviews, the following definitions of BD and BDA were used:

> ***BD** is rapidly growing volumes of data generated from activities conducted electronically, for example, social media activities, GPS usage, etc.* ***BDA** refers to concepts, processes, technologies, and*

[7] The industry definition of the IAB/ZEW Start-up Panel is based on the wz08 classification of NACE codes. NACE codes are combined into eleven industries: cutting-edge technology manufacturing, high-technology manufacturing, technological services, software, low-technology manufacturing, knowledge-intensive services, other company services, creative services, other consumer services, construction, and retail.

[8] For more details on the IAB/ ZEW Start-up Panel, see Rodepeter, Gottschalk, & Hottenrott, 2025.

[9] Additionally, all firms in our sample must have information on firm and founder characteristics and the performance measures introduced above. Table A.1 in the Appendix shows how that changes the distribution across the stratification criteria used for sampling. Deviations of our sample from the total number of firms interviewed in 2017 are minimal regarding the variables founding year and industry affiliation. The firms answering the question on BDA adoption did not significantly differ from firms not answering this question during the interviews. Thus, the representativeness of our sample should not be impaired.

software applications that help process the rapidly growing and diverse volume of data (from corporate or external data sources) for qualitative and quantitative analyses as a basis for management decisions.[10]

Based on this definition, founders were asked to indicate whether they use BDA within their management decision processes, which was affirmed by approximately 15% of the firms in our sample. It is important to note, however, that this information on BDA activity is, in contrast to the rest of the data set - which is available in a panel structure - a time-invariant firm characteristic. This is primarily due to the fact that the question on BDA usage was included in the 2017 questionnaire only, and not in earlier or subsequent surveys. Furthermore, the survey did not gather information on the timing of BDA adoption. Nevertheless, given that the firms in the sample are newly established ventures, with an average age of three years at the time of the survey, it is reasonable to assume that BDA adoption, if it occurred, took place at or shortly after the firm's formation.

BDA adopters can be found across all industries (Figure 1, left), and adoption increased substantially in more recent cohorts (Figure 1, right). This points towards strong cohort effects. Hence, despite having no data on the point in time when exactly start-ups introduced BDA, this suggests that the diffusion of BDA is still in progress within the (German) economy. Table 1 shows the correlation of BDA with some firm and founder characteristics like founder age, gender, team composition, educational background, founding motive, and whether the firm operates in the software industry. The displayed correlations support the construct validity of our BDA measure.

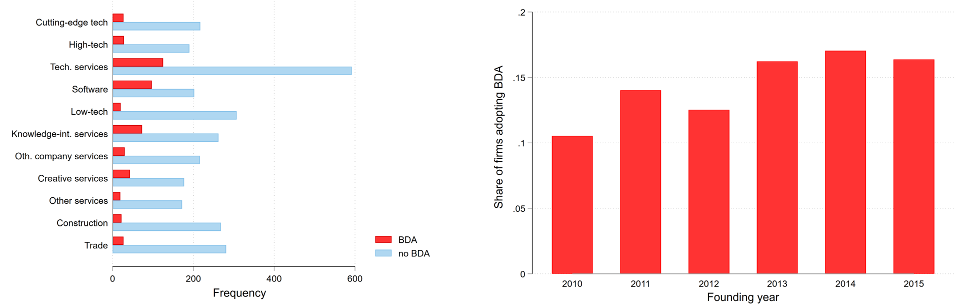

Fig. 1: BDA use by industry (left) and start-up cohort (right; indicated by founding year).

3.3 Firm and Founder Characteristics

Table 2 shows the information available on founder and firm characteristics. Using the IAB/ ZEW Start-up Panel, we have information on the founders' demographics (age, gender, and nationality), cognitive skills (education, industry and founding experience), founding motive, and whether the start-up was founded by a team or a solo founder. Apart from the founding year and industry affiliation discussed above, we also have information on the start-ups' geographical location (city vs. rural area, and East vs. West Germany).

[10]IAB/ ZEW Start-up Panel Questionnaire, 2017, p. 32; originally, the definitions and questions were stated and asked in German.

Table 1: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) BDA	1.0000						
(2) Founder age	-0.0400	1.0000					
(3) Female	-0.0146	0.0140	1.0000				
(4) Team	0.1092	-0.0557	0.2207	1.0000			
(5) Education	0.1247	0.1901	0.0332	0.2721	1.0000		
(6) Opportunity-driven	0.0586	-0.1313	0.0099	0.0790	0.0712	1.0000	
(7) Software industry	0.1347	-0.1076	-0.0361	0.0788	0.1100	0.0739	1.0000

The table shows Pearson's correlation coefficients of BDA and selected firm and founder characteristics.

Table 2: Summary Statistics of Founder and Firm Characteristics

	no-BDA				BDA				t-test
	mean	sd	min	max	mean	sd	min	max	p-value
Founder characteristics									
Founder age	42.15	9.83	18	95	41.04	9.49	20	66	0.000
Female founder	0.18	0.38	0	1	0.16	0.37	0	1	0.106
Foreign founder	0.10	0.29	0	1	0.11	0.31	0	1	0.070
Team	0.31	0.46	0	1	0.46	0.50	0	1	0.000
Educational level	5.53	2.58	1	9	6.44	2.52	1	9	0.000
Industry experience	15.71	9.97	1	60	14.17	9.72	1	45	0.000
Founding experience	0.40	0.49	0	1	0.56	0.50	0	1	0.000
Opportunity-driven	0.81	0.39	0	1	0.88	0.33	0	1	0.000
Firm characteristics									
Founding year	2013	1.65	2010	2015	2013	1.59	2010	2015	0.000
City	0.37	0.48	0	1	0.48	0.50	0	1	0.000
East Germany	0.14	0.35	0	1	0.11	0.31	0	1	0.001
Cutting-edge tech	0.08	0.27	0	1	0.06	0.23	0	1	0.001
High-tech	0.07	0.25	0	1	0.05	0.22	0	1	0.014
Tech. services	0.23	0.42	0	1	0.28	0.45	0	1	0.000
Software	0.07	0.26	0	1	0.18	0.38	0	1	0.000
Low-tech	0.11	0.31	0	1	0.04	0.20	0	1	0.000
Knowledge-int. services	0.09	0.29	0	1	0.14	0.35	0	1	0.000
Oth. company services	0.08	0.27	0	1	0.06	0.23	0	1	0.001
Creative services	0.05	0.22	0	1	0.08	0.27	0	1	0.000
Other services	0.05	0.22	0	1	0.03	0.17	0	1	0.000
Construction	0.09	0.29	0	1	0.04	0.20	0	1	0.000
Retail	0.08	0.27	0	1	0.04	0.21	0	1	0.000

The table shows the summary statistics for the variables used within entropy balancing, broken down by start-ups that are not adopting BDA (left) and those that are adopting BDA (right). In addition, the p-values resulting from two-sided t-tests comparing the two groups are provided.

Table 2 also presents a first descriptive comparison between founders who adopt BDA and those that do not. Results from two-sided t-tests reveal several statistically significant differences: BDA adopters tend to be younger, found more often in teams, and exhibit higher average levels of formal education, while having comparatively less industry-specific experience. Yet, they are more likely to be serial entrepreneurs, having previously established one or more start-ups, and are more often motivated by opportunity rather than necessity. An additional descriptive analysis on the fields of study of the subset of academic founders shows that knowledge in the fields of natural sciences, computer science, and business administration seems to be crucial when adopting BDA (compare Table A.2 in the Appendix). The founders' experience in previous business ventures indicates a set of soft skills, including management expertise. Apart from cohort effects shown in Figure 1, the decision on BDA-adoption is also influenced by the start-up's location: start-ups that are based in former East Germany are less likely to adopt BDA than their counterparts in the rest of Germany. In addition, start-ups that are located in cities are significantly more likely to adopt BDA than start-ups that are located in more rural areas. While these differences are noteworthy, they are largely consistent with theoretical expectations regarding the profile of data-driven, innovation-oriented founders. As such, the observed patterns lend further support to the construct validity of the BDA measure employed in the survey.

Besides the adoption of new technologies such as BDA, founder characteristics have also been shown to influence a nascent venture's success (Chandler & Jansen, 1992; Colombo & Grilli, 2010; Ganotakis, 2012). To overcome the resulting inherent selection bias, the founder characteristics shown in Table 2 will be used in the empirical analyses as variables for an entropy balancing preprocessing.

3.4 Firm Performance

Table 3 presents the summary statistics of the performance measures used in the subsequent analyses. In terms of firm survival, we observe whether a start-up is still active up to the end of the year 2023, allowing us to know whether it survived the first seven years of the firm life cycle (Rodepeter et al., 2025). However, firm closure can have several reasons and is not necessarily synonymous with failure (Wennberg, Wiklund, DeTienne, & Cardon, 2010). We use data on M&A from Creditreform to correct our survival statistic by firms that have been acquired by another firm, i.e., have successfully exited the market. Additionally, we observe whether firms have filed for insolvency within the first seven years, a measure that has been used to exclude the possibility of an 'intelligent exit', i.e., firm closure as a result of founders realizing that their business idea is not viable (Gottschalk & Müller, 2022). Approximately one-third of the firms in our data set that closed within the first seven years have actually filed for insolvency.

Table 3: Summary Statistics of Performance Variables

	mean	sd	min	max
Survival	0.91	0.28	0.00	1.00
Insolvency	0.03	0.16	0.00	1.00
Sales	494,180.74	1,600,075.97	0	80,000,000
Total costs	410,478.88	1,417,021.12	0	91,640,000
Operating costs	354,445.11	1,363,416.07	0	9,1640,000
Material costs	178,103.54	1,228,424.65	0	90,000,000
Personell costs	140,541.90	305,116.94	0	9,500,000
Other costs	35,767.41	106,315.44	0	7,000,000
Number of employees	4.56	7.06	0	205
VC	0.03	0.17	0	1
Bank financing	0.09	0.29	0	1

The table shows the summary statistics for the most important variables used in the following analyses.

