The Different Effects of Mass-Media Marketing and Personal Sales Budgets Across the Life Cycle of B2B High-Tech Start-ups

Abstract

In their early life-cycle stages, business-to-business (B2B) high-tech start-ups face severe challenges in establishing their first customer relationships. To generate business growth, they must convey the value of unfamiliar, innovative, complex offerings to customers, using the limited resources at their disposal. Prior research has not examined the different roles of mass-media marketing and personal sales communications in this challenging endeavor, despite principal differences between these activities in start-up contexts. To help B2B high-tech start-ups allocate financial resources to mass-media marketing and personal sales communications across early and later stages of their organizational life cycle, this article presents a longitudinal survey study involving founders of B2B high-tech start-ups. The findings indicate that start-ups spending a larger share of their budget on personal sales (i.e., higher personal sales expense ratio) exhibit stronger performance in earlier stages of their life cycle but weaker performance in later stages; however, still in later stages, these expenditures enhance certain performance metrics. Conversely, start-ups spending a larger share of their budget on mass-media marketing (i.e., higher mass-media marketing expense ratio) show stronger performance in later stages but weaker performance in earlier stages. High-tech start-ups can leverage these findings to improve their budget allocation and ensure persistent growth.

Keywords: mass-media marketing communications, personal sales communications, customer relationships, start-ups, life cycle, business-to-business, high-tech

Business-to-business (B2B) high-tech start-ups are prominent in diverse industries, including aerospace, advanced electronics, pharmaceuticals, medical devices, and software engineering. They are globally pervasive: In 2020, 61% of successful start-ups offered B2B solutions (Statista 2020). In recent years, there has been a 47% surge of such high-tech start-ups in the U.S. economy (Wu and Atkinson 2017). In the European Union, investments in B2B start-ups grew an astonishing 211% between 2015 and 2020 (McKinsey & Company 2021). In addition, B2B high-tech start-ups drive economic development, create jobs, and foster innovation: 85% of U.S. entrepreneurs create new jobs, and 36% offer new technologies or innovative products/services (Global Entrepreneurship Monitor 2018).

Despite their clear economic importance, B2B high-tech start-ups have difficulties establishing themselves in their markets. By their very nature, they face critical challenges in effectively building customer relationships, in that they are unknown to potential customers and offer complex products and business models that require extensive explanation (Konya-Baumbach et al. 2019; Slater and Mohr 2006). They frequently suffer from a liability of newness (Xiong and Bharadwaj 2011), as they lack a firm reputation, customer trust, and industry experience (Rao, Chandy, and Prabhu 2008; Read et al. 2009). However, these factors are indispensable to effectively build relationships in B2B high-tech settings.

Market communication activities are a central part of a start-up's broader marketing ecosystem, aligning with the AMA's definition of marketing as "the *activity*, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings [...]" (AMA, 2025, emphasis added). These activities can help start-ups overcome challenges in effectively building customer relationships. However, founders often underestimate their importance and lack the knowledge to employ different communication strategies effectively. Research has only begun to explore the specific roles of market communication activities in start-ups; yet these early studies tend to aggregate start-ups' communications designed for and targeting the mass-media (which we refer to mass-media marketing), and interpersonal communication (which we refer to as personal sales), without distinguishing their potentially unique effects and conceptual mechanisms (Table 1). With limited resources at their disposal, start-up managers need to know in which of the two areas they should allocate their expenditures.

Seeing these practical as well as conceptual reasons, we differentiate between the influence of a B2B high-tech start-up's mass-media marketing expense ratio (i.e., the share of budget spent on mass-media marketing communications) and personal sales expense ratio (i.e., the share of budget spent on personal sales communications) on its performance. We then explore the distinct effects of these expense ratios across the stages of a start-up's organizational life cycle (OLC). Drawing on qualitative interviews and a preliminary survey with 81 founders, we define mass-media marketing communications in the B2B high-tech start-up context as all activities initiated by start-ups to establish relationships with investors and customers through indirect, nonpersonal channels such as online content, advertising, and social media marketing (Lee, Sridhar, and Palmatier 2017). For better readability, we abbreviate mass-media marketing communications with mass-media marketing in the paper, when appropriate. We define personal sales communications in the same context as all activities of founders and employees to establish close, direct relationships with customers and investors through personal meetings (e.g., a founder who personally initiates cooperation with a customer at a trade fair). In our preliminary survey, 77% of the founders indicated the importance at each stage of a start-up's development to differentiate expenses for mass-media marketing and personal sales. Noting the differences in these communication activities, we ask: What are the differential effects of increasing the personal sales expense ratio or mass-media marketing expense ratio on start-up performance in B2B high-tech contexts?

We also investigate whether and how the effects of mass-media marketing and personal sales expense ratios vary throughout the OLCs of B2B high-tech start-ups. Start-ups pass through multiple development stages, each with unique challenges. Initially, they face the liability of newness, but once they have acquired their first customers, they can leverage this success in later stages (Fisher, Kotha, and Lahiri 2016). Recent research indicates systematic marketing activities might offer greater value in early stages than later (Mintz and Lilien 2024). However, these emerging insights require more profound examination because most pertinent research focuses only on data sets at specific OLC stages or, critically, does not differentiate communication activities (Table 1). Thus, we ask: What are the differing effects of mass-media marketing and personal sales expense ratios during earlier and later stages of start-ups' OLC?

Our conceptual model includes a start-up's personal sales expense ratio and mass-media marketing expense ratio as independent variables and the start-up's stage in the OLC as the key contingency. We test the model with different performance-based dependent variables (sales revenue and number of customers) and various operationalizations of a start-up's OLC stage. To address a research gap, in that empirical examinations refer only to late-stage start-ups (for an exception, see Mintz and Lilien 2024), citing the lack of archival data for younger firms, we compile a primary panel data set during four waves over 20 months, producing up to 598 start-up-wave observations. The data come from founders or top-level executives and corresponding interviewers. We employ panel regression models (accounting for unobserved heterogeneity among start-ups) and address potential selection biases and endogeneity concerns.

Table 1. Literature on Mass-Media Marketing Communications and Personal Sales Communications by Start-Ups

Study	Marketing as Communication Activity Perspective [1]	Communication Activity: Mass-Media Marketing	Communication Activity: Personal Sales	OLC Perspective	Research Setting	Data (OLC Stage)	Key Dependent Variables	Relevant Findings
Yli-Renko and Janakiraman (2008)	No, primarily processual	No	No	No	Longitudinal panel data from 180 young firms over a six-year period	Longitudinal (start-ups age between 1 and 10)	New product development	Relational embeddedness increases the number of new products developed.
Anderson et al. (2021)	No, primarily institutional	No	No	No	Multiyear field experiment with 930 Ugandan entrepreneurial firms (mostly B2C retailers and service providers)	Longitudinal (no restrictions on life-cycle stages)	Firm growth, sales, profits, total assets, total employees	Firm growth increased in marketing volunteer treatment group.
Song et al. (2008)	No, primarily institutional	No	No	No	Meta-analysis of 31 studies of success factors in new technology ventures	N.A. (diverse studies)	New venture performance	Founders' marketing experience increases new venture performance.
Xiong and Bharadwaj (2011)	No, primarily institutional	Yes	No	No	Panel data from 177 initial public offering (IPO) firms	Longitudinal (after IPO stage)	IPO values (financial capital)	Marketing or research-and-development B2B alliances can be deleterious if financial absorptive capacity is missing.
Yang and Gabrielsson (2017)	No, primarily processual	No	No	(No) [c]	Qualitative case and interview data from 4 international start-ups	Longitudinal	Entrepreneurial marketing	Marketing decision-making processes lead to entrepreneurial marketing.
Homburg et al. (2014)	No, primarily institutional	Yes	No	No	Secondary data of 2,945 new ventures	One year of data from Crunchbase	Venture capital funding	Chief marketing officers and their level of experience increase the likelihood of venture capital funding.
Zhao, Libaers, and Song (2015)	No, primarily institutional	(Yes) [b]	(Yes)	No	Panel data from 909 Chinese firms over a three-year period	Longitudinal (start-up age 3 years)	Product performance, product launch timing	Marketing resources have positive effects on product performance and timing of product launch.
De Jong, Zacharias, and Nijssen (2021)	Yes	No	Yes	No	71 young firms over a seven-year period; focus on companies that made a first sale	Longitudinal (after making a first sale)	Sales growth	Value-based selling improves firms' use of slack resources, so they grow effectively.
Pitkänen, Parvinen, and Töytäri (2014)	Yes	(Yes) [b]	Yes	No	Panel data from 95 Finnish early-stage companies	Cross-sectional (sizable number of customers, after first sale)	Significance of first sale, sales growth of new venture	Proactive sales orientation positively affects the significance of the start-up's first sale.
Mintz and Lilien (2024)	Yes	Yes [a,b]	No	Yes	Panel data from 693 U.S. B2C and B2B start-ups	Longitudinal (complete life-cycle stages)	Start-up valuation	Systematic marketing is most beneficial for early-stage B2B and late-stage B2C start-ups.
This study	Yes	Yes	Yes	Yes	Panel data with 407–598 start-up wave observations[d] of high-tech B2B start-ups	Longitudinal	Sales revenue, number of customers	Spending a larger share of budget on personal sales communications is more beneficial in early OLC stages; spending a larger budget share on mass-media marketing communications is more beneficial in later OLC stages.

[a]Study relies on a binary measure (1: systematic marketing; 0: no systematic marketing). [b]Study aggregates marketing and sales activities. [c]Four case studies from different life-cycle stages without a systematic investigation. [d]Sample sizes differ across model specifications. Notes: OLC = organizational life cycle; B2C = business-to-consumer. [1]In our differentiation, we refer to the American Marketing Association's marketing definition that differentiates marketing by *activities*, a set of *institutions*, and *processes* (AMA 2025).

The results show that mass-media marketing and personal sales expense ratios influence different performance criteria of B2B high-tech start-ups, and these effects vary depending on the current OLC stage. A higher sales expense ratio more strongly increases start-ups' performance in earlier OLC stages, when close relationships are important, but less in later stages. By contrast, a higher mass-media marketing expense ratio primarily increases start-ups' performance in later OLC stages, when start-ups seek rapid growth, but hardly in earlier stages. Various robustness checks confirm these findings.

We offer several implications for marketing research and practice. Although prior research indicates positive effects of marketing resources for start-up success (e.g., DeKinder and Kohli 2008), literature on specific sales resources in start-ups is nascent (Matthews, Chalmers, and Fraser 2018). By differentiating the effects of spending a larger share of the budget on personal sales or mass-media marketing, we provide actionable recommendations for resource-constrained start-ups. Early in their development, start-ups should spend a higher share of their budget in personal sales communications to build close customer and investor relationships. When ready to accelerate growth and expand their market reach, they should allocate more budget to mass-media marketing communications to boost performance in later stages. However, if a start-up aims to cultivate fewer but deeper customer relationships, continued expenses in personal sales can remain beneficial even at this more advanced stage.

Differential Effects of Expenses on Mass-Media Marketing and Personal Sales Communications

Mass-Media Marketing and Personal Sales Communications in B2B High-Tech Start-Ups

B2B high-tech start-ups provide technologically sophisticated products and services, mostly innovations (e.g., artificial intelligence solutions, cyber security systems, blockchain), as a core part of their often solution-based business models (Fisher, Kotha, and Lahiri 2016). Their offerings tend to be characterized by high complexity, the need to explain the offering to customers, and uncertainty on customers' part (e.g., Yli-Renko and Janakiraman 2008). For instance, AI start-ups often need access to sensitive company data to train their models, but B2B decision-makers may hesitate to share it due to unfamiliarity and trust issues. This creates unique challenges for B2B high-tech start-ups in establishing credibility and initiating first customer relationships, highlighting the critical role of both personal selling and mass-media marketing. In this section, we therefore differentiate mass-media marketing and personal sales in B2B high-tech start-ups based on the insights gathered from in-depth interviews with senior managers and founders, a quantitative founder survey, and prior research that distinguishes these essential activities in established firms.

Preliminary interviews. To inform our distinct conceptualization of start-ups' mass-media marketing and personal sales activities, we conducted in-depth interviews with 15 experienced senior managers and founders of B2B high-tech start-ups (7 h, 35 min total length; see Web Appendix A for details). We applied theoretical sampling to gather insights from a broad range of young and mature B2B start-ups across high-tech industries. Our semistructured interview guide and iterative research design allowed for follow-up questions, details, and examples; we also discussed the preliminary findings with founders (e.g., Tuli, Kohli, and Bharadwaj 2007). We present the original quotes verbatim. Please note that the practitioners used 'marketing' and 'sales' synonymously with mass-media marketing and personal sales, respectively.

Differentiating mass-media marketing and personal sales. The interviewees differentiate between communication activities designed for the mass-media, such as online marketing measures, social media marketing, and advertising (which practitioneers commonly refer to as "marketing" in narrower sense), and interpersonal communication activities, such as personal and direct interactions with customers or investors. Most of the interviewees (12 of 15) agreed that in B2B high-tech start-ups such (mass-media) marketing and (personal) sales communications are clearly distinct. For example, a key mass-media marketing activity for start-ups is establishing an appealing online presence and creating attention for the firm (as mentioned by 13 respondents). According to the founder of a professional service start-up: “[Mass-media] marketing takes time but at some point, it becomes easier. The press becomes aware, and suddenly you are getting published in [national newspapers]. You put that on your website and build up a name” (#2). This is particularly important for B2B high-tech start-ups that enter untapped niches or create entirely new categories of products and services. For them, mass-media marketing serves to make the market aware that such a solution even exists.

Respondents suggested personal representation at trade fairs as a key personal sales activity because, in B2B high-tech contexts, trade fairs are important for connecting with customers and achieving financial success. A cybersecurity start-up founder noted: “In [personal] sales, we attend trade fairs, where we proactively approach people. We give technical sales presentations because the whole topic of cybersecurity is quite special. It gives us the opportunity to stand out from competition” (#6). Such personal interaction is often needed to reduce customer uncertainty, for instance, when offerings require access to sensitive company data or substantial customer process changes, as is typical in data-driven high-tech solutions.

This distinction also aligns with research conducted in more mature firms (e.g., Homburg et al. 2017; Krohmer, Homburg, and Workman 2002). For example, Lee, Sridhar, and Palmatier (2017) differentiate the effects of expenses on personal selling activities and expenses on advertising activities on mature firms’ profitability. Our main study’s sample replicates these preliminary expert assessments: For instance, when we asked the respondents of our main study which mass-media marketing and personal sales activities they employ (Table 2), the majority mentioned social media marketing (45.4%) (e.g., LinkedIn, Facebook) and online marketing (34.0%) (e.g., SEO, advertising) as being typical mass-media marketing activities. The most commonly reported personal sales activities were in-person networking (56.7%) and direct acquisition (42.5%).

Conceptually, mass-media marketing and personal sales communications in B2B high-tech start-ups differ primarily in their approach to relationship-building (Table 2). In this context,

Table 2. Mass-Media Marketing and Personal Sales in B2B High-Tech Start-Ups

	Personal Sales in B2B High-Tech Start-Ups	**Mass-Media Marketing in B2B High-Tech Start-Ups**
Mission	**Network deepening**	**Network broadening**
Definition	Communication activities of founders and employees to establish close, personal relationships with (few) customers and investors through personal meetings	Communication activities of start-ups to establish multi-tie relationships with (many) customers and investors through indirect, nonpersonal channels
Examplary Roles (Representative Quotes[1] from Preliminary Interviews with Founders)	• **Generate Market Feedback:** "At the beginning, sales is more important in any case, because only then you can find out: what makes the market tick?" (#6) • **Build Trust**: "Sales really gets down to the nitty-gritty. You really look at the customer in detail. What's going on there? How can we help them and build trust?" (#5) • **Achieve Traction:** "When I need traction on the market, I get that through salespeople." (#7)	• **Generate Awareness**: "Increase the general awareness of our firm… [and] reduce complex topics to the essential three core points that concern the customer." (#14) • **Build Reputation**: "As soon as you have a product-market fit, you start to follow up with marketing budgets… build up a reputation, create content… [and] address as many customers as possible" (#3) • **Achieve Scalability:** "You have to implement all insights you learned from early sales into marketing… [to] keep up the pace and achieve scaling." (#10)
Measures	• Face-to-face communication with customers • Personal connection between salesperson and customer (person-based trust) • Personal selling	• Mass, less personal communication with customers • Connection between brand and customers (firm-based trust) • Advertising
Key studies	Dwyer, Schurr, and Oh 1987; Hite and Hesterly 2001; Lee, Sridhar, and Palmatier 2017; Palmatier 2008; Rouziès et al. 2005; Vaid, Ahearne, and Krause 2020	Hite and Hesterly 2001; Homburg et al. 2014; Lee, Sridhar, and Palmatier 2017; Rouziès et al. 2005; Song et al. 2008; Vaid, Ahearne, and Krause 2020
Typical activities mentioned in our main study sample	• Networking (trade fairs, congresses, events, pitches, meetups) (56.7%) • Direct acquisition (42.5%) • Personal sales presentations (9.6%) • Social selling (e.g., LinkedIn) (2.1%)	• SEO and advertising (e.g., Google Ads) (34.0%) • Website (23.3%) • Social media activities (e.g., LinkedIn) (45.4%) • Content creation (e.g., blogs, articles) (13.7%) • Information materials (e.g., flyers) (26.0%)

Notes: The percentages refer to the proportion of founders/start-ups that indicated the listed activities in the main study.
[1] Original quotes. Interviewees used the terms marketing and sales synonymously with mass-media marketing and personal sales, respectively.

mass-media marketing can create relationships with many customers, through different ties, with relatively little closeness. They enable reach and responsiveness to a broad customer base; according to the founder of a cybersecurity start-up: "it is simply about generating the highest possible number of leads via external channels" (#1). Conversely, personal sales activities require more time, effort, and direct, personal involvement. Various founders (N = 7) noted that explaining and customizing complex offerings for business customers require high-touch interaction and can result in prolonged, resource-intense sales cycles. As one industrial-service start-up founder explained, "Our technology requires a lot of explanation. We have to work individually with each customer in sales, which is a very long process until a customer is ready to buy from us. But when they do, they are tied to us. Yet a great deal of explanation and trust building is necessary beforehand" (#5). Thus, for start-ups, personal sales activities enable closer, more personal relationships, with relatively fewer customers per sales employee.