Further, we have detailed information on the start-ups' cost structure, which is reported in terms of R&D, investment, and operating costs. The latter comprise, on average, about 85% of the start-ups' total costs and can be broken down further into personnel, material, and other operating costs. We observe the start-ups' sales and the number of employees, and lastly, the IAB/ ZEW Start-up Panel also provides information on the start-ups' financing structure. Besides an indicator on bank lending, we have information on whether they could secure funding in the form of VC. The binary indicator *VC* (*Bank financing*) is equal to one if the start-up uses VC (money from bank loans) in the respective year. Summary statistics on these performance measures can be found in Table 3. A detailed description of all variables used in our empirical analyses is presented in Table A.3 in the Appendix.

3.5 Methodology

While the decision to adopt BDA clearly requires a careful assessment of potential gains and the significant risks and costs, it is likely that it is also driven by other endogenous factors. In line with upper-echelons theory, it has been shown that for start-ups, the adoption and investment decisions in the context of comparable technologies are highly dependent on founder and team characteristics (Brynjolfsson & McElheran, 2016; Chapman & Hottenrott, 2022; Ghobakhloo et al., 2012; Sahaym, Howard, Basu, & Boeker, 2016). Indeed, we can infer from Table 2 that in our sample of Germany-based start-ups, founders of BDA-adopting start-ups significantly differ from non-adopters with respect to various characteristics. As such, start-ups provide a valuable empirical setting for studying BDA adoption: The strategic decision to adopt BDA is typically made directly by the founder or founding team, on which we possess rich information, and generally outcomes and effects of such strategic decisions are easier to observe in small and young ventures, as their operational environments are less complex, with fewer overlapping strategies and less organizational inertia compared to established firms.

However, besides the decision to adopt BDA as a technology, founder characteristics have also been shown to influence start-up performance. Gompers, Kovner, Lerner, and Scharfstein (2010), for example, find that previously successful entrepreneurs – defining success as going public - are more likely to start another successful venture compared to first-time entrepreneurs and those who have failed before. Entrepreneurial experience, education (Criaco, Minola, Migliorini, & Serarols-Tarrés, 2014; Roche, Conti, & Rothaermel, 2020) - particularly a managerial education, optimally in combination with a technical education (Ganotakis, 2012) - and industry experience (Bosma, van Praag, Thurik, & de Wit, 2004; Ganotakis, 2012) positively influence the performance of newly founded companies. Here, differences can be observed for opportunity-based and necessity-based entrepreneurs (Baptista, Karaöz, & Mendonça, 2014). Further characteristics that have been shown to influence venture success are age (Azoulay, Jones, Kim, & Miranda, 2020), gender (Robb & Watson, 2012), and various attributes regarding the (composition of the) founding team (Beckman, Burton, & O'Reilly, 2007; Steffens, Terjesen, & Davidsson, 2012; Visintin & Pittino, 2014). According to Beckman et al. (2007), team composition also plays a vital role in a start-up's ability to attract venture capital, one of the measures we use for start-up performance. The other aforementioned characteristics of founders influencing start-up performance are also found to influence VC investments (Gimmon & Levie, 2010; Verheul & Thurik, 2001). For example, venture capitalists tend to fund start-ups whose founders have similar educational backgrounds and comparable professional experiences (Franke, Gruber, Harhoff, & Henkel, 2006).

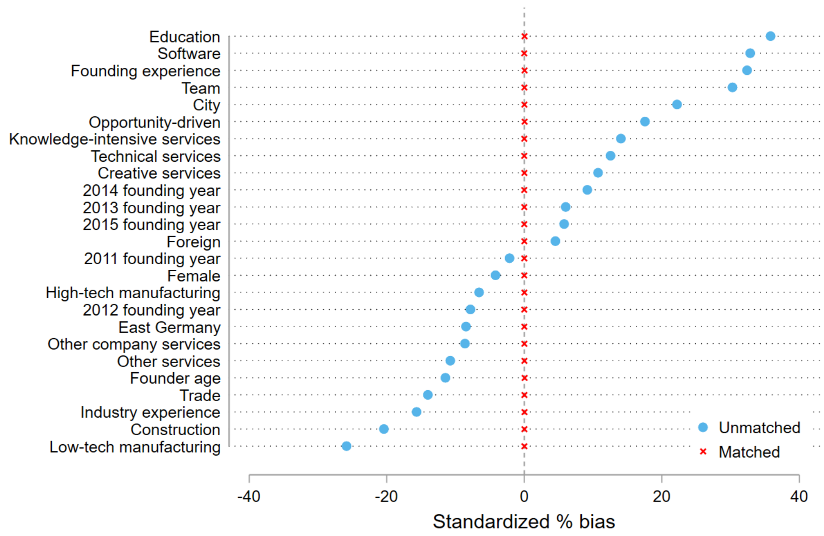

Fig. 2: Graph on the standardized bias across covariates before and after applying entropy balancing.

Overall, founder characteristics seem to significantly influence both the performance of a start-up and its decision to adopt a new technology. To measure the direct effect of BDA adoption on performance, it is obligatory to address these potential confounding effects of founder characteristics in the empirical analyses. To account for the non-randomness of BDA adoption, we introduce entropy balancing as a pre-processing method that reduces the fundamental differences induced by founder characteristics between BDA-adopting and non-BDA-adopting start-ups (Hainmueller, 2012). According to Hainmueller (2012) entropy balancing has several advantages over other balancing methods: It allows for a more extensive set of constraints and for weights to vary across units. The computational complexity is relatively low. The method ensures closeness to the base weights and prevents unnecessary information loss. The resulting weights can then be used in almost any estimation, including those that we will subsequently conduct to test the propositions developed in Section 2. Using this approach and a rich set of variables that determine selection into BDA adoption and likely also drive start-up performance more generally, we re-weight the sample of start-ups that do not use BDA to match the sample of start-ups that use BDA. This enables us to account for differences in the founders' cognitive and non-cognitive skills, as well as for differences in the firms' environment. The weighting, an integral part of entropy balancing, is done based on the first, second, and third moments of the preselected variables. By balancing not only on means, but also taking into account variance and skewness, we relax the assumption of linearity in balancing variables (Källberg & Waernbaum, 2023). An overview of the variables used for the balancing is provided in Table 2. Figure 2 depicts the standardized bias before and after applying entropy balancing across the covariates included in the balancing constraint. It illustrates how entropy balancing effectively reduces the bias regarding the chosen covariates. More detailed summary statistics, including variance and skewness, can be found in the appendix (see Table A.4). If not explicitly specified otherwise, all regression analyses are based on the balanced sample. Following doubly robust balancing as proposed by Zhao and Percival (2017), we also include the variables used for balancing as covariates in our regressions.

4 Empirical Results

In this section, we present the findings on the relationship between BDA and start-up performance. We compare the performance indicators introduced in section 2 between BDA adopters and a matched sample of non-adopters, focusing on survival, cost structure, sales, employee growth, and access to VC financing, providing further evidence on the perceived growth potential of BDA-enabled ventures. Our results presented in the following are robust regarding a series of robustness tests, including bootstrapped standard errors and applying propensity score matching instead of entropy balancing (compare Rosenbaum & Rubin, 1983).[11] All robustness tests are described in detail in the Appendix (compare Table A.5 - A.13).

Table 4: Logistic Regression Results on Start-up Survival and Insolvency

	survival	insolvency
BDA	0.608***	2.401***
	[0.452,0.815]	[1.442,4.027]
Employees t_0	0.953*	1.190***
	[0.907,1.002]	[1.107,1.280]
Firm controls	YES	YES
Industry controls	YES	YES
χ^2 firm controls	44.08***	37.98***
χ^2 industry controls	24.86***	23.00**
Observations	3,395	3,395

The table shows the odds ratios of the logistic regression on start-up survival and insolvency after 7 years with 95% confidence intervals in brackets. For the Wald-test of firm and industry controls, the χ^2-test statistics are reported. We transform the panel data into a cross-sectional format by aggregating to the firm level, resulting in one observation per firm. The sample is entropy is balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.1 Survival

To test Proposition 1 suggesting possible differences in venture risk, we analyze the start-ups' probability of (1) surviving the first seven years and (2) their probability of filing for insolvency in the first seven years. We transform the panel data into a cross-sectional format by aggregating to the firm level, resulting in one observation per firm. The results of the logistic regression on the start-ups' survival probability in column one in Table 4 show that BDA is indeed associated with a lower chance of survival. In the regression, we control for firm size at the foundation (approximated by the number of employees at t_0), for the ventures' industry of activity, and, following Zhao and Percival (2017), for the (weighted) firm-specific

[11] Propensity score matching is done based on nearest neighbor matching with replacement using the same set of matching variables as with entropy balancing. Figure A.1 in the Appendix shows that common support is sufficiently given, as distributions of propensity scores for treated and control units overlap substantially before matching. The applied matching procedure significantly reduced the selection bias in our data set (compare Figure A.2), and the following statistical analyses yield qualitatively robust results, see Table A.13.

characteristics that have also been used in the balancing process described before. With an odds ratio of 0.608, the probability of surviving the first seven years is significantly lower for BDA-adopting start-ups than for non-adopting start-ups. The reported odds ratio corresponds to an average marginal effect of -0.052, i.e., a decrease in the average probability of survival by 5.2 percentage points if a start-up adopts BDA.[12] As mentioned above, firm closure, i.e., non-survival, does not necessarily equal firm failure. In column two of Table 4, we test whether this lower survival probability also translates into higher insolvency rates. Although only a very small number of firms actually file for insolvency, we find that BDA is also associated with significantly higher insolvency rates. On average, using BDA is associated with an increase of 3.0 percentage points for insolvency (average marginal effect of 0.030). Overall, this implies, ceteris paribus, that employing BDA leads to a higher entrepreneurial risk.

4.2 Costs

One possible explanation for a lower survival probability is the potentially higher costs that come along with adopting BDA (compare Proposition 2). As argued above, adopting novel technology such as BDA usually requires more expensive infrastructure, more sophisticated management, and more skilled personnel (Müller et al., 2018). The results of the linear regressions on the start-ups' different cost components in Table 5 indeed show that the use of BDA is associated with an increase in the start-ups' operating costs. We focus specifically on operating costs, as they account for more than 85% of the start-ups' total cost structure in our data (compare Table 3). Since costs are skewed, we use logarithmic transformations of the different cost categories.[13] In Table 5, we again control for the size of the start-ups at business formation, the start-ups' industry affiliation, the observation year, and the (weighted) firm characteristics described above. The results show a 38% increase in operating costs for firms adopting BDA. We expand the analysis by running analogous regressions on the three components of operating costs: personnel, material, and other operating costs. The positive effect of BDA is particularly pronounced for personnel costs (compare column three in Table 5). Firms adopting BDA have, on average, 84% higher personnel costs than non-adopters. As a robustness check, we run the regressions using the number of employees each year as a control variable (comparable to a regression on costs per employee). We can show that the effect of BDA on personnel costs is only partially driven by higher employee growth. Indeed, while the size of the BDA coefficient decreases to some extent (i.e., BDA-adopting start-ups have a higher employee growth that is partially responsible for higher personnel costs, see also discussion below), the general effect prevails: BDA adopters incur higher costs per employee, that is, higher wages, speaking for more skilled and thus more costly personnel (compare Table 6).

4.3 Sales

Proposition 3.1, Proposition 3.2, and Proposition 3.3 concern the start-ups' sales volume and its dispersion both between and within firms. Referring to previous findings on the effect of BDA on incumbents, Proposition 3.1 suggests that, conditional on survival, the higher risk associated with BDA usage entails the potential for higher rewards, such as higher sales. We expect this to be more pronounced for high-performing ventures that are able to better leverage

[12]The average marginal effect is calculated as the partial effect of a variable on the outcome variable using the observed values of the covariates and then averaging the values of that first-order derivative over the entire sample.
[13]For the sake of retaining observations with zeros, we use $ln(x+1)$, with x being the dependent variable.

Table 5: Pooled Linear Regression Results on Start-up Costs

	ln(operat. costs)	ln(person. costs)	ln(material costs)	ln(other costs)
BDA	0.375***	0.837***	0.327***	0.352***
	[0.215,0.535]	[0.512,1.161]	[0.114,0.540]	[0.090,0.614]
Employees t_0	0.225***	0.448***	0.198***	0.269***
	[0.177,0.273]	[0.341,0.556]	[0.149,0.248]	[0.195,0.343]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
Year controls	YES	YES	YES	YES
F-test firm controls	11.68***	10.70***	4.74***	9.01***
F-test industry controls	9.91***	3.66***	38.28***	4.74***
F-test year controls	98.69***	93.73***	35.35***	35.80***
Observations	12,261	12,261	12,261	12,261

The table shows the regression coefficients of the linear regression on start-up costs with 95% confidence intervals in brackets. For the Wald-test of firm, industry, and year controls, the F-test statistics are reported. The sample is entropy is balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Pooled Linear Regression Results on Start-up Costs controlling for the Number of Employees

	ln(operat. costs)	ln(person. costs)	ln(material costs)	ln(other costs)
BDA	0.220***	0.585***	0.190*	0.191
	[0.069,0.371]	[0.266,0.903]	[-0.020,0.400]	[-0.069,0.450]
Employees	0.085***	0.142***	0.075***	0.090***
	[0.057,0.114]	[0.086,0.198]	[0.052,0.099]	[0.056,0.124]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
Year controls	YES	YES	YES	YES
F-test firm controls	7.93***	7.48***	3.02***	6.54***
F-test industry controls	9.91***	3.84***	38.40***	5.55***
F-test year controls	51.37***	51.01***	24.20***	23.37***
Observations	12,261	12,261	12,261	12,261

The table shows the regression coefficients of the linear regression on start-up costs with 95% confidence intervals in brackets. For the Wald-test of firm, industry, and year controls, the F-test statistics are reported. The sample is entropy is balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the benefits of BDA (see Proposition 3.2). Consistent with our expectation of higher risks associated with BDA adoption, we further expect higher intra-firm volatility (see Proposition 3.3).

Figure 3 presents an initial comparison of sales growth between firms that adopt BDA and those that do not adopt BDA - at the average/ median level and differentiating between higher- and lower-performing ventures. The descriptive analyses are complemented by pooled linear regressions on the logarithmized sales shown in Table 7. Since sales are skewed, we again use logarithmic transformations in all our analyses. We control for firm size (i.e., the number of employees at firm formation), firm age, industry, and (weighted) firm characteristics. To model BDA development over time, we also include an interaction term for *BDA* and *firm age*. Note that we explicitly do not control for year effects, as including the firms' age and founding year (one of the firm-specific characteristics) sufficiently captures any year effects.

As suggested in Proposition 3.1 and confirming previous findings for incumbents reported in the literature, Figure 3 and the results from the regression analyses in Table 7 show that, on

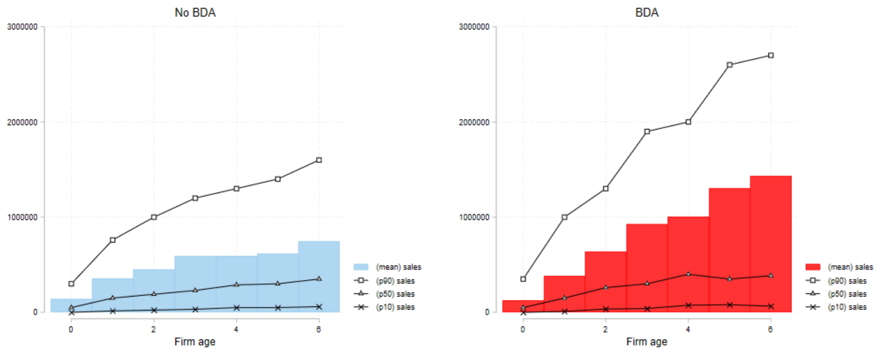

Fig. 3: Development of sales over firm age.

Note: Mean, median, as well as the 10%- and 90%-quantiles of sales and are calculated separately for *No BDA* (left) and *BDA* (right) and for each year of the firm age. Due to the unbalanced nature of the panel data set, the number of observations varies across firm age and are as follows: *No BDA*: 1,670 / *BDA*: 321 (Firm age = 0); 1,960 / 337 (1); 2,025 / 371 (2); 1,768 / 297 (3); 1,366 / 232 (4); 1,024 / 149 (5); 651 / 90 (6).

average, start-ups using BDA achieve higher sales than their counterparts that are not using BDA. With an increase of more than 28% this difference is significant - statistically and with respect to effect size.

While we can confirm Proposition 3.1, our results in Table 7 do not show a clear difference between high- and low-performing firms as brought forward in Propositon 3.2. In columns two and three, we use quantile regressions targeting the 0.9 and 0.1 quantiles of the logaritimized sales distribution in the respective year.[14] The coefficient of BDA for firms in the 0.9 quantile in column two is statistically significant, and slightly larger in size than the coefficient of our regression in column one. However, the effect of BDA for firms in the 0.1 quantile is statistically insignificant. Figure 4 illustrates the coefficients of BDA across the different quantiles and shows no statistically significant difference in the effects of BDA adoption on sales across quantiles. Note, that also the steeper growth trajectory over time for high-performing BDA-adopting firms depicted in Figure 3 is not reflected in the regression results as the coefficient of the interaction term of *BDA* and *firm age* is positive, yet not statistically significant.[15] Hence, conditional on survival, the higher entrepreneurial risk associated with BDA appears to pay off, and we see no difference between high- and low-performing ventures.

To verify Proposition 3.3, we also analyze the dispersion of sales over time at the level of the individual firm. To capture this intra-firm variance, we estimate pooled linear regression models using the logarithmized start-ups' normalized intra-firm sales variance as the dependent variable and again controlling for various variables, including (weighted) firm characteristics, industry affiliation, and firm size. By modeling both inter- and intra-firm variance, we are able to disentangle different dimensions of entrepreneurial risk. The results in column five of Table 7 show that start-ups adopting BDA are exposed to significantly higher sales variances.[16] This supports Proposition 3.3, indicating that start-ups adopting BDA exhibit greater intra-firm

[14] Quantile regression goes back to Koenker and Bassett (1978) and provides a method for estimating conditional quantiles, rather than the conditional mean as is the case in standard linear models (for more details, see Koenker, 2005; Koenker & Hallock, 2001).

[15] In Table 7 and 8 the *firm age* variable has been demeaned to ensure a meaningful interpretation of the coefficient.

[16] In addition to the regression results, variance homogeneity tests, i.e., t-tests on the differences in variances, and Levene tests report significantly higher variances in overall sales for start-ups using BDA. The results are statistically significant at the 1%-level. Levene tests are conducted using centering on the median to account for the asymmetry of the data (Conover, Johnson, & Johnson, 1981) and might be preferred in this case.