Effects of Mass-Media Marketing and Personal Sales Expense Ratios on B2B High-Tech Start-Ups' Performance

Having delineated the differences between mass-media marketing and personal sales in B2B high-tech start-ups, we now discuss the differential impact of allocating a higher share of budget to these different activities on start-up performance. Start-up performance is not unidimensional; it has various dimensions, such as sales revenue or the number of acquired customers (Fisher, Kotha, and Lahiri 2016)—both goals that managers in our interviews mentioned as key challenges. We consider how both categories of activities might affect these key metrics.

Mass-media marketing communications. Prior research on the role of marketing in start-ups concurs that expenses on marketing activities should be conducive to start-up performance (Mintz and Lilien 2024). Applied to our research, mass-media marketing can effectively promote high-tech start-ups' development and establish initial relationships through multiple, relatively less personal ties with a broad range of customers and other stakeholders. The founders who participated in our in-depth interviews agreed that in complex B2B settings, communicating a consistent, easy-to-understand message is crucial for generating stakeholder awareness and attracting customers. Online, content, and social media marketing, along with advertising, all increase such contacts, helping firms reduce information asymmetries and signal their reliability and legitimacy (Lee, Sridhar, and Palmatier 2017). A software start-up founder explained: "I have to somehow break this complex thing down to a clear message…. Our goal is to generate a consistent customer experience and to be perceived as attractive and professional by customers, business partners, and investors, and even our customers' customers" (#7).

Because, by definition, high-tech start-ups are unknown and inscrutable to potential customers (Rao, Chandy, and Prabhu 2008; Read et al. 2009), signaling legitimacy is a crucial prerequisite for building relationships with them (Song et al. 2008). The senior manager of a mature professional service start-up noted: "When you are fresh on the market, you have to start from scratch everywhere. You lack credibility when you approach customers who want to see use cases and success stories" (#4). Although customers often express uncertainty about start-ups' products and prospects, mass-media marketing activities can alleviate this uncertainty and contribute to the start-ups' performance by communicating relevant information.

Personal sales communications. Although the implications of personal sales activities for start-ups are relatively rarely explored, relationship marketing research unequivocally asserts the relevance of personal selling and personal attention in efforts to build close, profitable customer relationships (Palmatier, Scheer, and Steenkamp 2007; Schmitz et al. 2020). Personal sales communications can promote high-tech start-ups' development by laying a foundation for building and expanding personal relationships with customers. For example, to induce first-time customers to purchase innovative, complex offerings, high-tech start-ups can thus engage in face-to-face interactions and personal selling, which allow them to provide extensive explanations (Konya-Baumbach et al. 2019; Slater and Mohr 2006). Complex offerings likely create additional customer uncertainty, which can be alleviated through direct, personal collaborations (Ulaga and Kohli 2018). Such close sales-based collaborations can help start-ups understand customer needs and concerns more precisely (De Jong, Zacharias, and Nijssen 2021; Tuli, Kohli, and Bhardwaj 2007). Because B2B buying processes are often formalized and involve multiple actors, salespeople need to devote intensive personal attention to addressing them, reducing purchase uncertainty, and motivating customers to form close relationships with the firm (Fang, Palmatier, and Grewal 2011).

Potential for negative outcomes. Despite the potential benefits of mass-media marketing and personal sales, allocating a higher share of start-ups' budgets to these different activities may be less intuitive than expected. Research on entrepreneurship and resource endowments suggests the possibility of harmful effects (Bergmann and Brush 2001). Most start-ups operate with extreme resource scarcity, needing to trade off expenses on various resources (Homburg et al. 2014). Misallocated financial resources represent serious risks, as "you always have a limited amount of money and you have to think about where you're going to invest your money…Burning your [mass-media] marketing and [personal] sales budget can really hurt your start-up" (#7). Spending a larger share of the budget on mass-media marketing or personal sales might divert financial resources from other vital areas, such as product development, and ultimately be futile if product development efforts fail to produce high-quality, market-ready offerings (Ernst, Hoyer, and Rübsaamen 2010). Thus, our first research question (RQ) is:

> **RQ1:** What are the effects of a higher mass-media marketing expense ratio and a higher personal sales expense ratio on start-up performance on various dimensions (sales

revenue and number of customers)?

Effects of Mass-media Marketing and Personal Sales Expense Ratios Across the OLC

Integrating OLC Theory and Customer Relationship Management

High-tech start-ups face diverse challenges in building and retaining customer relationships across their OLCs. Existing OLC models describe firms' development across time and stages, across which business risks and opportunities vary , such that unique challenges arise for customer relationships (Fisher, Kotha, and Lahiri 2016). Although different life-cycle models depict slightly varying stages, they converge on two basic stages: (1) early development, in which start-ups create and test initial products and business models, with limited market activities, and (2) later growth, in which they scale up and penetrate the market.

In the earliest development phases, start-ups must arouse prospects' interest, create close links with initial customers, and closely collaborate with them in product development, testing, and product implementation (Coviello and Joseph 2012). A software start-up founder outlined these needs: "First, I have to generate traction somehow, that's important. Only if I generate traction and have first customers [can I] further develop my product" (#7). Learning from early failures and customer feedback also drives start-ups' progression, according to a cybersecurity founder: "In the beginning, we analyzed: Why didn't the customer want it? We directly asked them what the reasons were. Of course, it's always time-consuming to spend many resources on a customer you haven't won. But that helps a lot with the next customers" (#6).

In later development phases, start-ups must grow their customer bases and explore and expand business opportunities with existing customers (i.e., up-sell or cross-sell) (Dwyer, Schurr, and Oh 1987). As the chief strategy officer of a SaaS start-up noted: "The next important step was to show that it [the solution] does not only apply to one or two customers who we knew closely but that we can actually win over new customers. That our business is truly scalable and addresses a larger problem” (#14).

We operationalize a start-up’s OLC progression according to the venture’s age in terms of the time elapsed since its founding. Time assumes an essential role in OLC models (e.g., Hanks et al. 1994), as well as in research on early firm survivability (e.g., Le Mens, Hannan, and Pólos 2011). According to these models, over time, organizations progress through distinct stages, such as initial conception and growth (Fisher, Kotha, and Lahiri 2016; Kazanjian and Drazin 1989). The specific challenges, goals, and events that characterize each stage (e.g., Hite and Hesterly 2001) include establishing a business plan, first commercial success, and specific growth targets. Earlier developmental phases are characterized by the liability of newness, with younger firms most likely to fail (Hannan and Freeman 1984). As previously noted, start-ups can build legitimacy to reduce the liability of newness, but it takes time (Winkler, Rieger, and Engelen 2020). Venture age can signal legitimacy, but trust from stakeholders can be built only through time-intensive relationship processes (Nahapiet and Ghoshal 1998).

Although prior research frequently uses venture age to reflect start-ups’ OLC progression (e.g., Fisher, Kotha, and Lahiri 2016; Hanks et al. 1994), this indicator has limitations: High initial resources (e.g., equity capital) may help start-ups progress more quickly than their ages would suggest (Brüderl and Schüssler 1990). Moreover, organizational change (e.g., change in founder team) may alter start-ups’ developmental courses independently of their age (e.g., reset the liability of newness; Singh, House, and Tucker 1986). We account for such factors in our model. We also cross-validate our results with alternative measures for the start-up’s OLC progression: venture size (indicating limited resources, or the liability of smallness; Freeman, Carrol, and Hannan 1983), venture popularity (alternatively indicating liability of newness), and an index measure (combining markers for liabilities of smallness and newness).

Effects of Mass-Media Marketing and Personal Sales Expense Ratios in Earlier OLC Stages

Because of their vulnerability in early development stages, start-ups desperately need resources from initial reference customers. Such customers provide essential references that enable start-ups to begin building trust and legitimacy, through favorable word of mouth, which improves their chances of future customer acquisition. Moreover, such partners can be highly instrumental in new product development, which usually demands particular effort and collaboration in complex B2B settings. For example, early customers might share essential insights into their "needs, market trends, competitors' offerings, and complementary technologies" (Yli-Renko and Janakiraman 2008, p. 145). Therefore, to progress, start-ups first need to build relationships with their very first customers (Fisher, Kotha, and Lahiri 2016).

According to the literature on customer relationship management, firms should build close relationships and strong ties at the interpersonal level rather than through impersonal customer touchpoints, especially in high-tech B2B settings (Palmatier, Scheer, and Steenkamp 2007; Schmitz et al. 2020), in which firms seek mutual understanding through intensive, time-consuming exploration processes (Zhang et al. 2016). Because any "exploratory relationship is very fragile" (Dwyer, Schurr, and Oh 1987, p. 16), start-ups should actively work to build mutual understanding, credibility, and legitimacy, based on appropriate information shared through high-quality interactions and deep relationships (Jap and Ganesan 2000).

Personal sales communications. Because of their liability of newness, start-ups cannot cite their extensive experience or strong firm reputations to reassure customers they are reliable (Fisher, Kotha, and Lahiri 2016). Instead, they must evoke customer trust in founders and their visions (person-based trust) (Fang et al. 2008). To generate person-based trust, personal sales interactions, rather than impersonal mass-media communications, are essential; they generate individual connections and establish initial relational bonds (Gruber 2004). An early-stage property technology start-up interviewee emphasized: “We need to approach customers directly. [Mass-media] marketing is … less important, because at this stage, we need to contact companies very actively, arrange appointments, and enter into personal discussions” (#3). Spending a larger share of the budget on personal sales activities such as trade-fair appearances and personal visits serves this purpose.

Mass-media marketing communications. Allocating operating budget to mass-media marketing may be pivotal for performance in the early stages because such activities create numerous compelling touchpoints and identify relevant customers and investors to participate in early collaboration and product development efforts (Homburg et al. 2014). Social media activities can be particularly potent: By providing engaging content, such as sound representations of the start-up, its ideas, and products, start-ups can inspire customers and investors to start business relationships and signal firm legitimacy. Yet the founders we interviewed also noted a risk of spending on mass-media activities too early if products are not “market ready” or firms are not capable of handling a mass of customers. According to a property technology start-up founder: “One mistake that many start-ups make is that they burn money too early with [mass-media] marketing before they have found the famous product-market fit. Product-market fit is the magic word: I finally have a product that I feel resonates with a broad mass of people” (#3).

In summary, we conceive arguments for the beneficial effects of spending a larger share of the budget on mass-media marketing and personal sales in early start-up stages, though we note that prior research in complex B2B settings strongly emphasizes the need for interpersonal relationships that facilitate relationship development and foster firm performance (e.g., Alavi et al. 2021; Panagopoulos, Rapp, and Ogilvie 2017). This argument suggests the relative precedence of expenses on personal sales activities, so that B2B high-tech start-ups can build relationships with customers and ensure their performance in earlier OLC stages. Thus:

> **RQ2:** What are the effects of a higher mass-media marketing expense ratio and a higher personal sales expense ratio on start-up performance in earlier stages of the OLC?

Effects of Mass-Media Marketing and Personal Sales Expense Ratios in Later OLC Stages

In later OLC stages, start-ups have market-ready offerings and seek market growth; their focus shifts from developing new products to commercializing and selling existing ones to existing customers and broader bases of new customers (e.g., Jap and Ganesan 2000). To realize rapid market growth (Fisher, Kotha, and Lahiri 2016), they focus on producing their products at scale and distributing them profitably in larger quantities to mainstream markets (Kazanjian 1988). Penetrating those markets requires communicating why the offerings are better than existing solutions to a large number of customers (Yli-Renko and Janakiraman 2008).

Mass-media marketing communications. Spending a larger share of the budget on mass-media marketing can be essential, as an industrial service start-up founder noted: “The bigger you get and the better you are positioned, the more important marketing becomes to tap into customer segments that you didn't have on your radar before” (#5). A SaaS start-up founder also admitted: “Honestly, in the initial phase, I put much less into [mass-media] marketing than sales. We spent six times more money on sales than on marketing. But at some point, we have to do massive marketing…Then it’s a matter of people going to our homepage, to the AppStore, and downloading the app. At some point, it probably tips over from personal level to mass marketing” (#8).

Prior research identifies the particular effectiveness of mass-media marketing for targeting mass customer segments (e.g., Rust and Huang 2014). Mass-media marketing expenses can help start-ups grow by extending ties to existing customers and by capturing the attention of new customers. Mass-media marketing communications in the growth stage can help build broader sets of relational ties with customers (Palmatier 2008); whereas personal sales activities can promote cross- or up-selling for the most promising customers, large-scale mass-media campaigns inform entire customer bases of new business opportunities, products, or special offers. They also increase the density of start-ups' contacts with their growing customer bases, fortify these relationships, and stabilize their continuous growth (Palmatier 2008). Such activities (e.g., advertising) also attract attention from broader, previously unknown customer bases, providing a continuous stream of new potential customers (Zhao, Song, and Storm 2013). Online marketing activities might be particularly effective, because in these channels, customer references and referrals exert strong impacts and achieve wide reach (Mintz and Lilien 2024), especially in B2B high-tech contexts. Thus, a higher mass-media marketing expense ratio should be beneficial to start-ups' performance later when they attempt to achieve market growth.

Personal sales communications. Personal sales activities can strengthen customer relationships, enhancing information sharing and understanding of customer needs (Tuli, Kohli, and Bharadwaj 2007), which especially benefits start-ups which are new to the market (De Jong, Zacharias, and Nijssen 2021). However, allocating a larger share of budget from other essential activities, like mass-media marketing or operations, to personal sales may be risky in later stages: Start-ups need to produce, sell, and distribute their products at volume and in a cost-efficient manner, requiring substantial resources for scalable operations and broader-reach market communication (Kazanjian 1988). And critically, over-reliance on a few personal ties can limit market learning and "curtail opportunities to develop new and diverse products for other customers or new markets" (Yli-Renko and Janakiraman 2008, p. 134). For firms aiming for rapid customer growth, a high personal sales expense ratio may not be effective and could even impede progress at this stage. Accordingly, we ask:

> **RQ3:** What are the effects of a higher mass-media marketing expense ratio and a higher personal sales expense ratio on start-up performance in the later stages of the OLC?

Empirical Analysis

Data Collection and Sample

Because archival data on start-ups are sparse and often focus "on (the atypically) successful later-stage start-up firms" (Mintz and Lilien 2024, p. 221), we composed a unique dataset combining primary panel data with archival data sources (i.e., Amadeus, Crunchbase, and Google Trends). In our longitudinal, multiple data source study, we conducted telephone surveys with B2B high-tech start-ups across development stages and business models. In a multistep procedure, we identified the relevant population of B2B high-tech start-ups in the target country (Germany). We extensively reviewed reliable sources (e.g., governmental and academic initiatives and organizations promoting start-ups), resulting in a comprehensive longlist of relevant start-ups. Web Appendix B shows how we developed and validated our final sampling frame. We prescreened potential respondents to ensure they meet our definition of start-ups, requiring them to have been in operation for a maximum of ten years (e.g., Winkler, Rieger, and Engelen 2020) and to have pursued a commercial, profit-oriented purpose, targeting B2B markets. We randomly selected start-ups across high-tech industries, generating 1,079 contacts.