Table 7: (Pooled) Linear (Quantile) Regression Results on Start-up Sales

	ln(sales)	0.9 ln(sales)	0.1 ln(sales)	ln(sales variance)
BDA	0.282***	0.344***	0.387	0.420***
	[0.087,0.478]	[0.163, 0.524]	[-0.109, 0.882]	[0.233,0.607]
Firm age	0.568***	0.298***	0.763***	
	[0.516,0.621]	[0.260, 0.335]	[0.601, 0.925]	
BDA x firm age	0.040	0.065	-0.038	
	[-0.057,0.137]	[-0.028, 0.158]	[-0.245, 0.169]	
Employees t_0	0.198***	0.154***	0.194***	0.110***
	[0.153,0.242]	[0.107, 0.200]	[0.124, 0.264]	[0.072,0.148]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
F-test firm controls	3.81***	3.49***	2.03**	4.69***
F-test industry controls	7.60***	5.71***	2.15**	6.19***
Observations	12,261	12,261	12,261	3,395

The table shows the regression coefficients of the linear regression on start-up sales, as well as the regression coefficients of the respective quantile regression for the 0.9 and the 0.1 quantiles with 95% confidence intervals in brackets. For the Wald-test of firm and industry controls, the F-test statistics are reported. In columns two and three, the confidence intervals are based on cluster-adjusted bootstrapped standard errors with 1000 replications computed following Hagemann (2017). The sample is entropy balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year. In column four, we transform the panel data into a cross-sectional format by aggregating to the firm level, resulting in one observation per firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

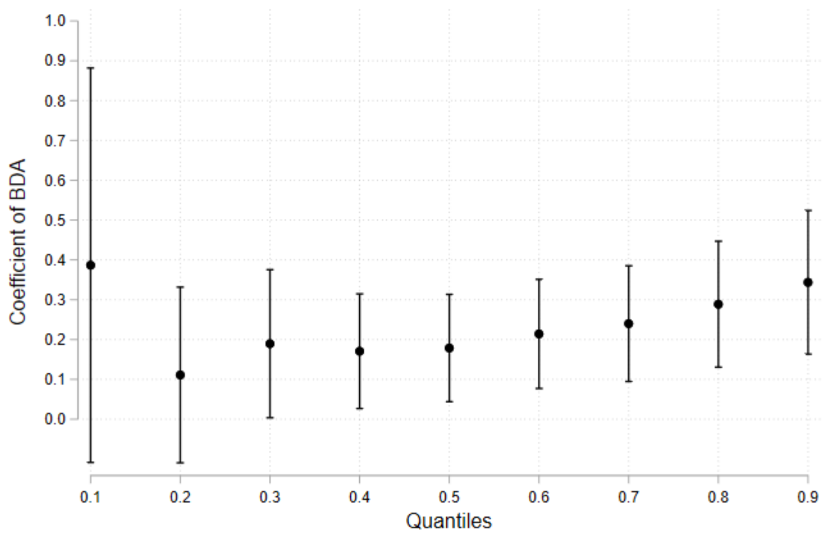

Fig. 4: Graph of the coefficients of BDA in the pooled linear quantile regressions of the effect of BDA on start-up sales.

variance, which is often associated with higher entrepreneurial risk. In combination with the higher costs associated with adopting BDA, this might explain why survival probabilities are lower for BDA-adopting firms.

Note, however, that in Figure 3, sales are given in absolute terms rather than on a per-employee basis. While controlling for firm size measured in terms of employees at t_0, the corresponding regression analyses do not include a control variable for the current number of employees each year, i.e., they capture only sales, not labor productivity. We run some

Table 8: (Pooled) Linear (Quantile) Regression Results on Start-up Sales controlling for the Number of Employees over time

	ln(sales)	0.9 ln(sales)	0.1 ln(sales)	ln(sales variance)
BDA	0.136	0.036	-0.047	0.420***
	[-0.056,0.328]	[-0.107,0.179]	[-0.462,0.368]	[0.233,0.607]
Firm age	0.528***	0.140***	0.543***	
	[0.475,0.580]	[0.117,0.164]	[0.459,0.627]	
BDA x firm age	-0.009	0.045	0.126	
	[-0.101,0.084]	[-0.032,0.121]	[-0.039,0.291]	
Employees	0.077***	0.146***	0.079***	0.110***
	[0.053,0.102]	[0.130,0.163]	[0.059,0.100]	[0.072,0.148]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
F-test firm controls	3.37***	3.47***	2.38***	4.76***
F-test industry controls	8.01***	7.41***	3.09***	6.21***
Observations	12,261	12,261	12,261	3,395

The table shows the regression coefficients of the linear regression on start-up sales, as well as the regression coefficients of the respective quantile regression for the 0.9 and the 0.1 quantiles with 95% confidence intervals in brackets. For the Wald-test of firm and industry controls, the F-test statistics are reported. In columns two and three, the confidence intervals are based on cluster-adjusted bootstrapped standard errors with 1000 replications computed following Hagemann (2017). The sample is entropy balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year. In column four, we transform the panel data into a cross-sectional format by aggregating to the firm level, resulting in one observation per firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

additional robustness analyses and control for the current number of employees in each year instead. While the effect of BDA on sales remains positive, it becomes statistically insignificant (columns one and two in Table 8). This implies that sales and the number of employees mostly grow at similar rates and confirms the notion that sales and employee growth are, particularly for start-ups, two sides of the same coin, i.e., both measure the growth of a start-up over time (see also Delmar et al., 2003 or Coad, Nielsen, and Timmermans, 2017).

4.4 Employee Growth

To test Proposition 4.1, we set up a model that is analogous to the previous one on sales volume. Already in Figure 5, which shows the number of employees over firm age for non-BDA-adopters on the left and BDA-adopters on the right, we observe - on average as well as at the 0.9 quantile - a much steeper growth trajectory for BDA-adopters.

This is confirmed by the regression analysis shown in Table 9. Column one shows the average effect of BDA on the number of employees, complemented with a quantile regression focusing on the 0.9 quantile in column two.[17] Newly founded ventures adopting BDA not only have, on average, 2.0 more employees but also have a significantly higher growth rate over time: For BDA-using start-ups, the average yearly increase in the number of employees is greater by an additional 0.612 full-time equivalent. Given that the firms in our sample have an average of 4.56 employees, this corresponds to 44% more employees on average and additional employee growth of about 13% each year.[18] We find considerable heterogeneity

[17] Regression results for the 0.1 quantile and, additionally, the 0.2 quantile in Figure 6 are not reported, as the bootstrapping algorithm does not converge in these instances. This is due to almost no variation in the dependent variable among firms in these quantiles, i.e., almost all firms in the 0.1 and 0.2 quantiles have only one employee.

[18] Note that in Table 9 the *firm age* variable has been demeaned to ensure a meaningful interpretation of the coefficient.

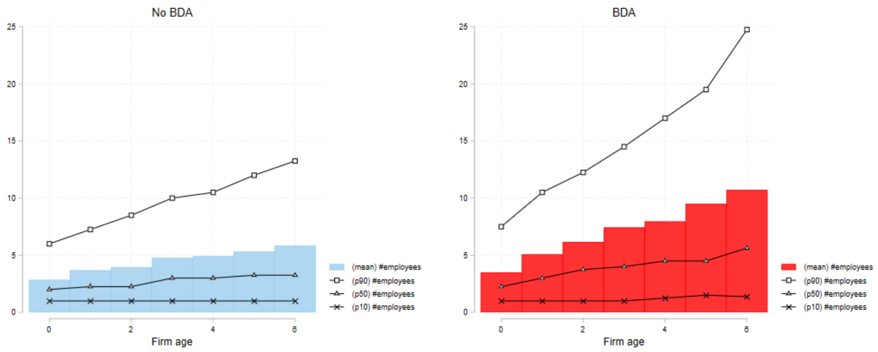

Fig. 5: Number of employees over firm age.

Note: Mean, median, as well as the 10%- and 90%-quantiles of sales and are calculated separately for *No BDA* (left) and *BDA* (right) and for each year of the firm age. Due to the unbalanced nature of the panel data set, the number of observations varies across firm age and are as follows: *No BDA*: 1,670 / *BDA*: 321 (Firm age = 0); 1,960 / 337 (1); 2,025 / 371 (2); 1,768 / 297 (3); 1,366 / 232 (4); 1,024 / 149 (5); 651 / 90 (6).

across low- and high-performing firms for these results. The effect is especially pronounced for high-performing firms, i.e., BDA-adopting firms in the 0.9 quantile of the distribution of the number of employees in the respective year. These firms have on average 3.8 employees more than their non-BDA-adopting counterparts, and the yearly increase of employees is greater by 1.3 employees. The coefficients of the respective quantile regressions are depicted in Figure 6 and show a steep increase in the effect of BDA on employee growth for the upper quantiles. Conditional on survival, BDA-adopting ventures grow more and faster, and this growth varies considerably across firms. The higher number of employees over time also explains that we find no statistically significant impact of BDA on labor productivity, as the growth in sales is matched by an equal growth in employees. Hence, as already mentioned above, the number of employees and sales volume seem to be different indicators for the same performance measure: a start-up's growth.

4.5 Financing

Finally, we analyze how the use of BDA affects the start-ups' financing sources, focusing particularly on VC. Based on general results in the literature and pointed out in Proposition 5, we anticipate that start-ups that use BDA are more likely to raise VC funding, particularly as VC investors are willing to bear higher risks if they expect to profit from the upside potential, i.e., if they expect the start-ups to perform well in the future. For this part of the analysis, we slightly adapt our pre-processing approach. As previous literature has shown (e.g., Gompers et al. 2020), founder characteristics heavily influence the selection process of investors, compelling us to rely once more on entropy balancing. As we want to avoid our results being driven by the firms' general innovation capacity instead of their BDA adoption, we employ one additional variable in the balancing procedure and proxy innovation potential by the information on whether the start-up had already held a valid patent at the time of foundation.[19] As shown by Häussler, Harhoff, and Müller (2008), Hsu and Ziedonis (2013), or

[19] The patents are not specifically related to BDA, but could be from any field or area. Moreover, we do not use any form of R&D intensity indicator here as this might introduce a problem of reversed causality or simultaneity. One cannot distinguish whether more intensive R&D activities lead to the start-up acquiring VC - as it seems more innovative and thus more attractive to the investor - or whether the additional funding via VC leads to the start-up being able to spend more on R&D expenditures.

Table 9: (Pooled) Linear Regression Results on Start-up Growth

	Employees	0.9 Employees
BDA	2.005***	3.776***
	[1.163,2.848]	[1.797, 5.755]
Firm age	0.539***	1.218***
	[0.390,0.687]	[0.991, 1.445]
BDA x firm age	0.612**	1.276***
	[0.143,1.080]	[0.365, 2.187]
Employees t_0	1.194***	1.878***
	[0.962,1.426]	[1.198, 2.557]
Firm controls	YES	YES
Industry controls	YES	YES
F-test firm controls	1.95**	1.38
F-test industry controls	1.66*	1.22
Observations	12,261	12,261

The table shows the regression coefficients of the linear regression on start-up growth with 95% confidence intervals in brackets. For the Wald-test of firm and industry controls, the F-test statistics are reported. In column two, the confidence intervals are based on bootstrapped standard errors (1000 replications) computed following Hagemann (2017). The samples are entropy balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

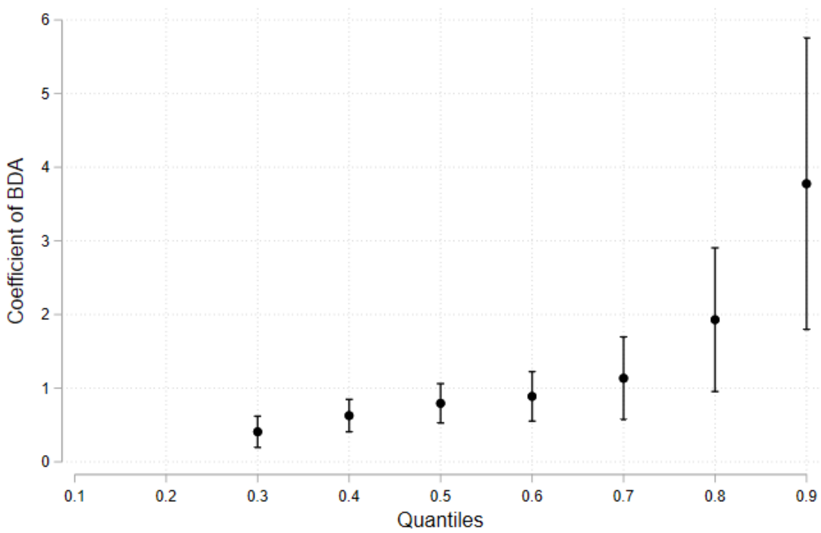

Fig. 6: Graph of the coefficients of BDA in the pooled linear quantile regressions of the effect of BDA on start-up growth.

Hottenrott, Hall, and Czarnitzki (2016) firms holding one or more patents are indeed more likely to secure external financing.[20] Weighting is again based on the first, second, and third moments of these variables, resulting in a matched sample of comparable start-ups in terms of their essential characteristics and degree of innovativeness.

[20]See also Hoenig and Henkel (2015) for a detailed overview of the literature on patents and VC financing.

Table 10 shows the results of the logistic regression on the presence of VC and bank funding. The latter serves as a benchmark allowing us to identify if the effects of BDA on founding are specific to VC or general in nature. Since the provision of debt, in contrast to equity, does not entitle to any upside potential beyond the upfront agreed interest, a firm's adoption of BDA may be evaluated differently by banks than by VC funds. Hence, regarding bank financing, we do not expect a positive impact of BDA adoption. In these final logistic regressions, we again control for firm size at firm formation, (weighted) firm characteristics, and industry effects. The results show that the odds of a start-up receiving VC funding are by a factor of 1.6 higher if it is using BDA compared to not using BDA (see column one in Table 10). This corresponds to an average marginal effect of 0.020, i.e., an increase of a start-up's probability to secure VC by 2 percentage points (equivalent to 67%).[21] As expected, the impact of adopting BDA on the start-ups' likelihood to receive financing from banks is statistically insignificant and negligible in terms of effect size.

Table 10: Logistic Regression Results on Financing Sources

	VC [0/1]	Bank Financing [0/1]
BDA	1.594**	1.066
	[1.111,2.287]	[0.843,1.346]
Employees t_0	1.071*	1.142***
	[0.997,1.152]	[1.069,1.221]
Patent	1.534	1.179
	[0.753,3.125]	[0.710,1.958]
Firm controls	YES	YES
Industry controls	YES	YES
Year controls	YES	YES
χ^2 firm controls	46.60***	73.26***
χ^2 industry controls	79.44***	34.02***
χ^2 year controls	11.68	23.38***
Observations	12,261	12,261

The table shows the odds ratios of the logistic regression on venture capital and bank financing with 95% confidence intervals in brackets. For the Wald-test of firm, industry, and year controls, the χ^2-test statistics are reported. The sample is entropy-balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, founding year, and a patent indicator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[21] Given the low probability to receive VC of 3% in the first place, 2 percentage points equal an increase in 67%.

5 Discussion and Conclusion

Our study contributes to a more nuanced understanding of the performance implications of the adoption of BDA in young and small companies. Contrary to the dominant narrative emphasizing BDA's potential for competitive advantage primarily in established firms (Brynjolfsson et al., 2021; Ertz et al., 2025; Müller et al., 2018; Tambe, 2014), our results demonstrate that start-ups can, under certain conditions, also benefit from BDA adoption. However, the effects are neither uniform nor guaranteed. Start-ups that adopt BDA have a substantially lower probability of survival and a higher probability of going bankrupt. While firm closures among young ventures do not necessarily equate to failure in a broader entrepreneurial context (Wennberg et al., 2010), the increased incidence of insolvency reinforces our argument and supports Proposition 1, highlighting the heightened entrepreneurial risk associated with BDA adoption. Additionally, BDA might result in some form of 'intelligent exit' (Gottschalk & Müller, 2022), where BDA enables earlier recognition of nonviable business models, potentially leading to quicker and less costly exits. The elevated risk for market exit is closely tied to two interrelated factors: financial resource constraints and uncertainty in outcomes. First, the implementation of BDA requires substantial upfront and ongoing investments in complementary capabilities, such as skilled labor, IT infrastructure, and organizational change (Ansari & Ghasemaghaei, 2023; Gupta & George, 2016). These costs weigh heavily on start-ups, which typically operate under tight financial constraints and limited access to capital. Consistent with Proposition 2, we show that BDA adopting start-ups incur substantially higher operating costs, primarily driven by personnel expenses. Start-ups adopting BDA report on average almost 84% higher personnel costs than their non-adopting counterparts. This aligns with findings from Tambe (2014), who emphasize the trade-off between the competitive gains of BDA adoption and the high labor costs of analytical talent. Second, as argued in Proposition 3.3, BDA-adopting start-ups experience significantly greater sales volatility, introducing additional uncertainty into their revenue streams. This combination of high fixed costs and unpredictable returns increases the likelihood of liquidity shortfalls and ultimately may contribute to higher exit rates among BDA adopting firms. An alternative interpretation of higher sales volatility is that BDA-using firms are better able to spot and respond to market opportunities. This could likewise result in higher sales volatility. While we cannot empirically disentangle these mechanisms, they have similar implications for the stability of revenue streams. We further find that, conditional on survival, BDA adoption is associated with notable performance premia, and the increased risk and high operating costs appear to be compensated in several ways. We can confirm Proposition 3.1 and Proposition 4.1 as firms that successfully integrate BDA into their operations exhibit higher sales and stronger employee growth. While we can not confirm Proposition 3.2, as the differences in the effects of BDA on logaritmized sales across quantiles are not statistically significant, we can indeed confirm Proposition 4.2. The performance benefits of BDA with regard to employee growth are not evenly distributed but are concentrated among firms in the upper performance deciles. Given the need for complementary resources, especially human capital, it is not surprising that BDA acts as a performance amplifier, yielding high returns primarily for those firms already positioned to leverage its potential. Lastly, our findings show a positive link between BDA adoption and the firms' ability to raise VC (Proposition 5). We interpret this as a market-based signal of perceived growth potential. Similar to how market valuation serves as an expectation metric in studies of established firms (Ertz et al., 2025; Ghasemaghaei, 2019), VC investment reflects investor confidence in the firm's scalability and ability to convert data-driven strategies into tangible returns. Taken together, our results directly address the question on whether BDA can be effectively implemented under severe resource constraints of young and small ventures and be leveraged in the intuitive, informal, and high-uncertainty context of entrepreneurship. Despite concerns about its fit with entrepreneurial decision-making, our findings show that BDA adoption is a high-risk high-reward strategy: it is associated with a higher probability of entrepreneurial failure, however, conditional on survival, also with higher sales and employee growth, as well as a greater likelihood of securing VC, demonstrating that BDA can indeed create value even in young, resource-constrained firms.