Professional telephone interviewers with start-up business experience conducted the surveys with (co)founders or top-level executives. The interviewers first underwent extensive training to ensure quality and consistency, comparability across interviewer ratings, and appropriate data handling (Web Appendix B). Each interview began with a structured survey, which used established measurement scales and closed-ended quantitative questions. The interviewers then engaged in semistructured, in-depth discussions with respondents about their start-ups' business model, communication activities commonly referred to as marketing or sales, and developmental course. All interviews were recorded and transcribed. After each interview, in another structured survey, interviewers rated each start-up's development according to respondent discussions (an independent rater rerated 20% of the interviews to evaluate reliability; Ø kappa: .77). The surveys spanned four waves, over 20 months, from September 2018 to April 2020. Key respondents were the same across all waves. We obtained 909 start-up-wave observations, but for the panel models, sample sizes varied between the dependent variables sales revenue (N = 407) and number of customers (N = 598) because of item nonresponses, which we address in our analytical strategy.

The diversity of our sample reduces potential selectivity concerns, often present in entrepreneurship research (e.g., Korteweg and Sorensen 2010), because it encompasses start-ups that are in earlier and later OLC stages, more and less successful, and from various B2B high-tech industries. Table 3 depicts our sample composition (panel A) and provides illustrative examples of B2B high-tech start-ups included in our sample (panel B). All start-ups offer a vast range of technologically sophisticated products and services (e.g., cybersecurity applications, innovative microbiological tests, ecological seed coating, blockchain-based vehicle diagnostics), have highly innovative business models, and operate in a variety of high-tech industries (IT/software engineering, SaaS, Industry 4.0). On average, at the first survey wave, the firms in our final sample had operated for 3.2 years and employed 16.1 employees. Notably, start-ups in our sample are rather young; yet high-tech start-ups tend to progress faster than mid-/low-tech start-ups (Almus and Nerlinger 1999). The 81 high-tech founders surveyed in our prestudy confirmed this assumption: Start-ups in their industry are, on average, 1.4 years old in the early conception stage and 3.9 years old in the later growth stage. On seven-point scales (7 = "strongly agree"), the interviewers rated them as innovative (5.23), complex (4.40), and advantageous relative to existing products (5.48).

Table 3. Sample Characteristics and Illustrative Examples of Start-ups in the Sample

A. Sample Composition					
Distribution of Venture Industry		**Distribution of Venture Age**		**Respondents Characteristics**	
IT/software engineering	23.5 %	< 1 year	18.4 %	(Co)founder	50.7%
SaaS	14.0 %	1–2 years	25.8 %	Chief executive officer	29.9%
Industry 4.0/industrial technology/production	17.0 %	2–3 years	13.9 %	Chief operating officer	1.0%
Bio-, nano-, medicine technology	6.5 %	3–4 years	15.4 %	Chief marketing officer	7.5%
Online marketplace/services	7.5 %	4–5 years	7.9 %	Chief sales officer	5.5%
Food tech	6.0 %	5–6 years	6.0 %	Other executive level	5.5%
E-commerce	3.0 %	> 6 years	12.4 %		
Consulting	5.5 %			Age	34.0 years
Online service portal	2.0 %			Female/male	12%/88 %
FinTech	1.0 %			Sales experience	8.7 months
Other (e.g., green tech, games, mobile, education)	14.0 %			Marketing experience	14.3 months

B. Illustrative Examples for B2B high-tech start-ups in the sample		
Business Model Description	**Venture Age (years)**	**Number of Customers**
B2B high-tech startup providing AI-driven, software-based quality assurance solutions that leverage advanced data visualization and analytics to optimize industrial production and reduce manufacturing defects.	1	1
Green-tech start-up transforming biomass into biochar for industrial clients through an innovative conversion process.	1	3
Logistics tech provider connecting intralogistics participants (robots, forklifts, humans) via hardware and software systems.	2	6
High-efficiency micro steam turbine manufacturer serving industrial sectors using process steam.	1	10
Manufacturer of precision optical surfaces (lenses, magnifiers) for research and industrial use.	2	30
Biotech firm supplying artificial cell culture media to pharmaceutical and academic institutions.	3	75
Smart logistics startup offering AI-driven supply chain optimization for manufacturers and logistics providers.	5	100
Motion capture system technology manufacturer serving B2B clients in healthcare, academia, and sports.	6	200
AI-driven Sales analytics systems helping B2B companies optimize sales outreach and tracking through a proprietary tracking tool.	3	400
Digital fundraising and specialized donor management IT solutions for nonprofits, offering CRM, automated payment systems, and consulting services.	9	1600
Edtech and 3D printing startup offering customized production tools for schools businesses, individuals.	4	5114

Notes: The sample composition is based on the effective research sample and data from the first wave.

Measures

We gathered measurement items from prior literature; we report all measures and items from the main analyses in the Appendix, then provide the measures of the instrumental variables in Web Appendix C. We used quasi-objective data for our focal models (Homburg et al., 2012) and multi-item scales for instrumental variables, unless the constructs were quasi-objective.

Dependent variables. We measured start-up performance via sales revenue (M = 617,485.20; Mdn = 180,000; SD = 2,396,498) and number of customers (M = 715.13; Mdn = 30;

SD = 2,574.08).[1] With these measures, we accounted for the multidimensional challenges that start-ups face simultaneously (Anderson et al. 2021; Xiong and Bharadwaj 2011).

Independent variable. We relied on a quasi-objective measurement of the mass-media marketing and personal sales expense ratios. On a 100-point constant sum scale (Homburg et al. 2017), we asked respondents to indicate how they would allocate their financial budgets across marketing, sales, product development, operations, and other activities. Figure 1 illustrates how the start-ups in our sample distribute their budgets. The start-ups, as expected, focus primarily on product development. However, they also allocate, on average, 15–20% of their budgets to mass-media marketing and personal sales. Furthermore, the three start-ups we illustrate in detail exemplify that budget allocation varies considerably among start-ups.

Web Appendix D provides descriptive information on the relationship between expense ratios and start-ups' specific mass-media marketing and personal sales communication activities. For example, according to a median split, start-ups with a high (vs. low) mass-media marketing expense ratio are significantly more likely to employ online marketing (e.g., SEO, e-mail marketing) ($\delta = 16.2\%$, $p < .01$) or social media marketing ($\delta = 13.2\%$, $p < .01$). Start-ups with a high (vs. low) personal sales expense ratio are more likely to engage in personal networking (e.g., trade-fair appearances) ($\delta = 7.5$ %, $p < .05$) and direct acquisition ($\delta = 6.9$ %, $p < .05$).

Moderating variable. We used venture age as the main indicator of a start-up's OLC progression and liability of newness (Freeman, Carrol, and Hannan 1983). We measured it according to the difference between the founding date and survey wave date in years.

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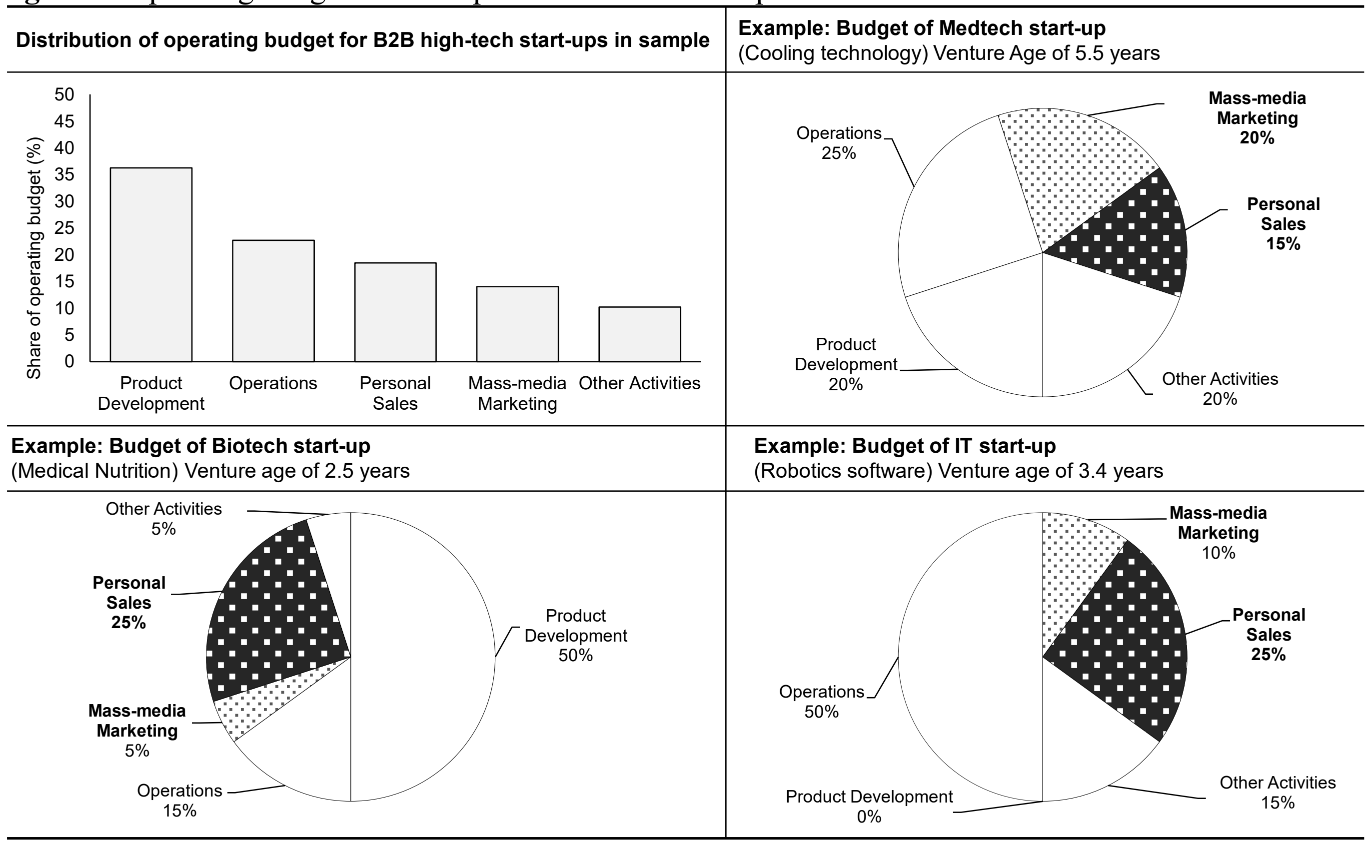
[1] The dependent variables exhibit a high degree of variance. Such variance is expected, as we consider start-ups in different OLC stages. The log transformations allowed us to smooth the distribution, as shown in Table 5.

Figure 1. Operating budget of start-ups in the research sample



Notes: The illustration covers data from the first wave of our analysis sample.

Control variables. Through a literature review, we identified relevant start-up internal (i.e., human capital, organizational legitimacy, and product development capability) and external (i.e., industry attractiveness) control variables. We controlled for change in the founder team, as it reflects changes in the start-up's human capital. Because financial and reputational assets can signal legitimacy, we controlled for financial liquidity, the number of investors[2] (e.g., Kaplan and Strömberg 2004), and whether the start-up had won an important prize. Start-ups with more available funds can spend more; those that have won important prizes can overcome the liability of newness, thereby lowering their mass-media marketing and personal sales expense ratios.

[2] We acknowledge that investors with a "hands-on" investment style can also nurture human capital by coaching start-ups in important areas such as marketing strategy.

While spending on product development may enhance performance, an excessive product orientation may decrease the willingness to allocate funds to mass-media marketing and personal sales communications. Thus, we controlled for a start-up's product development focus, measured as the extent to which it prioritizes product-related decisions and actions.

Moreover, we captured general industry attractiveness and industry attractiveness from a start-up's perspective, accounting for the number of start-ups and the closes-to-entries ratio per industry, using data from Crunchbase. Although the entry of many start-ups into an industry may signal general market potential, it might also make it more challenging for start-ups to grow because of fierce competition. High closes-to-entries ratios may signal that start-ups are finding it difficult to compete with more established companies. Moreover, by following research on more mature firms, we captured industry demand growth (i.e., five-year industry sales revenue growth) and industry concentration (Herfindahl–Hirschman index) with secondary data from the Amadeus database. Start-ups may thrive in growing industries, but dominant companies that characterize concentrated industries may also limit their performance.

Finally, we added start-up and wave dummies to account for potential unobserved heterogeneity across different start-ups and common economywide developments, respectively. Start-up dummies, for example, account for important variables, such as founder characteristics (e.g., gender, personality), founding team size, initial resource composition, or industry time-invariant effects. Table 4 summarizes our data.

Measurement Validity

Key informant bias. To reduce key informant concerns, we preselected only senior-position respondents (e.g., founders, top-level executives), who should be qualified to answer strategic questions. According to their LinkedIn data, on average, respondents had 8.7 years of work experience, 3.6 years of industry experience, 1.2 years of marketing experience, and .72 years of sales experience. Moreover, key informant bias is unlikely, because most of our variables relate to each start-up's current situation and internal information, with a low level of abstraction. Key informants tend to evaluate such variables accurately (Homburg et al. 2012).

Table 4. Descriptive Statistics and Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Sales revenue[a]	1													
2. Number of customers[a]	.16	1												
3. Mass-media marketing expense ratio (%)	-.02	.31	1											
4. Personal sales expense ratio (%)	.01	.10	.17	1										
5. Venture age	.37	.19	-.10	-.07	1									
6. Product development focus	.04	-.20	-.27	-.25	.08	1								
7. Liquidity	.19	-.02	.05	-.11	.06	.10	1							
8. Number of investors	.10	.12	.12	-.03	.01	.03	.05	1						
9. Change founder team	.00	-.04	.07	.07	.00	.02	-.06	-.04	1					
10. Prizes won	-.05	-.04	.02	.06	-.10	.05	-.05	.01	-.02	1				
11. Industry start-up entries	.04	-.05	-.02	-.06	-.02	.12	.07	-.10	-.05	-.05	1			
12. Ind. Start-up closes-to-entries (%)	-.01	.11	-.02	-.05	.01	.01	-.04	-.03	.01	-.05	.08	1		
13. Industry concentration (%)	-.03	.08	.01	-.03	-.02	-.03	-.03	-.03	.06	-.07	-.06	.05	1	
14. Industry growth (%)	.05	.02	-.01	.06	-.05	-.03	.02	.01	-.10	-.09	.15	-.07	-.09	1
M	10.90	3.91	14.74	20.17	3.45	5.37	4.38	3.14	.10	.13	188.49	4.28	3.11	9.37
SD	4.07	2.13	12.27	14.16	2.30	1.71	1.62	6.58	.35	.40	159.56	3.92	5.07	3.67
Min	0	0	0	0	0	1	1	0	0	0	10	0	.18	-16.54
Max	17.62	9.9	90	95	11.8	7	7	150	3	3	539	24	43.63	26.39

Notes: Correlations with absolute values above .08 are significant at the 5% level. [a] log-transformed.

Common method variance (CMV). Threats of CMV were low. First, we investigated the effects of mass-media and personal sales expense ratios moderated by venture age; prior analytical and simulation studies show that CMV cannot create but can only deflate such interactive effects. Second, we separated the items used to measure the independent and dependent variables in the survey and avoided common scale properties (i.e., open-ended scales for the dependent variables and constant-sum scales [percentages] for mass-media and personal sales expense ratios). Third, evaluating the variables requires a low level of abstraction, which reduces CMV. Finally, start-up dummies and our instrumental variable strategy reduce CMV threats (Vomberg and Klarmann 2021).