Our study makes several important contributions to the existing literature. First, we extend research on BDA adoption to the context of newly founded companies, a domain that has received less attention so far. Existing findings derived from large, established firms cannot be directly translated to young ventures, which operate under fundamentally different conditions. We adopt a deliberately broad definition of start-ups, without selecting based on industry, legal form, or founder characteristics. This approach also speaks to the view that BDA, as a tool to enhance decision-making, holds relevance across industries. Our results are grounded on a large-scale empirical analysis of a representative sample of 3,395 start-ups over a period of eight years that allows us to draw generalizable insights about the performance implications of BDA adoption in early-stage ventures. Second, we explore the characteristics of founders and founding teams associated with BDA adoption. Our findings show that BDA-adopting start-ups are more likely to have interdisciplinary founding teams that combine expertise in technical domains, such as computing, statistics, and machine learning, with business and management know-how (also compare Akhtar et al., 2019). Apart from their educational background, the founders' experience in previous business ventures indicates a set of soft skills, including management expertise. The literature has repeatedly pointed out the importance of such skills when deploying BDA (Gupta & George, 2016; Wang et al., 2019). Third, we contribute to both the BDA and entrepreneurship literature by employing a diverse set of performance indicators that capture the multifaceted nature of early-stage venture development, including forward-looking indicators such as the likelihood of receiving VC. And lastly, we contribute to the literature on entrepreneurial finance by examining the role of venture capital in supporting BDA adoption. Our findings suggest that VC funding is more likely among BDA-adopting start-ups, indicating that investors recognize the high-growth potential of these firms despite their elevated risks and operational costs. VC investment thus serves not only as a performance signal but also as a critical enabler of BDA-driven strategies in the start-up ecosystem. These findings are relevant for both entrepreneurs and policymakers in the area of innovation. BDA adoption can, despite its cost- and risk-driving potential, still be beneficial from an ecosystem perspective. Knowledge spillovers through employee mobility, cooperation, or competition can benefit the innovation system more generally, even if the returns to the individual entrepreneur are rather uncertain.

Our study is not without limitations. While the analyses are based on survey data that captures BDA usage across various applications and settings, the definition of BDA used here is relatively broad. It encompasses concepts, processes, technologies, and software applications within a single binary indicator. Future research could benefit from a more nuanced differentiation of BDA adoption. This need is also emphasized by Ghasemaghaei (2021), who highlights the importance of distinguishing among different BD characteristics instead of treating it as a singular construct. Additionally, exploring the intensity of BDA usage, the quality of BDA resources and competencies, or its strategic relevance to a start-up's business model could offer further insights (compare Ji-fan Ren, Fosso Wamba, Akter, Dubey, & Childe, 2017, and Ghasemaghaei et al., 2018). While we assume that the very young start-ups in our sample have adopted BDA from the outset and are simply too young to have already undergone major strategic changes, the time-invariant nature of our BDA measure limits our ability to observe and analyze the effects of adoption within a single firm. From a methodological perspective, we address endogeneity concerns using entropy balancing, which is particularly relevant given that founders and their characteristics heavily influence strategic decisions like BDA adoption in start-ups. Entropy balancing reduces selection bias based on observable variables; however, it does not eliminate all endogeneity concerns. While we thus do not claim to show causality, we can show causality conditional on our set of observables. Nevertheless, if unobserved factors that influence both treatment and performance outcome are strongly correlated with the set of observed characteristics included in the balancing constraint, the potential for further omitted variable bias is limited. This perspective is supported by Lechner and Wunsch (2013), who argue that detailed observable data can effectively proxy for unobservables, reducing concerns about unmeasured confounding. The IAB/ZEW Start-up Panel provides a particularly suitable context for entropy balancing, as it contains exceptionally rich information on both founders and start-ups, including demographics, but also cognitive and non-cognitive skills. However, we cannot separate BDA effects on growth from VC effects on venture development. It is possible that BDA increases the chances of raising VC, which then drives employee and sales growth, rather than directly impacting growth. Disentangling these drivers would require more fine-grained data, especially on the adoption timing and the moment founders started to engage with investors.

Another limitation with regard to the analysis of firm failure is that we do not observe founders' careers post-exit. It could be that experience with BDA shapes founders' prospective job opportunities. Further research could study these labor market dynamics in more detail. Finally, our conclusions rely, in part, on the assumption that VC funding serves as an indicator of future firm performance. Venture capitalists seek to maximize returns during exit events, leading them to invest in start-ups they perceive to have high future market value. Given that venture capitalists typically employ sophisticated and rigorous evaluation processes when making investment decisions (Gompers et al., 2020; Hellmann & Puri, 2000; Kaplan & Strömberg, 2004), we argue that securing VC funding is a reliable forward-looking performance measure. However, the reliability of venture capitalists' ability to identify high-potential start-ups could be questioned. Research has shown that VC investment decisions may be influenced by biases related to factors such as location (Cumming & Dai, 2010), gender (Eddleston, Ladge, Mitteness, & Balachandra, 2016), and similarities in education or professional experience (Franke et al., 2006). While we attempt to control for many of these attributes, we cannot fully rule out the possibility that the venture capitalists' decision is influenced by a form of 'buzzword bias', hype, or herding behavior that may explain some of the observed investment patterns.

We encourage more research on the performance effects of BDA adoption, particularly for young and small firms for which the decision to adopt a technology such as BDA can have far-reaching consequences. As BDA usage continues to grow among both private and public actors, we expect learning effects at both individual and collective levels. Consequently, it is essential to examine the differences in performance outcomes between early and late adopters, as well as the potential returns to specialization in BDA that lead to companies in-sourcing BDA capacities.

Acknowledgements. We thank Sandra Gottschalk and Marius Berger for their help in data access and preparation. We further want to thank Maikel Pellens for his highly appreciated feedback and Claudia Steinwender for valuable comments. We are also indebted to seminar participants at the CBE seminar at NHH Bergen, the IAB Research Seminar, the RWI Research Seminar as well as to conference participants at REGIS Summer School 2023, the DRUID23 annual conference, the Summer 2023 BGPE workshop, the CISS Summer School 2023, the ZEW Conference of the Dynamics of Entrepreneurship (CoDE23), the 6th RISE Workshop 2023, the 2024 Annual Conference of the German Economic Association for helpful comments and constructive feedback.

Appendix A   Additional Tables & Figures

Table A.1: Distribution of Start-ups across Industries and Founding Year in the Sample vs. the whole IAB/ZEW Start-up Panel

	#Sample	**Share sample**	**Share whole panel**
Industry Classification			
Cutting-edge tech	244	7.19	6.61
High-tech	218	6.42	5.72
Tech. services	717	21.12	19.05
Software	299	8.81	9.30
Low-tech	327	9.63	9.85
Knowledge-int. services	335	9.87	9.31
Other company services	246	7.25	7.58
Creative services	220	6.48	6.91
Other services	191	5.63	6.96
Construction	290	8.54	9.15
Retail	308	9.07	9.58
Founding Year			
2010	366	10.78	6.49
2011	403	11.87	7.21
2012	483	14.23	8.63
2013	672	19.79	12.17
2014	762	22.44	19.85
2015	709	20.88	23.55
Total	3,395	100.00	100.00

The first two columns of the table show the composition of our sample regarding industry classification and founding year. For all these firms, the IAB/ZEW Start-up Panel offers full information, including information on whether or not the respective firm adopts BDA. The last column shows the composition of the universe of start-ups participating in the survey in 2017, i.e., the unrestricted sample of the IAB/ZEW Start-up Panel in that year.

Table A.2: Summary Statistics of Founders' Fields of Study

	no-BDA				BDA				t-test
	mean	sd	min	max	mean	sd	min	max	p-value
Biology	0.02	0.13	0.00	1.00	0.03	0.17	0.00	1.00	0.002
Chemistry	0.03	0.16	0.00	1.00	0.01	0.12	0.00	1.00	0.009
Computer science	0.10	0.29	0.00	1.00	0.20	0.40	0.00	1.00	0.000
Mathematics	0.01	0.11	0.00	1.00	0.02	0.13	0.00	1.00	0.290
Pharmacy	0.00	0.06	0.00	1.00	0.00	0.06	0.00	1.00	0.811
Physics	0.04	0.19	0.00	1.00	0.03	0.17	0.00	1.00	0.105
Other science	0.02	0.14	0.00	1.00	0.02	0.12	0.00	1.00	0.263
Medicine	0.02	0.13	0.00	1.00	0.02	0.15	0.00	1.00	0.366
Mechanical engineering	0.15	0.35	0.00	1.00	0.10	0.30	0.00	1.00	0.000
Mechatronics	0.01	0.07	0.00	1.00	0.01	0.08	0.00	1.00	0.614
Electrical engineering	0.13	0.33	0.00	1.00	0.10	0.29	0.00	1.00	0.001
Civil engineering	0.11	0.31	0.00	1.00	0.07	0.26	0.00	1.00	0.001
Other engineering	0.10	0.31	0.00	1.00	0.10	0.30	0.00	1.00	0.513
Business administration	0.32	0.47	0.00	1.00	0.43	0.50	0.00	1.00	0.000
Social science	0.04	0.19	0.00	1.00	0.06	0.24	0.00	1.00	0.000
Law	0.05	0.21	0.00	1.00	0.06	0.23	0.00	1.00	0.097
Humanities	0.04	0.20	0.00	1.00	0.05	0.22	0.00	1.00	0.183
Art	0.04	0.21	0.00	1.00	0.04	0.21	0.00	1.00	0.927
Other	0.01	0.11	0.00	1.00	0.03	0.16	0.00	1.00	0.000

The table shows the summary statistics for the fields of study of the subset of founders with an academic background, broken down by start-ups that are not adopting BDA (left) and those that are adopting BDA (right). In addition, the p-values resulting from two-sided t-tests comparing the two groups are provided.