Model Specification

We first considered a model that links start-up performance to mass-media marketing and personal sales expense ratios over time:

(1) $\mathbf{Perf}_{it} = \alpha_0 + \alpha_1\text{Mass-media Marketing}_{it} + \alpha_2\text{Personal Sales}_{it} + \alpha_3\text{VentureAge}_{it} + \alpha_4\text{Mass-media Marketing}_{it} \times \text{VentureAge}_{it} + \alpha_5\text{Personal Sales}_{it} \times \text{VentureAge}_{it} + u_{it}$,

where the coefficients α_1 and α_4 (α_2 and α_5) capture the effects of mass-media marketing (personal sales) expense ratios. Identifying these effects is challenging due to issues common in observational data. First, start-ups' expense ratios and performance may hinge on common economic developments; therefore, we included wave dummies. Second, heterogeneity among start-ups may explain different expense ratios and performance levels. For example, founders with greater social skills will likely approach customers more effectively (Homburg et al. 2014). Because many of these unobserved variables would remain time-invariant in our observation period, we incorporated start-up dummies to account for unobserved correlated heterogeneity. A significant Hausman test ($p < .01$; Wooldridge 2002) supported our modeling approach. Third, we included time-varying control variables:

(2) $\mathbf{Perf}_{it} = \alpha_0 + \alpha_1\text{Mass-media Marketing}_{it} + \alpha_2\text{Personal Sales}_{it} + \alpha_3\text{VentureAge}_{it} + \alpha_4\text{Mass-media Marketing}_{it} \times \text{VentureAge}_{it} + \alpha_5\text{Personal Sales}_{it} \times \text{VentureAge}_{it} + \boldsymbol{\alpha}\mathbf{Control}_{it} + \boldsymbol{\alpha\theta}_{\mathbf{t}} + \boldsymbol{\alpha\mu}_{\mathbf{i}} + \varepsilon_{it}$,

where Perf is a vector of performance variables (sales revenue and number of customers), Mass-media marketing (Personal Sales) indicates the respective expense ratios, Venture Age is the start-up's age, Control is a vector of control variables (specified previously), θ (μ) is a vector of wave (start-up) dummies, and ε is the residual error term for start-up i in wave t. Next, we refine our identification strategy by addressing several practical issues we faced.

Addressing Potential Selection Bias

We find no evidence challenging our sample's representativeness. Yet, selection biases in panel data can also stem from two other sources: panel attrition and item nonresponse (Elwert and

Winship, 2014), which reduce the number of cases available for analysis. Using Heckman's (1979) two-step model, we reduce the threat of panel attrition bias; we estimate the probability of panel attrition in the next wave (Attrition: 1 = "attrition in the next wave") with a probit model (Equation 3) that includes all variables from Equation 2 (first-stage estimation results are in Web Appendix E, Table E1). We then included the calculated inverse Mills ratio (IMR) in the main analysis. For identification, we used interviewer-assessed respondent discomfort (Discomfort; Web Appendix C), which satisfied both relevance and exclusion criteria—likely affecting the probability of remaining in the sample but not start-up performance.

According to literature on panel attrition, respondent burden in the prior wave affects next-wave participation. Respondent discomfort is an important source of respondent burden (e.g., Bradburn 1978; Kleinert, Christoph, and Ruland 2021). Less comfortable respondents are less likely to return (relevance criterion), which we corroborate empirically ($p < .01$). Although experiences during the prior survey may explain next-period attrition, such experiences should not influence start-ups' sales revenues or numbers of customers (exclusion criterion). Thus,

(3) $\text{Attrition}_{i(t+1)} = \delta + \delta \textbf{Focal Variables}_{it} + \delta \text{Discomfort}_{it} + \pi_{it}.$

We further addressed potential bias resulting from item nonresponse regarding sales revenue. Item nonresponse frequently occurs in survey-based research and can depend on organizational or survey-related factors (Vomberg and Klarmann 2021). In contrast with established, formalized firms, start-ups may struggle to obtain and provide relevant sales revenue data, and managers likely regard information about their sales revenues as sensitive. We again followed Heckman's (1979) two-step approach. In the first stage (Equation 4), we regressed item nonresponse (Nonresponse: 1 = "no information on sales revenue available") on the variables from Equation 2 (Web Appendix E, Table E2). We leveraged three respondent-related instrumental variables according to interviewers' assessments of respondents' confidence levels in their start-ups, fatigue during the survey, and how structured they appeared (Web Appendix C). The more confident respondents are in their start-ups, the more likely they are to report (even nonfavorable) performance variables. Moreover, more structured respondents are likely better prepared and more likely to collect information about the variables in advance. Respondent fatigue may decrease the willingness to answer. A joint chi-square test documents the strength of these instruments ($p < .01$), confirming the relevance criterion. Because all instruments focus on respondents in specific interviewer situations, they are theoretically unrelated to the dependent variable, satisfying the exclusion restriction. Therefore,

(4) $\text{Nonresponse}_{it} = \phi + \phi\textbf{Focal Variables}_{it} + \phi\text{Respondent Confidence}_{it} + \phi\text{Structured Respondent}_{it} + \phi\text{Respondent Fatigue}_{it} + \zeta_{it}$.

Addressing Potential Endogeneity of Mass-Media Marketing and Personal Sales Expenses

Control function approach. Although we account for time-varying control variables and wave and start-up dummies, an omitted variable bias could still pose endogeneity concerns. For example, a founder's expectation of performance levels from mass-media marketing and personal sales communication outcomes could determine a start-up's resource allocation decisions, thereby introducing a correlation with our model's error term. To address these concerns, we relied on a two-step control function approach (Petrin and Train 2010). We included residuals from the first stage (Equation 5) in the second stage (Equation 7) to correct for potential endogeneity. To obtain the residuals, we regressed the potentially endogenous variables (mass-media marketing and personal sales expense ratios) on the variables from our main model (Equation 2) and instrumental variables (Equation 5). The first-stage regression (without subscripts) is as follows:

(5) $\textbf{END} = \eta + \eta\textbf{END'} + \eta\textbf{Controls} + \eta\textbf{PWIV} + \eta\textbf{IMR} + \psi$,

where END (END’) is a vector of the potentially endogenous variables, excluding the focal one; Controls is a vector of the control variables, including wave and start-up dummies; PWIV is a vector of peer-weighted instrumental variables (specified hereinafter and in Web Appendix F); IMR is a vector of inverse Mills ratios (Equations 3 and 4); and ψ is a vector of the error terms. First-stage models for interactive effects are not necessary for the control function approach (Papies, Ebbes, and Van Heerde 2017).

Relevance criterion. Following prior marketing research (e.g., Germann, Ebbes, and Grewal 2015), we used weighted measures of *peer* (start-ups in the same one-digit SIC) firms as our sources of instrumental variables. Regarding criteria for instrumental variables, we argue that industry characteristics are key determinants of a start-up’s expenditure decisions (relevance criterion). According to the theory of institutional isomorphism (DiMaggio and Powell 1983), start-ups mimic industry standards and norms to gain legitimacy among customers and investors to overcome the liability of newness (Homburg et al. 2014). Thus, industry-aggregated measures of mass-media marketing and personal sales expense ratios likely influence a start-up’s expenditure decisions. If a start-up’s peers engage frequently in mass-media marketing activities, the start-up is also likely to spend more on such activities to gain legitimacy.

The first-stage auxiliary regression models demonstrate that peer-weighted industry mass-media and personal sales expense ratios are positively and significantly related to mass-media marketing (Web Appendix G, Table G1; $b_{\text{PW\_Mass-media Marketing}} = .47$, $p < .01$) and personal sales (Table G2; $b_{\text{PW\_Personal Sales}} = .49$, $p < .01$) expense ratios, respectively. Moreover, in both regression models, the Sanderson–Windmeijer F-statistics are highly significant (*p*s < .01). Both tests confirm the relevance of our selected instrumental variables.

We also assessed the possibility of weak instrumental variables. Weak instrumental variables are mainly problematic when many instruments are used (Rossi 2014), which does not apply in our case. For models with two potentially endogenous variables, the critical values for a 10% and 15% relative size bias are 7.03 and 4.58, respectively (Stock and Yogo 2002). The magnitude of the Sanderson–Windmeijer statistics (Web Appendix G, Table G1: F = 10.55; Table G2: F = 11.52) we observed is in line with previous studies (e.g., Manacorda and Tesei 2020) and shows that the chosen instruments reject the null hypothesis of weak instruments.

Exclusion criterion. The proposed instrument (i.e., the peer-weighted mass-media marketing and personal sales expense ratios) must not correlate with any omitted variables that are part of the error term to meet the exclusion criterion (Wooldrige 2002). As discussed above, the founders' individual performance expectations of mass-media marketing and personal sales communication may constitute an omitted variable. However, there are both substantive and empirical reasons against such correlation of the peer-based instruments with individual founders' performance expectations.

First, founders' performance expectations often stem from tacit entrepreneurial knowledge— the implicit, experiential insights entrepreneurs develop over time that are difficult to codify or communicate (Wuytens et al. 2022). As such, these expectations are typically difficult to articulate and externally validate. Since they are neither disclosed nor reliably inferred by outsiders, it is unlikely that peer firms are aware of a start-up's internal performance expectations—or that these expectations systematically influence their own expense decisions. This supports the validity of the exclusion restriction.

Second, even if peers somehow had access to this implicit knowledge, it should be unlikely that they would be able to coordinate their behavior in such a way that they could systematically mimic the performance expectations of a given start-up (see Germann, Ebbes, and

Grewal 2015 for a comparable argument). For a correlation between the peer-weighted instruments and the omitted variable to emerge, such coordination would be necessary. To illustrate: on average, we include 22 peer start-ups per focal start-up across all waves and industries (although this number varies due to panel attrition). Coordinated responses by 22 independent start-ups to the internal expectations of a single start-up should be highly implausible. Furthermore, these same start-ups would then need to repeat this coordination process for every other start-up in their industry. Prior research has also shown that coordination among peer firms to jointly monitor and emulate specific strategies of a particular firm is generally uncommon (Han, Mittal, and Zhang 2017).

Granularity criterion for peer instruments. In addition to the general requirements for instrumental variables (relevance and exclusion), peer instruments should exhibit sufficient variance, also called the instrument's "granularity" (Lim, Tuli, and Grewal 2020). The peer instruments must vary sufficiently at the start-up level, not just at the peer-group level.

Most researchers define peer groups on the basis of a single characteristic (e.g., the company's or the start-up's main industry or sector). Without further adjustments, this procedure would result in completely overlapping peer groups. If start-ups i and j are in the same group, their peers match, and without further adjustments, the two start-ups would receive the same instruments (lack of granularity). Shi, Grewal, and Sridhar (2021) show that such instruments cannot identify peer influence. Completely overlapping peer groups result in linear dependence between the endogenous and exogenous peer variables. To break down such linear dependence and thus increase granularity, researchers traditionally exclude the focal company from calculating the average value. However, the exclusion of a single start-up does not sufficiently increase the instrument variance (Lim, Tuli, and Grewal 2020). Thus, besides excluding the focal start-up, we use weighted relative values of the expense ratios, resulting in *partially* overlapping groups. Even if start-ups i and j operate in the same industry, their peer instruments differ on the start-up level given different weighting factors, thereby attenuating granularity concerns. Our approach follows that of Lim, Tuli, and Grewal (2020) and is similar in spirit to other approaches addressing granularity (e.g., Shi, Grewal, and Sridhar 2021). We define the peer-weighted instrumental variables (PWIV) as

$$(6)\quad PWIV_{it} = \frac{\sum_{1}^{Ps}[w_{i\,pst} \times IV_{pst}]}{\sum_{1}^{Ps} w_{ipst}},$$

where w_{ipst} is the weight of the relationship between the focal start-up i and peer start-up p in the Standard Industrial Classification– (SIC-) defined sector s at time t and IV_{pst} is the instrumental variable score of peer start-up p in SIC-defined sector s at time t.

We detail the operationalization of our weighted instruments along with illustrative examples of their measurement in Web Appendix F. We identify peer start-ups as those operating in the same one-digit SIC-sector. We chose on the one-digit level to allow for permeability across more fine grained industry boundaries when start-ups evolve. Within each sector, we position the focal start-up relative to its peers using the classic multidimensional scaling method (MDS). We use product- (e.g., product complexity), financial- (e.g., liquidity), and OLC-related metrics (e.g., venture age) to determine the similarities between start-ups, reflecting characteristics typically discussed in the start-up OLC literature (e.g., Kazanjian 1988; Kazanjian and Drazin 1989). Research shows that similar peers can exert a significant influence on the focal start-up (Hasan and Koning 2017; Hsu 2007). In abbreviated form, we determine the weights (Web Appendix F) based on the results from the MDS. Reassuringly, we find substantial variation in the peer-weighted mass-media marketing (M = 14.78; SD = 3.39; Min = 2.64; Max = 36.12) and personal sales expense ratios (M = 19.67; SD = 4.26; Min = 6.13; Max = 41.09) across SIC sectors (see also Web Appendix H).

Equation 7 represents our final model. We include the different IMRs (IMR vector, Equations 3 and 4) and the effects of the two residual error terms ($\hat{\boldsymbol{\psi}}$ vector, Equation 5).

(7) $\mathbf{Perf}_{it} = \alpha_0 + \alpha_1\text{Mass-media Marketing}_{it} + \alpha_2\text{Personal Sales}_{it} + \alpha_3\text{VentureAge}_{it} + \alpha_4\text{Mass-media Marketing}_{it} \times \text{VentureAge}_{it} + \alpha_5\text{Personal Sales}_{it} \times \text{VentureAge}_{it} + \boldsymbol{\alpha}\,\mathbf{Control}_{it} + \boldsymbol{\alpha}\theta_t + \boldsymbol{\alpha}\mu_i + \boldsymbol{\alpha}\mathbf{IMR} + \boldsymbol{\alpha}\hat{\boldsymbol{\psi}} + \varepsilon_{it}$.

Results

Model estimation. We employed the conditional mixed process routine (command CMP) in Stata (Roodman 2011), which falls in the maximum likelihood class of estimators. It allowed us to include different dependent variables and enabled a flexible error structure with cross-correlations among equations. We log-transformed the dependent variables. We mean-centered the predictor and moderator variables (e.g., Lim, Tuli, and Grewal 2020) to enhance the interpretability of the interactive effects. The variance inflation factors for all variables are less than 10, so multicollinearity is unlikely to be a concern; observed t-values and sample size further attenuate potential multicollinearity concerns (Mason and Perreault 1991).

We employed bootstrap to obtain standard errors that also account for the additional variation that arises from our use of estimates (i.e., IMRs from Equations 3 and 4 and $\hat{\boldsymbol{\psi}}$s from Equation 5). We use 500 bootstrap samples (Lim, Tuli, and Grewal 2020) to first obtain 500 sets of predicted IMRs (from the estimation of Equations 3 and 4) and control function residuals (from the estimation of Equation 5). We then use each set of IMRs and predicted residuals to estimate Equation 7 (Papies, Ebbes, and Van Heerde 2017). The bootstrap variance leads to conservative estimates and thus increases confidence in our results (Hahn and Liao 2021).

Main results. Table 5 presents the main results. We first report the unmoderated results addressing RQ1 (Models 1–3) and then discuss the moderated results to address RQ2 and RQ3 (Models 4–6). To provide a transparent view of our findings (Germann, Ebbes, and Grewal 2015), we report results without endogeneity corrections (Models 1 & 4), with IMRs (Models 2 & 5), and with control function corrections (Models 3 & 6). Overall, our results remain robust across different model-identifying assumptions.

We focus on the fully specified models (Models 3 & 6). The IMRs for panel attrition are significant for sales revenue and indicate positive selection effects (Model 3: $b_{\text{Attrition}} = .590$; $p < .01$). Start-ups that continue to respond in the panel systematically exhibit higher sales revenues than those that no longer respond. Thus, start-ups with higher revenues are disproportionately represented in the sample. Except for the marginally significant correction term of the personal sales expense ratio in Model 3 ($b_{\text{CF PSR}} = -.065$, $p < .10$), none of the remaining correction terms from the control function approach are significant in Models 3 and 6. Moreover, Models 3 and 6 demonstrate that incorporating these terms does not alter the substantive results.

Regarding the unmoderated effects, Model 3 shows that the personal sales expense ratio is positively related to sales revenues ($b_{\text{Personal sales}} = .030$, $p < .05$). All other unmoderated effects of the mass-media marketing and personal sales expense ratios are not significant. Model 3 does not show significant effects of the control variables, which is comparable to prior investigators (Homburg et al. 2014; Mintz and Lillien 2024) who only observed few significant control variables. Existing research suggests that founders' human capital may be a particularly important control variable (e.g., Honoré 2022); we account for this by modeling (significant) startup fixed effects. Moreover, our conservative identification approach using fixed effects, control function corrections, and bootstrapping leads to large standard errors (Germann, Ebbes, and Grewal 2015; Han and Liao 2021; Petersen 2008), In line with this explanation, we observe a few significant control variables in Model 2 which become non-significant in Model 3.

The interactive effects (RQ2 and RQ3), show that for the dependent variables, all but one effect of the mass-media marketing and personal sales expense ratios depend on the venture's age (Model 6). For the number of customers ($b_{\text{Mass-media} \times \text{Venture age}} = .006$, $p < .01$) the performance-enhancing effects of the mass-media marketing expense ratio grow stronger over a start-up's OLC, but the beneficial effects of the personal sales expense ratio become weaker over time, for sales revenue ($b_{\text{Personal sales} \times \text{Venture age}} = -.013$, $p < .05$) and number of customers ($b_{\text{Personal sales} \times \text{Venture age}} = -.005$, $p < .05$). The interaction between mass-media expenses and venture age on sales revenue is in the expected direction ($b_{\text{Mass-media} \times \text{Venture age}} = .005$; $p = .20$) but is only significant in Model 4. Overall, the effects of the mass-media marketing and personal sales expense ratios depend strongly on the OLC phase.

Floodlight analysis. We conducted floodlight analyses to examine the simple effects of the mass-media marketing and personal sales expense ratios on venture age (Figure 2). At the median value of venture age (50%-percentile), sales revenues increase more strongly with the personal sales expense ratio than the mass-media marketing ratio. The effect reverses for the number of customers, a pattern that aligns with our theoretical discussion: A larger customer base results from the network-broadening potential of mass-media activities. Yet the network-deepening aspect of personal sales activities explains the stronger effect on sales revenue; it leads to closer customer relationships and allows cross-selling.

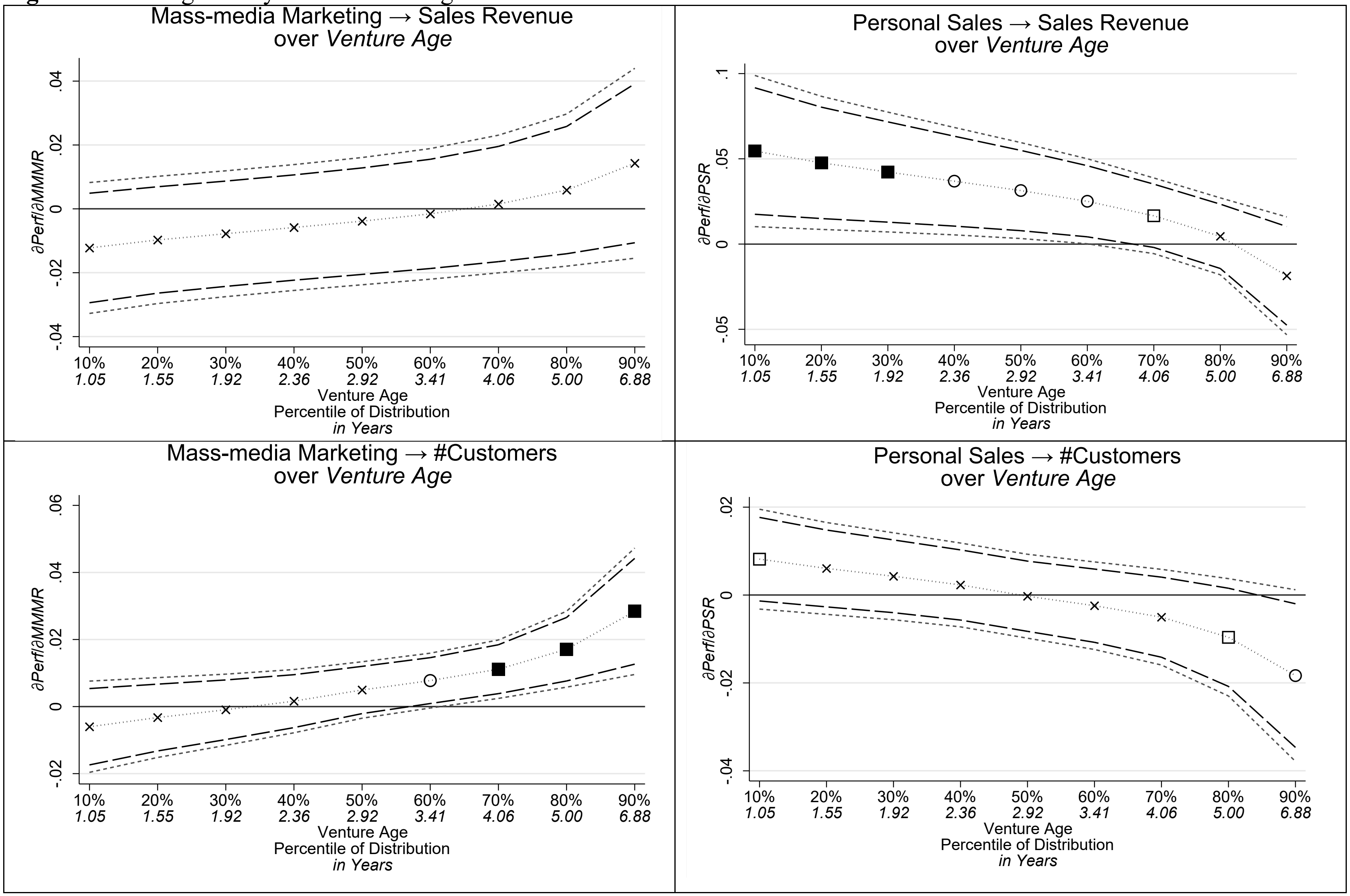
The relative effects of the expense ratios depend largely on the OLC. Both types of expense ratios can have positive and negative performance effects (yet the negative effects are mostly non-significant).

Table 5. Effects of Mass-media Marketing and Personal Sales Expense Ratios in the OLC

	Model 1: Unmoderated Results without IMR and CF		**Model 2: Unmoderated Results with IMR and without CF**		**Model 3: Unmoderated Results with IMR and CF**		**Model 4: Moderated Results without IMR and CF**		**Model 5: Moderated Results with IMR and without CF**		**Model 6: Moderated Results with IMR and CF**	
	Sales Rev.	#Customers	Sales Rev.	#Customers	Sales Rev.	#Customers	Sales Rev.	#Customers	Sales Rev.	#Customers	Sales Rev.	#Customers
MMMR	-.009 (.008)	.003 (.006)	-.008 (.012)	.003 (.006)	-.011 (.013)	.003 (.005)	-.002 (.008)	.008 (.004)*	.000 (.013)	.008 (.004)**	-.001 (.014)	.008 (.004)**
PSR	.030 (.012)**	.002 (.005)	.030 (.015) **	.002 (.004)	.030 (.015)**	.003 (.004)	.026 (.012)**	-.004 (.005)	.026 (.014)*	-.004 (.004)	.024 (.015)*	-.003 (.004)
Venture age	2.338 (.935)**	.622 (.337)*	1.457 (.995)	.648 (.307) **	1.259 (1.150)	.915 (.505)*	2.295 (.943)**	.573 (.320)*	1.374 (1.000)	.585 (.298)**	1.031 (1.204)	.814 (.474)*
MMMR × age							.003 (.002)*	.006 (.003)**	.003 (.003)	.006 (.002)***	.005 (.004)	.006 (.002)***
PSR × age							-.011 (.006)*	-.005 (.002)**	-.012 (.006)**	-.005 (.002)**	-.013 (.006)**	-.005 (.002)**
Controls												
Product focus	-.209 (.119)*	-.009 (.029)	-.215 (.124) *	-.009 (.028)	-.123 (.160)	-.030 (.059)	-.179 (.120)	-.003 (.029)	-.183 (.123)	-.003 (.027)	-.069 (.167)	-.018 (.056)
Liquidity	.194 (.123)	-.036 (.046)	.163 (.133)	-.036 (.044)	.149 (.163)	-.066 (.068)	.203 (.122)*	-.038 (.045)	.182 (.134)	-.038 (.043)	.179 (.171)	-.064 (.064)
Number of investors	.038 (.039)	.014 (.016)	.047 (.070)	.014 (.016)	.042 (.078)	-.003 (.026)	.045 (.039)	.014 (.016)	.054 (.072)	.014 (.017)	.055 (.081)	.000 (.025)
Change founder team	-.027 (.463)	.621 (.376)*	.135 (.707)	.621 (.403)	.384 (.883)	.421 (.458)	.092 (.450)	.689 (.381)*	.221 (.699)	.690 (.409)*	.553 (.890)	.518 (.454)
Prizes won	.719 (1.152)	.134 (.266)	.701 (1.103)	.125 (.183)	.653 (1.194)	.180 (.225)	.711 (1.166)	.165 (.260)	.714 (1.126)	.158 (.175)	.640 (1.249)	.205 (.212)
Industry start-up entries	-.003 (.007)	.001 (.002)	.001 (.007)	.001 (.001)	.005 (.010)	.000 (.004)	-.002 (.007)	.001 (.002)	.002 (.007)	.001 (.001)	.007 (.011)	.001 (.004)
Industry start-up closes-to-entries	-.027 (.058)	.015 (.029)	-.019 (.074)	.016 (.023)	-.006 (.096)	.015 (.036)	-.027 (.056)	.009 (.028)	-.012 (.073)	.010 (.022)	.002 (.098)	.011 (.035)
Industry concentration	.098 (.100)	-.045 (.030)	.124 (.122)	-.047 (.024) *	.150 (.169)	-.017 (.056)	.105 (.102)	-.049 (.030)	.136 (.125)	-.050 (.025)**	.159 (.179)	-.023 (.053)
Industry growth	-.087 (.103)	.026 (.040)	-.104 (.110)	.028 (.032)	-.124 (.136)	.038 (.052)	-.104 (.103)	.025 (.038)	-.124 (.113)	.026 (.031)	-.155 (.144)	.033 (.049)
$IMR_{Nonresponse}$			-.511 (1.675)		-.608 (1.755)				-.260 (1.672)		-.296 (1.762)	
$IMR_{Attrition}$			.564 (.164)***	-.014 (.048)	.59 (.191)***	-.013 (.079)			.594 (.163)***	-.007 (.048)	.620 (.199)***	-.006 (.074)
CF MMMR					.082 (.143)	.015 (.071)					.084 (.154)	.016 (.065)
CF PSR					.056 (.082)	-.065 (.039)*					.082 (.094)	-.054 (.037)
Wave & start-up dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. (#Start-Ups)	407 (210)	598 (265)	407 (210)	598 (265)	407 (210)	598 (265)	407 (210)	598 (265)	407 (210)	598 (265)	407 (210)	598 (265)
Log-likelihood	-1,219.22		-1,215.51		-1,209.21		-1,208.90		-1,204.89		-1,199.48	

*** $p < .01$; ** $p < .05$; * $p < .10$ (two-tailed tests). *Notes:* MMMR = mass-media marketing expense ratio. PSR = personal sales expense ratio. We report unstandardized coefficients. Continuous variables are mean-centered to ease the interpretation of interaction effects. SE = bootstrap standard errors derived from 500 bootstrap replications (except in Models 1 & 4: these models contain no calculated endogeneity corrections; thus, SEs are clustered at the start-up level). We estimated the models using multiple equation CMP in Stata. Models 2, 3, 5, and 6 account for item nonresponse on “sales revenue” and panel attrition with inverse Mills ratios (IMRs). Model 3 and Model 6 include control function (CF) corrections for the mass-media and personal sales expense ratios.

Figure 2. Floodlight analysis of moderating effects.



■ $p < .01$; ○ $p < .05$; □ $p < .10$; × $p > .10$ (one-tailed tests). Long-dashed and short-dashed lines represent the 90% and 95% confidence intervals, respectively (two-tailed tests).

Notes: MMMR = mass-media marketing ratio; PSR = personal sales ratio. We base the plots on Model 6 in Table 5. Venture age is the horizontal axis: It ranges from the 10th percentile to the 90th percentile in our dataset. It also shows the raw values of the venture ages scores, i.e., before applying any variable transformations. The vertical axis is the marginal effect of MMMR (or PSR) on the dependent variables.

For personal sales, we first observe positive effects on sales revenue and the number of customers in earlier stages and then observe negative effects. This pattern reverses for mass-media marketing: Positive effects in terms of the number of customers emerge only in later OLC stages, affirming the need to distinguish between mass-media marketing and personal sales expenses when predicting their performance effects.

Robustness Checks

As we detail next, important robustness checks consistently confirm our main findings. Overall, the effects of the mass-media marketing and personal sales expense ratios depend on the OLC.

OLC-stage measurement. In Web Appendix I, we report the analyses with alternative OLC-stage markers. In addition to venture age (main analysis), we rely on venture popularity (e.g., Hite and Hesterly 2001; we employ Google trends data), venture size (e.g., Winkler, Rieger, and Engelen 2020), and a venture development index. These alternative measures widely replicate the pattern of our results (see Table 6 for an overview). Here, we even observe significant positive interactive effects between the mass-media marketing expense ratio and the OLC measures for sales revenues. Because the measures explore different facets of the OLC but provide largely consistent results, they strongly support the validity of our findings.

Table 6. Interaction Effects with Alternative OLC Markers

	Sales Revenue	#Customers
M1: Personal sales exp. x Venture popularity	**-.0014****	**-.0004****
M2: Personal sales exp. x Venture size	**-.014****	**-.009*****
M3: Personal sales exp. x Venture development index	**-.075****	**-.020****
M1: Mass-media marketing exp. x Venture popularity	**.0022****	**.0009*****
M2: Mass-media marketing exp. x Venture size	**.013***	**.024*****
M3: Mass-media marketing exp. x Venture development index	**.109****	**.090*****

***$p < .01$; **$p < .05$; *$p < .10$ (one-tailed tests). Notes: All models (M1–M3) include controls and endogeneity corrections (see Model 6, Table 5); significant effects ($p < .10$) are in bold.

Peer-weighted Instruments. Further, we alternatively use a distance measure to weigh the peer instruments, as geographically closer start-ups influence each other more than more distant ones (Raz and Gloor 2007). The robustness check replicates our results (Web Appendix J).

Discussion

Theoretical Implications

Building and maintaining customer relationships is vital to firms' stability and prosperity (e.g., Palmatier, Scheer, and Steenkamp 2007). High-tech start-ups have great difficulties explaining their value to customers, who may not understand the benefits offered by the start-ups' innovative products. The two instruments crucial to meeting this challenge—mass-media marketing and personal sales communications—both serve to build successful customer relationships (e.g., Rouziès et al. 2005). To extend the literature on entrepreneurship and marketing, we disentangle the impact of spending a larger share of the budget on mass-media marketing and personal sales activities on start-ups' performance. Our panel regressions, which are robust for various specifications and operationalizations, show that while a higher mass-media marketing expense ratio tends to increase start-up performance in later OLC stages, a higher personal sales expense ratio particularly promotes start-up performance in earlier stages.

Prior research on entrepreneurial marketing agrees that marketing activities can help boost start-ups' success (e.g., DeKinder and Kohli 2008), but empirical literature has not clearly distinguished expenses on personal sales versus mass-media marketing activities. Other fields unrelated to start-ups (e.g., marketing organization, marketing innovation) prominently note the organizational differences between the marketing and sales function in general (e.g., Ernst, Hoyer, and Rübsaamen 2010). In line with this seminal research, our results underline the distinct effects of mass-media marketing and personal sales expense ratios for B2B high-tech start-ups' success, pointing to the critical need to disentangle these market activities.

With regard to expenses on personal sales activities, we build on prior research that implies their relevance in high-complexity contexts (Alavi et al. 2021), customer relationships (e.g., Tuli, Bharadwaj, and Kohli 2010), and start-ups (e.g., De Jong, Zacharias, and Nijssen 2021). We offer unique empirical evidence that spending a larger share of a B2B high-tech start-up's limited budget on personal sales activities can have a decisive impact on its development, but most significantly in early stages and less in later stages. Similarly, we extend entrepreneurial studies emphasizing the importance of (mass-media) marketing communication activities (e.g., Anderson et al. 2021; Song et al. 2008) and customer relationship management research emphasizing the importance of multiple ties in dynamic environments (Tuli, Bharadwaj, and Kohli 2010). Our findings demonstrate that both mass-media marketing and personal sales are crucial for B2B high-tech start-ups as they progress through their OLC. We also show that the effectiveness of these activities varies across different OLC stages, highlighting the need for start-ups to align their budgets with their respective OLC stages. However, we do not determine which specific mass-media marketing and personal sales activities are most effective in which OLC stages—this remains an avenue for future research.

Unlike previous research, we go beyond the beneficial effects of expenses on personal sales and mass-media marketing activities and identify ambivalent effects on different facets of start-up performance. These findings are novel, as while prior research has uncovered the positive effects of general marketing activities in start-ups, it has not differentiated expenses on mass-media marketing and personal sales communications and uncovered negative effects. Although we did not fully anticipate this effect pattern, we arrive at some post hoc rationalizations for these negative effects. Because start-ups face resource scarcity, particularly in their early stages (Kazanjian 1988), excessive financial expenses on mass-media marketing communications in these phases may subtract financial resources from areas vital to start-up performance. Past entrepreneurial research indicated the particular danger for start-ups to misallocate budgets (e.g., Lee and Kim 2024). A start-up's growth may shift out of balance, resulting in opportunity costs. Especially in the B2B high-tech context, effective new product development assumes an existential role and may require extensive resources (Homburg et al. 2017). Furthermore, a higher mass-media marketing expense ratio may prove detrimental if excessive mass-media activities attract an influx of customers prematurely. In our preliminary interviews, founders noted that if products are not adequately prepared for the market or firms lack the capacity to handle a large customer base, such higher expenses on mass-media marketing communications may backfire. Future research should explore, in more detail, the conceptual mechanisms underlying such potentially adverse effects for start-ups.