Table A.3: Description of Variables

Variable Name	**Variable Description**
BDA	The start-up is using BDA for management decisions.
Founder age	Age of the founder when founding the start-up. For teams, it is the average age.
Female	At least one founder is female.
Foreign	At least one founder is not German.
Team	The start-up was founded by more than one person.
Education	Highest educational level of the founders, ranging from 1 to 9 corresponding to whether the founders have (1) no degree, a degree from (2) an apprenticeship, (3) a vocational school, (4) a master school, (5) an academy for civil servants, (6) a vocational academy, (7) a technical college, (8) a university, or (9) a PhD/ habilitation.
Industry experience (t)	Years of experience in the industry the start-up operates in.
Founding experience	At least one founder has founded a start-up before.
Opportunity-driven	The start-up was founded to implement a business idea, to increase earnings, or to allow more self-determined work.
Urban	The start-up was founded in a city.
East Germany	The start-up was founded in East Germany (Brandenburg, Mecklenburg-Western Pomerania, Saxony, Saxony-Anhalt, Thuringia).
Firm age (t)	Age of the firm in the respective year t.
Founding year	Year the start-up was founded in.
Industry	The main industry the start-up operates in. Industry classification is defined according to WZ2008 with aggregation to 11 industries (cutting-edge tech manufacturing, high-tech manufacturing, technical services, software, low-tech manufacturing, knowledge-intensive services, other company services, creative services, other services, construction, and retail).
Patent	The start-up has already held a patent before the foundation.
Survival	The start-up is still operating after 7 years.
Sales (t)	Sales of the start-up in the respective year t.
Total costs (t)	Total start-up costs in the respective year t. They are composed of investment costs, R&D costs, and operating costs.
Investment costs (t)	Investment costs of the start-up in the respective year t.
R&D costs (t)	Research and Development expenditures of the start-up in the respective year t.
Operating costs (t)	Operating costs of the start-up in the respective year t.
Personnel costs (t)	Personnel costs of the start-up in the respective year t.
Material costs (t)	Material costs of the start-up in the respective year t.
Other operating costs (t)	Operating costs that do not fall in the category of material costs or personnel costs of the start-up in the respective year t.
Employees (t_0)	Number of employees at the start-up's foundation date.
Employees (t)	Number of employees of the start-up in the respective year t.
VC (t)	The start-up has used VC funding in the respective year t.
Bank financing (t)	The start-up uses a bank loan in the respective year t.

Table A.4: Treatment and Control Group after Entropy Balancing

	no BDA			BDA		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Founder age	41.04	89.97	0.24	41.04	89.97	0.24
Female founder	0.16	0.14	1.83	0.16	0.14	1.83
Foreign founder	0.11	0.10	2.51	0.11	0.10	2.51
Team	0.46	0.25	0.16	0.46	0.25	0.16
Educational level	6.44	6.34	-0.97	6.44	6.34	-0.97
Industry experience	14.17	94.52	0.73	14.17	94.53	0.73
Founding experience	0.56	0.25	-0.26	0.56	0.25	-0.26
Opportunity Driven	0.88	0.11	-2.27	0.88	0.11	-2.27
Founding Year 2011	0.14	0.12	2.06	0.14	0.12	2.06
Founding Year 2012	0.14	0.12	2.03	0.14	0.12	2.03
Founding Year 2013	0.21	0.17	1.40	0.21	0.17	1.41
Founding Year 2014	0.23	0.18	1.31	0.23	0.18	1.31
Founding Year 2015	0.17	0.14	1.72	0.17	0.14	1.72
City	0.48	0.25	0.08	0.48	0.25	0.08
East Germany	0.11	0.10	2.47	0.11	0.10	2.47
High-tech	0.05	0.05	4.10	0.05	0.05	4.10
Tech. services	0.28	0.20	0.97	0.28	0.20	0.97
Software	0.18	0.15	1.69	0.18	0.15	1.69
Low-tech	0.04	0.04	4.58	0.04	0.04	4.58
Knowledge-int. services	0.14	0.12	2.09	0.14	0.12	2.09
Oth. company services	0.06	0.05	3.90	0.06	0.05	3.90
Creative services	0.08	0.07	3.12	0.08	0.07	3.12
Other services	0.03	0.03	5.45	0.03	0.03	5.45
Construction	0.04	0.04	4.55	0.04	0.04	4.55
Retail	0.04	0.04	4.42	0.04	0.04	4.42

The table shows the summary statistics of the balancing variables for treatment (BDA) and control group (no BDA) after we applied entropy balancing.

Table A.5: Logistic Regression Results on Start-up Survival and Insolvency with Bootstrapped Standard Errors

	survival	insolvency
BDA	0.607***	2.403***
	[0.451,0.817]	[1.402,4.120]
Employees t_0	0.953	1.189***
	[0.897,1.013]	[1.096,1.291]
Firm controls	YES	YES
Industry controls	YES	YES
χ^2 firm controls	40.03***	30.37**
χ^2 industry controls	23.29**	16.28*
Observations	3,395	3,395

The table shows the odds ratios of the logistic regression on start-up survival and insolvency after 7 years with 95% confidence intervals in brackets. Standard errors are calculated using cluster-adjusted bootstrapping with 1000 replications. For the Wald-test of firm and industry controls, the χ^2-test statistics are reported. We transform the panel data into a cross-sectional format by aggregating to the firm level, resulting in one observation per firm. The sample is entropy is balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Pooled Linear Regression Results on Start-up Costs with Bootstrapped Standard Errors

	ln(operat. costs)	ln(person. costs)	ln(material costs)	ln(other costs)
BDA	0.375^{***}	0.837^{***}	0.327^{***}	0.352^{***}
	[0.214,0.537]	[0.516,1.157]	[0.110,0.543]	[0.089,0.615]
Employees t_0	0.225^{***}	0.448^{***}	0.198^{***}	0.269^{***}
	[0.177,0.273]	[0.343,0.554]	[0.149,0.248]	[0.194,0.343]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
Year controls	YES	YES	YES	YES
χ^2 firm controls	183.36^{***}	165.90^{***}	72.52^{***}	138.52^{***}
χ^2 industry controls	97.04^{***}	38.61^{***}	360.20^{***}	48.45^{***}
χ^2 year controls	825.39^{***}	805.92^{***}	306.03^{***}	293.30^{***}
Observations	12,261	12,261	12,261	12,261

The table shows the regression coefficients of the linear regression on start-up costs with 95% confidence intervals in brackets. Standard errors are calculated using cluster-adjusted bootstrapping with 1000 replications. For the Wald-test of firm, industry, and year controls, the χ^2-test statistics are reported. The sample is entropy is balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Pooled Linear Regression Results on Start-up Costs Controlling for the Number of Employees with Bootstrapped Standard Errors

	ln(operat. costs)	ln(person. costs)	ln(material costs)	ln(other costs)
BDA	0.220^{***}	0.585^{***}	0.190^{*}	0.191
	[0.069,0.371]	[0.273,0.896]	[-0.024,0.403]	[-0.069,0.450]
Employees	0.085^{***}	0.142^{***}	0.075^{***}	0.090^{***}
	[0.054,0.116]	[0.081,0.202]	[0.050,0.101]	[0.054,0.126]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
Year controls	YES	YES	YES	YES
χ^2 firm controls	121.76^{***}	117.41^{***}	45.68^{***}	98.39^{***}
χ^2 industry controls	95.79^{***}	40.92^{***}	355.81^{***}	52.38^{***}
χ^2 year controls	406.90^{***}	404.64^{***}	205.81^{***}	187.71^{***}
Observations	12,261	12,261	12,261	12,261

The table shows the regression coefficients of the linear regression on start-up costs with 95% confidence intervals in brackets. Standard errors are calculated using cluster-adjusted bootstrapping with 1000 replications. For the Wald-test of firm, industry, and year controls, the χ^2-test statistics are reported. The sample is entropy is balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: (Pooled) Linear (Quantile) Regression Results on Start-up Sales with Bootstrapped Standard Errors

	ln(sales)	0.9 ln(sales)	0.1 ln(sales)	ln(sales variance)
BDA	0.282***	0.344***	0.387	0.423***
	[0.083,0.482]	[0.163, 0.524]	[-0.109, 0.882]	[0.239,0.607]
Firm age	0.568***	0.298***	0.763***	
	[0.517,0.620]	[0.260, 0.335]	[0.601, 0.925]	
BDA x firm age	0.040	0.065	-0.038	
	[-0.058,0.137]	[-0.028, 0.158]	[-0.245, 0.169]	
Employees t_0	0.198***	0.154***	0.194***	0.110***
	[0.151,0.244]	[0.107, 0.200]	[0.124, 0.264]	[0.071,0.148]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
χ^2 firm controls	59.57***	52.29***	30.40**	71.82***
χ^2 industry controls	75.46***	57.13***	21.48**	62.00***
Observations	12,261	12,261	12,261	3,395