Limitations and Further Research

The limitations of our study offer opportunities for further research. First, since we focus only on the first stages of start-ups and do not examine their progression into mature firms, our findings cannot speak to how mass-media marketing and personal sales affect performance in advanced life-cycle stages. Without early-stage resource constraints, expenses on mass-media marketing activities could become even more vital to reaching the mainstream market and developing into established firms (Yli-Renko and Janakiraman 2008). Further research could explore the role of start-ups' mass-media marketing and personal sales communications in more advanced stages of development, at the transition between start-up and mature firm.

Relatedly, we collected our data during relatively stable periods. However, various factors, such as economic crises (e.g., financial crises), security catastrophes (e.g., terrorist attacks), weather catastrophes (e.g., floods), policy reforms (e.g., data protection regulations), and public health emergencies (e.g., the COVID-19 pandemic), can rapidly alter the start-up ecosystem. These changes can significantly impact end-customer behavior, potentially delaying purchases or increasing price sensitivity, making customer acquisition more challenging for B2B high-tech start-ups (Hartmann et al., 2024). Yet, these changes may also present opportunities for start-ups, as established companies may become more receptive to agile solutions enabled by start-ups' offerings (Kalaignanam et al. 2021). Therefore, we urge future research to investigate the strategies and dynamics of B2B high-tech start-ups during such extraordinary circumstances.

Last, because far less data exist on start-ups in external databases than on mature companies, studying them is difficult. We used a self-collected longitudinal survey data set; however, surveys can lead to systematic biases (Vomberg and Klarmann 2021), such as key informant bias. Although our survey design and analytical strategy safeguard against many potential biases, we call for replications of our study with secondary data when such data becomes available. Investigators could match primary survey with secondary archival data. In addition, we focus on key performance metrics suggested by start-up research (i.e., sales revenues, number of customers). Thus, future research could incorporate cost-related performance metrics to test the effect of marketing and sales expenses on start-ups' profitability.

Managerial Implications

Start-ups must spend their budget carefully, as over 90% of start-ups fail (Startup Genome, 2019), largely due to ineffective mass-media marketing and personal sales efforts (CB Insights 2019). For more than 77% of the start-ups in our preliminary survey, setting proper individual expenses on mass-media marketing and personal sales activities at different stages of start-ups' lifecycles is critical to their survival. In addition, our interviews showed that many start-ups lack awareness of the importance of marketing communications, particularly activities of mass-media marketing and personal sales. To enhance start-up managers' awareness and understanding of the performance impacts of their mass-media marketing and personal sales expenses, we illustrate the economic importance of our findings in Table 7. This quantification can also support external communication with investors. In the start-up context, evaluations of the effectiveness of strategic decisions can be difficult due to the lack of established success metrics (Mintz and Lilien 2024). Table 7 can help start-up managers in their communication with external investors.

First, our findings imply that a higher personal sales expense ratio accelerates high-tech start-up development because personal sales communications can establish deep personal relationships with customers. Personal communication activities are especially important at the beginning of high-tech start-ups' OLCs. Despite their scarce resources at this stage, start-ups should spend part of their budget on personal sales communications to develop initial, close networks with customers. By increasing the personal sales expense ratio by 10 percentage points in earlier stages (Table 7), start-ups can substantially increase their sales revenue (US$291,903.25). The increase in the number of customers is 29.76 but not significant.

Table 7. Marginal Effects of Mass-media Marketing and Personal Sales Expense Ratios on Start-Up Performance Across the OLC.

	Marginal Effects			
	Sales Revenues		**#Customers**	
	In %	**ΔUSD**	**In %**	**ΔCust.**
Mass-media Marketing Expense Ratio				
Early OLC	-9.17	-56,603.80	-0.80	-5.72
Late OLC	0.94	5,801.79	**12.01*** **	**85.91**
Personal Sales Expense Ratio				
Early OLC	**47.27***, [a]**	**291,903.25**	4.16	29.76
Late OLC	**18.34***	**113,247.26**	-5.63	-40.29

****p* < .01; ***p* < .05; **p* < .10 (one-tailed tests)

Notes: We indicate increases in mass-media marketing and personal sales expense ratios of ten percentage points. Early OLC (Late OLC) = the marginal effects of the mass-media marketing and personal sales expense ratios in the early (late) OLC. Here, early (late) means the venture age is the 30% (70%) percentile of our observed data range. We multiply the marginal effects by 100 to facilitate interpretation. We derive the changes in dollar value (ΔUSD) and number of customers (ΔCust.) by multiplying the marginal effects by the average start-up within the respective samples. We calculate the marginal effects using the results from Table 5 before mean-centering; significant marginal effects ($p < .10$, one-sided) are in bold.

[a]While +47% additional sales revenue may appear large at first glance, this magnitude reflects the relatively low absolute sales revenues in the early OLC stage of start-ups. Considerable increases in sales revenues can be achieved in this stage through the acquisition of a few reference key accounts (Kazanjian 1988).

Second, to achieve market growth and expand their customer base, start-ups should spend a higher proportion of their budget on mass-media marketing activities in later stages. Increasing the mass-media marketing expense ratio by 10 percentage points corresponds to acquiring an additional 85.91 customers (Table 7), demonstrating the effectiveness of expenses on mass-media marketing activities in broadening a start-up's customer base.

However, we also caution managers against spending excessive shares of their restricted budget on mass-media marketing or personal sales activities, as this may leave insufficient financial resources for other vital activities, such as product development. When investing in mass-media marketing and personal sales activities, managers should carefully consider their start-ups' OLC stages and the full spectrum of potential expenditures their firms face. Notably, we do observe that in later OLC stages, a higher personal sales expense ratio is associated (although not significantly) with a reduction in the number of customers (-40.29). Our interviews suggest that personal sales primarily deepen relationships with selected customers, which may explain why an increased personal sales expense ratio relates to a narrower customer base.

Start-ups must evaluate the strategic significance of this effect with nuance. The number of customers acquired is an important growth target. However, we also observe a positive effect on sales revenue during this stage (US$113,247.26), indicating that a higher personal sales expense ratio may allow start-ups to serve fewer but more valuable customers. Given that start-ups must simultaneously pursue multiple growth objectives, our findings do not imply that they should avoid personal sales expenses in later OLC stages. Instead, they should balance customer breadth with revenue goals to align with their strategic priorities.

Appendix. Measurements

Dependent Variables	**Data Source**
Sales Revenue [a] • What was your sales revenue in the prior year?	**Panel survey**
Number of Customers [a] • How many customers do you have in total?	**Panel survey**
Independent and Moderating Variables	
We provided respondents with the following definitions: *"'Marketing' refers to activities of customer communication that are not of personal nature; 'Sales' refers to activities geered towards personal contact and communication with customers and investors"*	
(Mass-media) Marketing Expense Ratio[a] (adapted from Fang, Palmatier, and Grewal 2011) • What percentage of your total budget do you invest on average per month in marketing activities? (0–100%)	**Panel survey**
(Personal) Sales Expense Ratio[a] (adapted from Fang, Palmatier, and Grewal 2011) • What percentage of your total budget do you invest on average per month in sales activities? (0–100%)	**Panel survey**
Venture Age [a] • Difference between date of founding and survey wave in years	**Panel survey**
Control Variables (Time-variant)	
Degree of Product Development Focus [b (κ: .73), 1] • I rate this start-up's prioritization of product development as high.	**Panel survey**
Liquidity [a] • How high do you estimate the liquidity of your start-up? (1–7 scale; 1 = "low liquidity/significant financial bottlenecks," 7 = "high liquidity/substantial liquid funds available")	**Panel survey**
Number of Investors [a] • How many investors have you already attracted to your company?	**Panel survey**
Change Founder Team [a] • In the past quarter, there was a major change in the founding team.	**Panel survey**
Prizes Won [a] • In the past quarter, we won important prizes.	**Panel survey**
Industry Start-Up Entries • Number of start-up entries per industry	**Crunchbase**
Industry Start-Up Closes-to-Entries • Ratio: Number of start-up closes to number of start-up entries	**Crunchbase**
Industry Concentration • Herfindahl–Hirschman index: sum of squared market shares	**Amadeus**
Industry Growth • Five-year average industry sales growth	**Amadeus**
Additional Variables - Figure 1	
Product Development Expense Ratio [a] (adapted from Fang, Palmatier, and Grewal 2011) What percentage of your total budget do you invest on average per month...in product development activities? (0–100%)	**Panel survey**
Operation Activities Expense Ratio [a] (adapted from Fang, Palmatier, and Grewal 2011) What percentage of your total budget do you invest on average per month...in operation activities? (0–100%)	**Panel survey**
Other Activities Expense Ratio [a] (adapted from Fang, Palmatier, and Grewal 2011) What percentage of your total budget do you invest on average per month...in other activities? (0–100%)	**Panel survey**

[a] Founders of start-up, [b [κ]] Interviewer: Cohen's kappa κ based on 20% of data per survey wave. We compared interviewer ratings with ratings of a second independent rater, who received the same training as the interviewer and listened to the recorded survey interviews.
[1] 1 = "totally disagree"; 7 = "totally agree."

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The Different Effects of Mass-Media Marketing and Personal Sales Budgets Across the Life Cycle of B2B High-Tech Start-ups

Web Appendices

Web Appendix A: Preliminary Studies

Qualitative In-Depth Interviews with 15 B2B High-Tech Founders

To acquire the interview candidates for the preliminary study, we approached a diverse set of founders of B2B high-tech start-ups, identified from a national start-up database. In preparation for the interviews, we informed the candidates about the topic and general outline of the interviews and asked for permission to record them. All interviews were conducted by telephone and recorded and transcribed verbatim. Table A1 presents the sample.

Table A1. Sample for Qualitative Interview Study

No.	Interview Duration (min.)	Industry	Start-Up Age (years)	Position	Gender	Age	Experience (years)		
							Start-Ups	Sales	Marketing
1	28	Software/SaaS (cybersecurity)	3	Founder and CEO	Male	30	6	10	10
2	44	Professional services (HR services)	10	Founder and CEO	Male	38	12	10	11–12
3	36	Construction (property tech)	1	Chief revenue officer	Male	31	2	9	9
4	27	Professional services (HR services)	7	Senior manager	Female	32	6	8	12
5	24	Industrial services (3D printing)	2-3	Founder and CEO	Male	31	5	4-5	0-1
6	37	Software/SaaS (cybersecurity)	3	Founder and CEO	Male	28	4-5	1-2	2
7	38	Software/SaaS (light control)	5	Founder and CEO	Male	36	5	12	12
8	24	Software/SaaS (construction)	1	Founder and CEO	Male	41	7	12	4–5
9	25	Software/SaaS (CRM software)	6	CSO	Male	41	8	14	8
10	21	Software/SaaS (HR services)	4-5	Founder, board adviser	Female	37	13	13	19–20
11	19	IT (RFID technology)	5	CEO	Male	56	5	30	30
12	39	Professional services (M&A)	5	CMO	Male	32	7	4	6
13	29	Industrial services (logistics)	5-6	CEO	Male	50	10	8-9	10
14	41	Software/SaaS (cybersecurity)	6	CSO	Male	44	2	13	8
15	21	Energy (solar technology)	5	Founder and CEO	Male	52	16	22	16

The semistructured interview guide (Table A2) consists of four parts. We began the interviews with an initial warm-up question about the start-ups' business model and current development. In Part I, we then asked the founders to describe all their marketing and sales functions, activities, and targets in detail. First, we asked an open-ended question about the role of marketing and sales in founders' start-ups without explicitly requiring them to differentiate between both functions. The open-ended nature of the question served to unpack the interviewees' own understanding of marketing and sales in their organization and to prevent biasing them unduly in either direction. Second, we asked interviewees to deliberately contrast the roles of (1) marketing and (2) sales. The purpose of this question (and secondary questions) was to let respondents themselves contrast the two functions and to capture their rationales for differentiation ("Why do you think these activities are more 'sales'?"). Note that for questions in Parts II and III, we refrained from deliberately repeating the question for each of the functions, to keep the interview flowing and prevent repetitive elements.

Part II of the interview guide included questions about core challenges in the B2B high-tech market and the particular value of marketing and sales activities. In Part III, we specifically asked about the value of marketing and sales during start-ups' OLC. We encouraged the founders to describe their past experiences, outlook for the future, and planned activities. The interview guide ended with Part IV on demographic questions. We also iteratively added questions during the course of the study to challenge and advance the preliminary findings and continued the interviews until we reached theoretical saturation (e.g., Zeithaml et al. 2020). For example, we added specific questions to challenge findings from previous interviews, such as the beneficial role of sales activities in start-ups' early OLC.

We analyzed the transcripts by coding the statements by the underlying themes, as is common practice in qualitative research (e.g., Macdonald, Kleinaltenkamp, and Wilson 2016). In the first step, two experienced researchers (not part of the author team, independent research assistants with >2 years of experience in analyzing qualitative data material) separately coded each interview line by line. Second, one of the authors with a high degree of experience in qualitative data analysis synthesized the results of the initial codings. Finally, we asked two independent marketing researchers (not part of the author team) to judge and validate the codes assigned to key quotes.

Table A2. Interview Guide

Warm-Up Question Please briefly describe the business model and the current development of your start-up.
Part 1: Marketing and Sales in Start-Ups: • What is the role of sales and marketing in start-up companies? • In the following, we deliberately contrast marketing and sales. What are the (different) roles of sales and marketing in your start-up? - Which of your activities would you assign to marketing? Why do you think these activities are more "marketing"? What are the targets of your marketing activities? - Which of your activities would you assign to sales? Why do you think these activities are more "sales"? What are the targets of your sales activities?
Part 2: Challenges in Complex B2B Markets • What are the particular challenges of start-ups in sales and marketing in your area? • What role do sales and marketing activities play when a start-up offers very complex high-tech goods or services? What is their value? • Looking back on your experience in your start-up and in your industry, what mistakes do you observe in the marketing and sales area? • Do you see differences to start-ups in other areas, such as start-ups with a clear B2C focus?
Part 3: Start-ups' OLC Thinking about the development of a start-up over time: • Have you adjusted your sales and marketing activities in the past? Will you adjust your sales and marketing activities in the future? (How? Why?) • Are there phases in which either sales or marketing is particularly important? (In which phases? Why?) • Provocative question: Experts claim that one of the two functions is particularly important at the beginning of the start-up, which one could it be? (Why?)
Part 4: Ending/Demographics: • Some researchers claim that sales and marketing are the same thing in start-ups. What do you think? • What is your age? • What is your gender? • How would you describe your position in the start-up? • How many years of experience do you have with start-ups? • How many years of experience do you have with marketing? • How many years of experience do you have with sales? • How long does your start-up exist? • In which industry is your start-up operating?

Quantitative Preliminary Survey Among 81 High-Tech Founders

We conducted a new survey with start-up founders to validate our differentiation of mass-media marketing and personal sales activities. Initially, we intended to recruit 100 start-up founders in the United Kingdom across high-tech industries through Prolific. We prescreened respondents such that they needed to be founders of a start-up and to operate in B2B high-tech industries. Respondents received £2 for taking part in the survey. We excluded 19 responses from analysis because respondents either failed the attention check or their start-ups were too old (>10 years since founding) to be interpreted as start-ups by common standards (e.g., Winkler, Rieger, and Engelen 2020). Table A3 provides an overview of the sample composition.

Table A3. Sample Composition

Respondents Characteristics	Average
Age	38.04 years
Female/male/N.A.	37%/60.5%/2.5%
Sales experience	6.6 years
Marketing experience	4.9 years
Venture age	2.4 years
Founder team size	3.5 founder
Venture size (no. of employees)	54.3 employees

Following our qualitative in-depth interviews, the goals of this preliminary survey were to track which specific activities founders typically assign to either the mass-media marketing or personal sales function and to provide validation for our definitions. In the first part of the survey, we therefore asked respondents to recall their start-ups' customer relationship activities without prompt and predefined categories. We then asked them to categorize their activities into a predefined longlist of activities we derived from the in-depth discussions with founders during the qualitative interviews and from the literature. Last, we asked them to self-prioritize these activities according to the importance for their business. In the second part of the survey, we presented respondents with our definitions of mass-media marketing and personal sales activities and asked them to evaluate, for each of the predefined categories, whether these correspond more to the one or the other. We then asked them to assess the importance of differentiating mass-media marketing and personal sales according to our definition in the high-tech start-up context. Next, we asked respondents to evaluate typical characteristics of their start-up and industry (e.g., average age at different OLC stages). We collected demographic characteristics at the end (e.g., age, gender, experience).

Web Appendix B: Quantitative Survey: Sampling Frame and Interviewer Training Process

Sampling Frame

After defining the target sample (B2B high-tech start-ups), we conducted several consecutive steps to develop our final sampling frame (Figure B1).

Figure B1. Development of sampling frame for the B2B high-tech start-up panel.

Step of sampling frame development	Procedure
Conceptualization of target group for research	
1. Identification of relevant population of B2B high-tech in target country	Examination of nationwide, annual *panel of founders* on economic boundary conditions and infrastructure per region, sector and industry
2. Primary generation of reliable longlist with active, relevant individual B2B high-tech start-ups	Screening of participants and members of *government and academic initiatives* to promote start-up, such as (state-sponsored) B2B networking trade fair, innovation networks, governmental funding programs and founders' competition
3. Supplementation of longlist with further B2B high-tech start-ups	Screening of contributors to *(nongovernmental) online and offline start-up communities*, such as influential news websites of the national start-ups scene, as well as press releases
4. Validation of final longlist of B2B high-tech start-ups	Examination of publicly available information from company databases, websites, and news to *validate information* on start-ups' industry, age, active status, and target market and *prescreen* potential survey participants
5. Complementation of contact details for longlist of B2B high-tech start-ups	Complementation of (missing) contact information of founders by direct search of social media profiles (LinkedIn, Xing), start-ups' websites, and search engines

First, we worked to identify the relevant population of B2B high-tech start-ups in the target country (Germany). We reviewed a nationwide panel survey (organized by a registered association and interest group) of founders, start-up trends, and start-ups' economic and infrastructural boundary conditions to identify potential regional clusters of B2B high-tech start-ups and relevant sectors. Second, to generate a comprehensive, reliable longlist of relevant and active B2B high-tech start-ups, we drew on information from governmental and academic initiatives to promote start-ups in Germany. In detail, we screened (1) members of regional innovation, digitalization, and science networks that promote cooperation between high-tech start-ups and established high-tech firms, under the auspices of the federal ministry of economics; (2) attendees at the largest, nationwide annual networking trade fair for B2B start-ups, supported by the state; (3) participants in a nationwide founders' competition; (4) lists of members of regional and superregional chambers of commerce and industry; (5) entries in a governmental database intended to connect founders with potential investors, organized by the federal ministry of economics; and (6) participants in start-up funding programs run by state-owned banks. Third, not all relevant start-ups participate in academic or governmental support programs, so we also screened nongovernmental online and offline start-up communities, including influential news websites that profile newly founded start-ups and press releases by a business angel community. Fourth, we validated the final longlist and prescreened potential respondents by examining publicly available information about the start-ups' industry, age, active status, and target markets. We relied on company databases, start-ups' websites, and news (search engines) to gather this information. Fifth, we addressed any missing contact information by searching founders' social media profiles, start-ups' websites, and search engines.

Interviewer Training Process

The professional telephone interviewers had start-up business experience. To improve the quality of the telephone survey and make it as reliable as possible, we implemented an intensive training process with all interviewers during a one-day workshop. We repeated this training for each of the four panel waves because we could not employ the same interviewers for all waves.

The training covered two basic topics: (1) operative data collection procedures and (2) knowledge of start-up concepts. First, we developed a systematic data collection process involving preparation for the interview, contacting the start-up, documenting the results, and performing quality control and verification checks of the results. In the training, we extensively discussed and practiced this process with all interviewers. For realism and to ensure the quality of the process, we also simulated telephone surveys in role-play exercises. During the workshop, interviewers conducted practice telephone surveys, with specific efforts to help them learn how to handle and resolve founders' uncertainties. We carefully instructed the interviewers on how we needed them to document the responses.

Second, to ensure their sufficient knowledge of start-ups, we trained the interviewers on potential business models and market environments for B2B high-tech start-ups. These lessons centered on information about different start-up types, key performance indicators for start-ups, and the different stages of the OLC. Moreover, we discussed various marketing and sales activities with interviewers, to give them an in-depth understanding of pertinent practices.

To test for reliability of interviewer ratings, we had a second, independent rater rerate start-ups' development from the interview recordings. This independent rater received the same training as the interviewers and rerated 20% of the interviews per each survey wave. As Web Appendix C (measurement table) shows, this additional check yielded acceptable values for interrater reliability (Cohen, 1960), confirming the reliability of our interviewer ratings.

Web Appendix C: Measurements of Instrumental Variables for the Selection Models

Variables for Potential Panel Attrition Bias	IR	κ
Respondent Discomfort [1, a]	N.A.	.75
• The entrepreneur made an uneasy impression.		
Variables for Potential Item Nonresponse Bias		
Respondent Confidence [1, a]		
(CA = .93, CR = .93, AVE = .82)		
• The entrepreneur seemed very confident about the start-up.	.85	.80
• The entrepreneur made a very confident impression when talking about the success of the start-up.	.84	.81
• The entrepreneur seemed very convinced of his/her plan.	.76	.78
Structured Respondent [1, a]		
(CA = .93, CR = .93, AVE = .81)		
• The entrepreneur appeared very structured.	.80	.75
• The entrepreneur communicated very clearly.	.85	.69
• The entrepreneur formulated at a high linguistic level.	.78	.74
Respondent Fatigue, [1, a]	N.A.	.77
• What impression did the entrepreneur make on you? Tired–Energized (revsverse-coded)		

Notes: CA = Cronbach's alpha, CR = composite reliability, AVE = average variance extracted, IR = indicator reliability, κ = interrater reliability for interviewer ratings.

Data sources: [a] Interviewer (cross-validated through interrater reliability test with a second, independent rater; see Web Appendix B).

Scales: [1] Likert scale, 1 = "totally disagree"; 7 = "totally agree."

Web Appendix D: Descriptive Information on B2B High-Tech Start-Ups' Mass-Media Marketing and Personal Sales Activities at Lower or Higher Expense Ratios

Here, we aim to provide more concrete insights into how lower (or higher) mass-media marketing and personal sales expense ratios manifest in B2B high-tech start-ups' operations. These descriptives help illustrate in more detail the concrete activities underlying the different expenses. To that end, we compared the distribution of particular marketing (sales) activities mentioned by the founders across start-ups (Table D1). For example, start-ups with a higher mass-media marketing expense ratio are more likely to engage in online, social media, and content marketing than start-ups with a lower marketing expense ratio. Notably, however, a higher mass-media marketing expense ratio does not seem directly related to start-ups' offline marketing activities.

Table D1. Distribution of Mass-Media Marketing and Personal Sales Activities in Start-Ups by Expense Ratios

	Mass-Media Marketing Expense Ratio				
	Lower		**Higher**		
	M	SD	M	SD	Test
Mass-media Marketing Activities					
Online marketing	**30.0%**	45.9	**46.2%**	49.9	$p < .01$
Social media marketing	**41.1%**	49.3	**54.3%**	49.8	$p < .01$
Content marketing	**11.9%**	32.5	**17.2%**	37.8	$p < .05$
Offline marketing	**30.2%**	45.9	**29.3%**	45.5	$p > .10$
Referral marketing	**16.3%**	36.9	**15.9%**	36.6	$p > .10$
	Personal Sales Expense Ratio				
	Lower		**Higher**		
	M	SD	M	SD	Test
Personal Sales Activities					
Networking	**55.6%**	49.7	**63.1%**	48.3	$p < .05$
Direct acquisition	**40.3%**	49.0	**47.2%**	50.0	$p < .05$
Pers. sales presentations	**9.8%**	29.8	**12.8%**	33.5	$p > .10$
Social selling	**1.8%**	13.4	**3.2%**	17.6	$p > .10$
Partner sales	**10.9%**	31.3	**16.7%**	37.3	$p < .05$

Notes: Lower and higher mass-media marketing or personal sales expense ratios reflect levels below or above the median level of each variable for the full sample.

Web Appendix E: Results of the First-Stage Probit Models

Table E1. Next-Period Attrition

Dependent Variable: Next-period attrition			
Independent Variables	*Coef.*	*SE*	
Mass-media expense ratio	.00	(.00)	
Personal sales expense ratio	.01	(.00)	
Venture age	.07	(.02)	***
Product development focus	.03	(.03)	
Liquidity	.00	(.03)	
Number of investors	.02	(.01)	**
Change founder team	-.20	(.21)	
Prizes won	-.03	(.17)	
Industry start-up entries	.00	(.00)	*
Industry start-up closes-to-entries	-.00	(.01)	
Industry concentration	.00	(.01)	
Industry growth	-.02	(.01)	
Respondent discomfort in prior wave survey	.12	(.04)	***
Wave dummies	Yes		
Pseudo-R^2	.06		
Obs.	597		
Wald χ^2 (d.f.)	41.40 (14)		
Log-pseudo-likelihood	–330.91		

*** $p < .01$; ** $p < .05$; * $p < .10$. (two-tailed tests)
Notes: This table shows unstandardized coefficients (B) with standard errors (SEs) clustered at the start-up level. The model illustrates the relevance of our instrumental variables. Because the dependent variable is next-period attrition, we cannot estimate the model for the last wave of our data collection.

Table E2. Nonresponse Sales Revenue

Dependent Variable: Nonresponse Sales Revenue			
Independent Variables	*Coef.*	*SE*	
Mass-media expense ratio	.01	(.00)	
Personal sales expense ratio	-.00	(.00)	
Venture age	-.05	(.02)	**
Degree of product development focus	.03	(.03)	
Liquidity	.06	(.03)	*
Number of investors	-.00	(.01)	
Change founder team	-.24	(.18)	
Prizes won	.12	(.13)	
Industry start-up entries	.00	(.00)	
Industry start-up closes-to-entries	.03	(.01)	**
Industry concentration	.01	(.01)	
Industry growth	.00	(.02)	
Respondent confidence	-.09	(.06)	*
Structured respondent	-.11	(.04)	***
Respondent fatigue	.09	(.04)	**
Wave dummies		Yes	
Pseudo-R²		.05	
Obs.		725	
Wald χ^2 (d.f.)		49.59 (17)	
Log-pseudo-likelihood		–470.53	
Joint test of the instrumental variables (χ^2 (d.f.))		13.40 (3) ***	

*** $p < .01$; ** $p < .05$; * $p < .10$. (two-tailed tests)
Notes: This table shows unstandardized coefficients (B) with standard errors (SEs) clustered at the start-up level. The model illustrates the relevance of our instrumental variables.

Web Appendix F: Operationalization of Peer-Weighted Instruments

We calculate the peer-weighted instruments in four steps (Lim, Tuli, and Grewal 2020; Moon, Tuli, and Mukherjee 2023) and illustrate the calculation using an example from our data. In the first step, we position the focal start-up in relation to its peers (i.e., the other start-ups in the SIC sector). For this purpose, we use the classic multidimensional scaling method (MDS) (Borg and Groenen 2003; Kruskal and Wish 1978). The MDS provides a two-dimensional positioning map for each SIC sector per survey wave. For this positioning, we included (1) product-related, (2) financial-related, and (3) OLC-related start-up characteristics, typically discussed in the start-up OLC literature (e.g., Kazanjian 1988; Kazanjian and Drazin 1989).

The product-related characteristics relate to the complexity of the products (start-ups likely align their mass-media and personal sales activities with those of peers facing similar challenges to convince customers; Hasan and Koning 2017; Hsu 2007) and the extent to which start-ups focus on product development. For example, research shows that the implementation of chief marketing officers by new ventures provides positive signals to the market and grants legitimacy, which may motivate peers to follow the new venture's example. To capture the positioning based on financial resources, we consider liquidity and the number of acquired investors. Prior research has shown that start-ups with similar financing (e.g., liquidity-increasing venture capital) are more likely to cooperate and align their commercialization activities (Hsu 2006). Furthermore, we consider the age of the start-up (venture age) to position the start-ups on their degree of maturity. Prior research has shown that emerging firms tend to learn (and borrow) ideas and strategies for their business model from similarly developed peer firms (see McDonald and Eisenhardt [2020] and their notion of "parallel play" behavior of emerging firms). Finally, we use a self-reported summary evaluation, in which the founders jointly evaluate the product-related and financial aspects of their start-ups as well as their progress in the OLC.[1] Table F1 contains the measurement of the variables not part of our main model.

In the second step, we quantify a start-up's similarity to its peers. Using the positioning map from the first step, we determine the Euclidean distances between all start-ups in a sector and per survey wave. Smaller (larger) Euclidean distances indicate that the two start-ups are more similar (less similar). Table F2 illustrates the calculation. In the SIC sector, Start-up 1 is more similar to Start-up 2 (Euclidean $\text{distance}_{1,2}$ = .820) and less similar to Start-up 9 (Euclidean $\text{distance}_{1,9}$ = 2.429).

In the third step, we calculate the weighting factors for the relationship between the focal start-up and its peers (Equation F1). The total Euclidean distance of Start-up 1 is the sum of the Euclidean distances between Start-up 1 and all its peers, which equals 16.247. As the Euclidean distance between Start-up 1 and Start-up 3 is 3.486, the weight of the relationship between this pair of start-ups is .785.

$$\text{(F1) } w_{i,p,s,t} = \frac{(\text{Total Distancei,s,t} - \text{Distancei,p,s,t})}{\text{Total Distancei,s,t}},$$

where w is the weight of similarity between start-up i and its peer p in sector s at the time of survey wave t, Total Distance is the total Euclidean distance between the focal start-up and all its peers in sector s, and Distance is the Euclidean distance between the focal start-up and its peer p in survey wave t.

[1] We could have positioned the start-ups using the dependent variables (e.g., sales revenue). However, as we discuss in the main article, the dependent variables have missing values, which would have influenced the weighting of the instruments. The self-reported summary score is, therefore, a comprehensive proxy at this point. It also includes these essential performance aspects.

In the fourth step, we calculate the weighted peer instruments according to the following formula (Equation F2). The weighting factors mean that more similar (less similar) peer start-ups are weighted more (less). The weight thus reflects findings from previous research: Companies primarily imitate the actions of other, similar companies (e.g., Shi, Grewal, and Sridhar 2020).

$$\text{(F2) } WPIV_{it} = \frac{\sum_1^{Ps}[w_{i\,pst} \times IV_{pst}]}{\sum_1^{Ps} w_{ipst}},$$

where WPIV is the weighted peer instrument of start-up i at the time of survey wave t, w is the weight of similarity between start-up i and its peer p in sector s at the time of survey wave t, and IV_{pst} is the instrumental variable score of the peer start-up.

Table F1. Measurement of Additional Variables for MDS

Variables	IR	κ
Product Complexity [1, a]		
(CA = .90, CR = .91, AVE = .77)		
• The products/services offered by the start-up are complex.	.85	.75
• The products/services offered by the start-up are technologically sophisticated.	.69	.69
• The products/services offered by the start-up are complicated.	.76	.74
Founder Self-Reported Life-Cycle Stage [b] (adapted from Kazanjian 1988)	N.A.	N.A.
• **Conceptualization Stage:** Within the Seed Stage, the start-up is in the concept development phase and does not generate any sales yet. The current activities of the company focus on product development and design or the development of a range of services, securing adequate financial resources and market development.		
• **Commercialization Stage:** The start-up company is currently completing a market-ready offer and is realizing initial sales, but the company still needs to be firmly established in the market.		
• **Growth Stage:** The start-up has a market-ready offer and is achieving strong sales and/or customer growth. The focus is on the issue of how the product/service can be produced and distributed profitably in larger quantities.		

Notes: CA = Cronbach's alpha, CR = composite reliability, AVE = average variance extracted, IR = indicator reliability, κ = interrater reliability for interviewer ratings.
Data sources: [a] Interviewer, [b] Self-rated by founders and cross-validated by two independent researchers.
Scales: [1] Likert scale, 1 = "totally disagree"; 7 = "totally agree."