The table shows the regression coefficients of the linear regression on start-up sales, as well as the regression coefficients of the respective quantile regression for the 0.9 and the 0.1 quantiles with 95% confidence intervals in brackets. Standard errors are calculated using cluster-adjusted bootstrapping with 1000 replications. For the Wald-test of firm and industry controls, the χ^2-test statistics are reported. The samples are entropy balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year. In column five, we transform the panel data into a cross-sectional format by aggregating to the firm level, resulting in one observation per firm.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: (Pooled) Linear (Quantile) Regression Results on Start-up Sales with Bootstrapped Standard Errors Controlling for the Number of Employees

	ln(sales)	0.9 ln(sales)	0.1 ln(sales)	ln(sales variance)
BDA	0.136	0.084	0.336	0.422***
	[-0.059,0.331]	[-0.056, 0.225]	[-0.132, 0.805]	[0.243,0.601]
Firm age	0.528***	0.162***	0.786***	
	[0.476,0.580]	[0.130, 0.194]	[0.633, 0.938]	
BDA × firm age	-0.009	0.047	-0.084	
	[-0.100,0.083]	[-0.031,0.125]	[-0.277, 0.109]	
Employees	0.077***	0.122***	0.059***	0.110***
	[0.051,0.104]	[0.097,0.147]	[0.032, 0.087]	[0.074,0.145]
Firm controls	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES
χ^2 firm controls	52.44***	52.06***	35.68***	72.51***
χ^2 industry controls	79.56***	74.14***	30.92***	62.16***
Observations	12,261	12,261	12,261	3,395

The table shows the regression coefficients of the linear regression on start-up sales, as well as the regression coefficients of the respective quantile regression for the 0.9 and the 0.1 quantiles with 95% confidence intervals in brackets. Standard errors are calculated using cluster-adjusted bootstrapping with 1000 replications. For the Wald-test of firm and industry controls, the χ^2-test statistics are reported. The samples are entropy balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year. In column five, we transform the panel data into a cross-sectional format by aggregating to the firm level, resulting in one observation per firm.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: (Pooled) Linear Regression Results on Start-up Growth with Bootstrapped Standard Errors

	Employees	0.9 Employees
BDA	2.005***	3.776***
	[1.152,2.858]	[1.797, 5.755]
Firm age	0.539***	1.218***
	[0.390,0.687]	[0.991, 1.445]
BDA × firm age	0.612***	1.276***
	[0.146,1.077]	[0.365, 2.187]
Employees t_0	1.194***	1.878***
	[0.964,1.424]	[1.198, 2.557]
Firm controls	YES	YES
Industry controls	YES	YES
χ^2 firm controls	28.87**	20.77
χ^2 industry controls	16.41*	12.20
Observations	12,261	12,261

The table shows the regression coefficients of the linear regression on start-up growth with 95% confidence intervals in brackets. Standard errors are calculated using cluster-adjusted bootstrapping with 1000 replications. For the Wald-test of firm and industry controls, the χ^2-test statistics are reported. The sample is entropy balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, and founding year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Logistic Regression Results on Financing Sources with Bootstrapped Standard Errors

	VC [0/1]	Bank Financing [0/1]
BDA	1.566**	1.055
	[1.070,2.293]	[0.825,1.350]
Employees t_0	1.068*	1.143***
	[0.993,1.150]	[1.068,1.223]
Patent	1.529	1.273
	[0.649,3.606]	[0.717,2.261]
Firm controls	YES	YES
Industry controls	YES	YES
χ^2 firm controls	55.25***	66.14***
χ^2 industry controls	44.32***	41.56***
χ^2 year controls	10.51	23.36
Observations	12,261	12,261

The table shows the odds ratios of the logistic regression on venture capital and bank financing with 95% confidence intervals in brackets. Standard errors are calculated using cluster-adjusted bootstrapping with 1000 replications. For the Wald-test of firm, industry, and year controls, the χ^2-test statistics are reported. The sample is entropy-balanced using weights for the founders' age, gender, nationality, team composition, educational background, industry experience, founding experience, motive, geographic location, industry, founding year, and a patent indicator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Logistic Regression Estimating the Propensity to Adopt BDA

	Coefficient	Std. Error	p-value
Founder age	-0.012	0.004	0.001
Female	-0.219	0.075	0.003
Foreign	0.090	0.087	0.304
Team	0.366	0.060	0.000
Education	0.073	0.012	0.000
Founding experience	-0.009	0.003	0.006
Opportunity-driven	0.435	0.058	0.000
Urban	0.146	0.080	0.069
East Germany	0.111	0.055	0.044
Industry experience	-0.183	0.084	0.029
High-tech manufacturing	-0.041	0.155	0.790
Technical services	0.495	0.117	0.000
Software	0.973	0.127	0.000
Low-tech manufacturing	-0.447	0.161	0.005
Knowledge-intensive services	0.680	0.129	0.000
Other company services	0.058	0.152	0.703
Creative services	0.738	0.146	0.000
Other services	-0.092	0.180	0.610
Construction	-0.208	0.162	0.200
Retail	-0.074	0.161	0.647
Founding year 2011	0.180	0.107	0.092
Founding year 2012	0.044	0.106	0.681
Founding year 2013	0.369	0.100	0.000
Founding year 2014	0.373	0.099	0.000
Founding year 2015	0.309	0.104	0.003

The table shows the regression coefficients of the logistic regression used for propensity score matching. The variables used for matching are the same that are used for entropy balancing in Tables 4 - 10 (except for the patent indicator in Table 10).

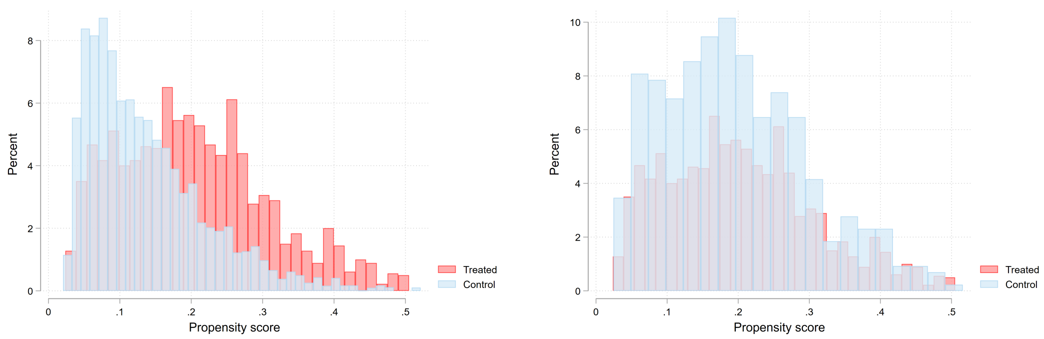

Fig. A.1: Histogram of propensity scores by treatment status before (left) and after (right) matching.

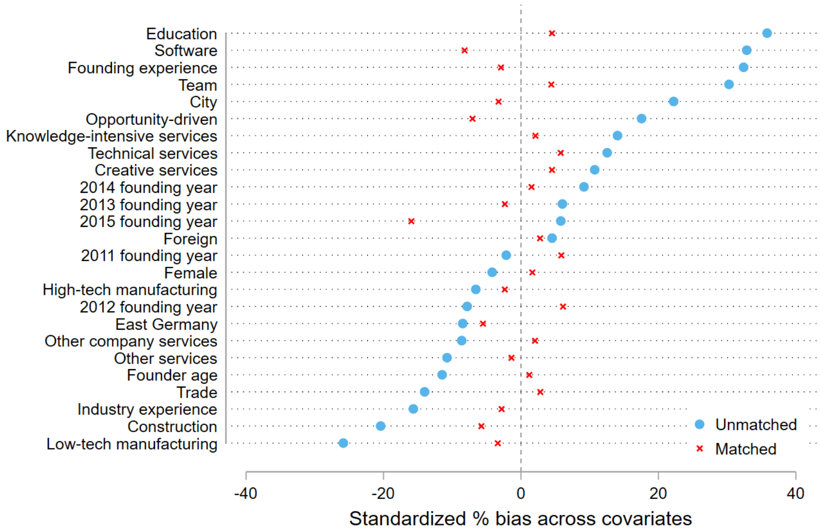

Fig. A.2: Graph on the standardized bias across covariates before and after applying propensity score matching. With an average bias of 4.3% this matching is considered to be sufficiently balanced.

Table A.13: Average Treatment Effect on the Treated (ATT) after Propensity Score Matching

		Treated Mean	Control Mean	Difference	Std. Error	T-stat.
Survival	Unmatched	0.874	0.920	-0.047	0.007	-6.50***
	ATT	0.874	0.881	-0.007	0.013	-0.58
Insolvency	Unmatched	0.080	0.047	0.033	0.006	5.75***
	ATT	0.080	0.053	0.027	0.010	2.63***
Operating costs	Unmatched	11.678	11.312	0.366	0.056	6.50***
	ATT	11.678	11.295	0.383	0.094	4.09***
ln(personnel costs)	Unmatched	9.755	8.553	1.202	0.121	9.90***
	ATT	9.755	9.121	0.634	0.194	3.27**
ln(material costs)	Unmatched	9.824	9.877	-0.054	0.076	-0.71
	ATT	9.824	9.475	0.349	0.131	2.67***
ln(other costs)	Unmatched	8.428	8.111	0.317	0.096	3.30***
	ATT	8.428	8.065	0.362	0.160	2.26**
ln(sales)	Unmatched	11.750	11.613	0.137	0.070	1.96*
	ATT	11.750	11.463	0.287	0.122	2.34**
ln(sales variance)	Unmatched	11.287	10.770	0.517	0.046	11.20***
	ATT	11.287	10.729	0.558	0.076	7.30***
Employees	Unmatched	6.427	4.241	2.186	0.179	12.20***
	ATT	6.427	4.793	1.634	0.330	4.95***
VC	Unmatched	0.060	0.025	0.035	0.004	8.01***
	ATT	0.060	0.043	0.017	0.009	2.01**
Bank financing	Unmatched	0.080	0.095	-0.015	0.007	-2.05**
	ATT	0.080	0.096	-0.016	0.012	-1.36

The table shows the average treatment effect on the treated after propensity score matching for all outcome variables used in the main analyses. Propensity score matching is based on nearest neighbor with replacement using the same set of matching variables as with entropy balancing (compare Table A.4 or Table A.12).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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