Table F2. Examples of the Measurements of the Peer-Weighted Industry Mass-media and Personal Sales Expense Ratio

Start-Up ID	Start-Up's Expense Ratios		Euclidean Distance									Weights									Peer-Weighted Industry Expense Ratios	
			Start-Up ID									*Start-Up ID*										
	Mass-media[a]	Personal Sales	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	Mass-media	Personal Sales
1	5	5	—	0.820	3.486	2.295	2.500	1.587	1.656	1.474	2.429	—	0.950	0.785	0.859	0.846	0.902	0.898	0.909	0.850	18.728	23.173
2	30	40	0.820	—	2.726	1.860	2.104	1.032	2.398	2.209	1.616	0.944	—	0.815	0.874	0.857	0.930	0.838	0.850	0.891	15.434	18.325
3	30	2	3.486	2.726	—	3.385	1.948	2.874	5.120	4.543	1.265	0.862	0.892	—	0.866	0.923	0.887	0.798	0.821	0.95	15.665	23.280
4	10	10	2.295	1.860	3.385	—	3.708	0.839	3.067	3.734	2.164	0.891	0.912	0.839	—	0.824	0.960	0.854	0.823	0.897	18.285	22.217
5	10	30	2.500	2.104	1.948	3.708	—	2.907	4.085	3.008	1.958	0.887	0.905	0.912	0.833	—	0.869	0.816	0.865	0.912	18.200	19.617
6	20	20	1.587	1.032	2.874	0.839	2.907	—	2.722	3.061	1.610	0.905	0.938	0.827	0.950	0.825	—	0.836	0.816	0.903	16.911	20.922
7	30	30	1.656	2.398	5.120	3.067	4.085	2.722	—	1.652	3.992	0.933	0.903	0.793	0.876	0.835	0.890	—	0.933	0.838	15.314	19.681
8	0	20	1.474	2.209	4.543	3.734	3.008	3.061	1.652	—	3.700	0.937	0.906	0.806	0.840	0.871	0.869	0.929	—	0.842	19.319	21.082
9	20	30	2.429	1.616	1.265	2.164	1.958	1.610	3.992	3.700	—	0.870	0.914	0.932	0.884	0.895	0.914	0.787	0.802	—	17.061	19.488

Notes: ID = Identification number. [a] These are the actual mass-media and personal sales expense ratios the founders reported for their individual start-up in our survey. The exemplary anonymized values indicate individual start-ups in our sample (extracted from the second panel wave) that belong to one SIC sector.

Table F3. Description of Exemplary Comparison Set depicted in Table F2

ID	Biotech, Medtech, and Food Tech
1	Biotech start-up offering novel production routines for amino acid for organic solvents used in cosmetics and consumer goods
2	Biotech start-up offering innovative and degradable packaging for consumer goods made from recycled materials
3	Biomedical start-up developing novel organic care products and cosmetics with biomedical properties, such as microbial protection
4	Ecotech start-up offering novel 3D printing procedures based on organic, renewable materials
5	Food tech developing new production routines for and produces organic, isotonic beverages
6	Food tech start-up producing organic pet food with high nutrient density and customized formulae based on pet health data
7	Biomedical start-up producing biophysical cosmetics and developed proprietary formulations to target specific medical conditions
8	Biotech start-up offering compostable packaging for consumer goods based on artificially cultivated plant fibers
9	Biotech start-up offering flexible, rapidly biodegradable packaging for beverages and consumer goods

Notes: The start-ups grouped in this SIC sector (manufacturing start-ups in areas of biotech, medtech, and food tech) offer innovative, sustainable products and packaging in the fields of pharmaceuticals, cosmetics, food, and consumer goods. The biotech start-up ID 9 develops novel, rapidly biodegradable packaging with high material durability for beverages. Its closest peers are the biomedical start-up ID 3 (Euclidean distance 1.265, see Table F2), which develops novel organic care products and cosmetics with biomedical properties, such as microbial protection, and start-up ID 6 (Euclidean distance 1.610), which specializes in organic pet food with high nutrient density. Its most distant peer in this comparison set is the biomedical start-up ID 7, which produces biophysical cosmetics with medical properties.

Web Appendix G: Results of the Auxiliary Regression Models

Table G1. Mass-media Expense Ratio

Dependent Variable: Mass-media Expense Ratio			
Independent Variables	*Coef.*	*SE*	
Venture age	-.66	(4.31)	
Degree of product development focus	-.80	(.49)	
Liquidity	.43	(.51)	
Number of investors	.17	(.05)	***
Change founder team	-.61	(2.40)	
Prizes won	-1.67	(1.73)	
Industry start-up entries	-.05	(.02)	**
Industry start-up closes-to-entries	-.29	(.36)	
Industry concentration	-.62	(.32)	*
Industry growth	.21	(.32)	
$IMR_{Attrition}$	-.21	(1.16)	
Peer-weighted industry mass-media expense ratio	.47	(.18)	***
Peer-weighted industry personal sales expense ratio	-.05	(.19)	
Wave dummies		Yes	
Start-up dummies		Yes	
R^2		.68	
Obs.		725	
Sanderson–Windmeijer multivariate F-test of excluded instruments ($F(df_1;df_2)$)		10.55 (1, 297) ***	

*** $p < .01$; ** $p < .05$; * $p < .10$. (two-tailed tests, one-tailed for the directional effects)
Notes: This table shows unstandardized coefficients (B) with standard errors (SEs) clustered at the start-up level. The model illustrates the relevance of our instrumental variables.

Table G2. Personal Sales Expense Ratio

Dependent Variable: Personal Sales Expense Ratio			
Independent Variables	*Coef.*	*SE*	
Venture age	2.78	(5.29)	
Degree of product development focus	-.51	(.65)	
Liquidity	-.36	(.58)	
Number of investors	-.18	(.06)	***
Change founder team	-4.14	(3.57)	
Prizes won	1.02	(2.67)	
Industry start-up entries	-.01	(.03)	
Industry start-up closes-to-entries	-.07	(.47)	
Industry concentration	.43	(.62)	
Industry growth	.02	(.52)	
$IMR_{Attrition}$	-.25	(1.59)	
Peer-weighted industry mass-media expense ratio	.17	(.19)	
Peer-weighted industry personal sales expense ratio	.49	(.20)	***
Wave dummies		Yes	
Start-up dummies		Yes	
R^2		.68	
Obs.		725	
Sanderson–Windmeijer multivariate F-test of excluded instruments ($F(df_1;df_2)$)		11.52 (1, 297) ***	

*** $p < .01$; ** $p < .05$; * $p < .10$. (two-tailed tests, one-tailed for the directional effects)

Notes: This table shows unstandardized coefficients (B) with standard errors (SEs) clustered at the start-up level. The model illustrates the relevance of our instrumental variables.

Web Appendix H: Histograms of the Weighted Peers' Instruments by Industry

Figure H1. Mass-media Expense Ratio

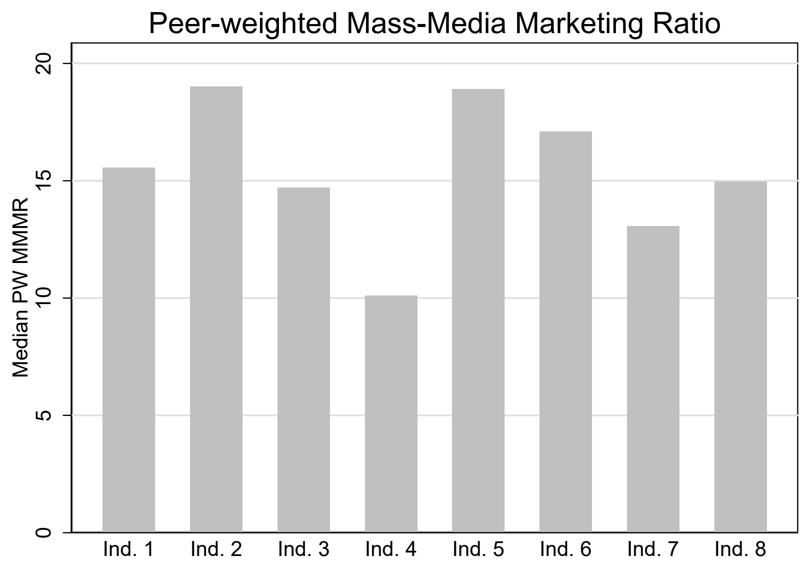
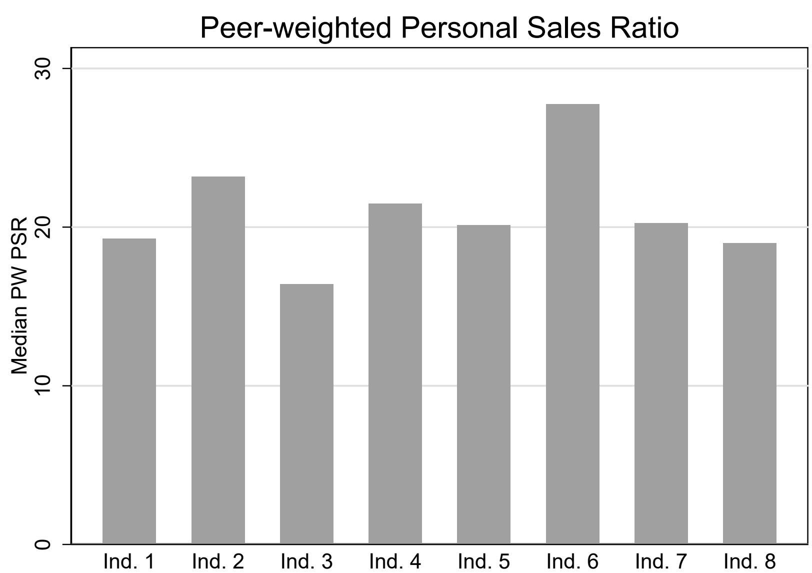


Figure H2. Personal Sales Expense Ratio



Notes. PW MMMR = Peer-weighted mass-media marketing ratio; PW PSR = peer-weighted personal sales ratio. The histograms are generated based on the raw values of the weighted peers' scores, i.e., before applying any variable transformations.

Web Appendix I: Replication with Alternative OLC-Stage Measures

(Relative) Venture Size

We measure venture size as the number of employees in the start-up minus the size of the founder team at the respective survey wave divided by the average number of employees for start-ups in the same industry.

Venture Popularity

To measure venture popularity (e.g., Hite and Hesterly 2001), we collected data on web search interest scores from Google Trends. Such data are frequently used in marketing research to study, for example, the perceived importance of product features (Du, Hu, and Damangir 2020) and consumer mindsets (Jia, Yang, and Jiang 2022). Google Trends does not provide absolute search interest data but relative search interest scores based on a 0–100 scale and, in comparison, within or between start-ups. Therefore, we needed to compare each start-up with a sensible reference.

Our procedure was as follows: First, we compared the search interest scores of ten randomly selected start-ups per each relevant B2B high-tech industry. From this selection, we chose the start-up closest to the average search interest and used this start-up to serve as a reference for the comparison. That is, the resulting search interest scores reflect the relative search interest compared with the reference start-up in the industry. Second, we then collected the search interest scores for each of the start-ups in our sample and for each time point of the respective survey waves. We could not find unique Google Trend results for four start-ups, as their names matched generic search terms, and therefore were unable to include these start-ups in this replication.

Venture Development Index

We constructed an index, incorporating markers for both start-ups' liabilities of newness and liabilities of smallness (nonfinancial and financial). The index is based on transformative events (e.g., "new reference customer won"), as well as thresholds for venture size or debt capital (see Table H1). In this index, we thus include critical markers for start-up progression, or start-ups' current resource endowments (HR, operational, financial), and transformative events that can mark the transition from one OLC stage to a more advanced OLC stage.

Table I1 provides an overview of our alternative measures for start-ups' OLC-stage progression. Table I2 shows the regression results. Overall, the pattern of results for the alternative OLC markers replicates our findings from the main analysis. Thus, our results are not sensitive to the choice of the OLC marker.

Table I1. Alternative Measurements for Start-Ups OLC Development

OLC Marker	Early/Late OLC indicated by…	Operationalization	Description	Exemplary Sources
Venture age (main OLC indicator)	Liability of newness	Years since foundation	Younger (vs. mature) firms are widely unknown and lack legitimacy	Stinchcombe, 1965; Freeman, Carroll, and Hannan 1983; Winkler, Rieger, and Engelen 2020
Venture size	Liability of smallness	No. of employees minus founder team size	Smaller firms lack internal resources and capabilities	Freeman, Carroll, and Hannan 1983; Winkler, Rieger, and Engelen 2020; Hite and Hesterly 2001
Venture popularity	Liability of newness	Google Trends score	Younger (vs. mature) firms are widely unknown and lack awareness in the market	Fisher, Kotha, and Lahiri 2016; Homburg et al. 2014
Venture development index	Liability of newness	• Reference customer won • Important investor won	Firms that won reference customers or important investors signal legitimacy to (future) stakeholders and potential shareholders	Stinchcombe, 1965
	Liability of smallness (nonfinancial)	• Many new employees hired • More than eight employees employed • More than seven strategic partners	Firms with more resources (e.g., HR, operational) are capable of coping better with environmental challenges and competitors	Freeman, Carroll, and Hannan 1983; Winkler, Rieger, and Engelen 2020
	Liability of smallness (financial)	• Debt capital acquired • More than €250,000 of debt capital	Firms with more financial resources are capable of coping better with environmental challenges and competitors	Freeman, Carroll, and Hannan 1983

Notes: We chose the thresholds for debt capital, number of employees, and strategic partners based on important percentiles within the start-up growth stage.

Table I2. Alternative Operationalizations of the OLC Stage

OLC-Marker:	**Venture Popularity**				**Relative Venture Size**				**Venture Development Index**			
Dependent Variable	**Sales Revenue**		**#Customers**		**Sales Revenue**		**#Customers**		**Sales Revenue**		**#Customers**	
Independent Variables	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
Mass-media expense ratio	-.008	(.019)	.003	(.005)	.001	(.018)	.015	(.005)***	-.004	(.020)	.002	(.004)
Personal sales expense ratio	.036	(.019)**	.004	(.004)	.013	(.016)	-.004	(.004)	.017	(.014)	.006	(.005)
OLC	.008	(.024)	.005	(.005)	.130	(.255)	.143	(.133)	4.97	(3.247)*	.976	(.497)**
Mass-media ratio × OLC	**.0022**	**(.0012)****	**.0009**	**(.0003)*****	**.013**	**(.010)***	**.024**	**(.007)*****	**.109**	**(.065)****	**.090**	**(.020)*****
Personal sales ratio × OLC	**-.0014**	**(.0008)****	**-.0004**	**(.0003)****	**-.014**	**(.008)****	**-.009**	**(.004)*****	**-.075**	**(.040)****	**-.020**	**(.011)****
Prod. development focus	-.013	(.193)	-.001	(.062)	-.085	(.196)	-.020	(.103)	-.024	(.208)	-.015	(.072)
Liquidity	.143	(.176)	-.068	(.066)	.004	(.158)	-.068	(.087)	-.029	(.200)	-.080	(.082)
Number of investors	.046	(.092)	-.001	(.026)	.019	(.069)	.000	(.028)	-.001	(.082)	-.014	(.029)
Change founder team	.605	(1.079)	.560	(.460)	.505	(1.295)	.535	(.544)	.261	(1.128)	.502	(.505)
Prizes won	.564	(1.240)	.271	(.232)	.110	(1.083)	.125	(.262)	-.070	(1.298)	.013	(.257)
Industry start-up entries	.005	(.009)	.000	(.003)	.002	(.008)	-.001	(.003)	.010	(.009)	-.001	(.003)
Ind. SU closes-to-entries	-.029	(.103)	.018	(.036)	-.001	(.118)	-.012	(.067)	-.026	(.119)	.004	(.039)
Industry concentration	.104	(.209)	-.003	(.070)	.208	(.218)	-.022	(.090)	.148	(.180)	.012	(.063)
Industry growth	-.152	(.159)	.004	(.048)	-.240	(.162)	.031	(.065)	-.151	(.132)	.000	(.046)
$IMR_{Nonresponse}$	-.954	(2.497)			-.106	(2.154)			-1.006	(3.04)		
$IMR_{Attrition}$	.635	(.191)***	.110	(.063)*	.828	(.177)***	.104	(.067)	.271	(.189)	.045	(.065)
CF mass-media exp. ratio	.099	(.131)	.034	(.073)	.087	(.133)	.001	(.074)	.088	(.189)	.029	(.074)
CF personal sales exp. ratio	.096	(.093)	-.055	(.032)*	.081	(.084)	-.051	(.054)	.091	(.093)	-.055	(.036)
Wave dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Start-up dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Obs.	406		597		389		567		396		584	
Log-likelihood	-1,183.02				-1,098.49				-1,082.07			

*** $p < .01$; ** $p < .05$; * $p < .10$ (two-tailed tests, one-tailed for the directional effects).

Notes: This table presents the unstandardized coefficients. SE = bootstrap standard errors derived from 500 bootstrap replications. The models are estimated using multiple equation CMP in Stata. The models account for item nonresponse on “sales revenue” with an IMR. All models contain IMRs to control for panel attrition and control function corrections (CF) for mass-media and personal sales expense ratios. Sample sizes vary due to missing values.

Web Appendix J: Replication with Air-Distance-Weighted Instrumental Variables

	Model 3: Unmoderated Results with IMR and CF						Model 6: Moderated Results with IMR and CF					
Dependent Variable:	**Sales Revenue**			**#Customers**			**Sales Revenue**			**#Customers**		
Independent Variables	*Coef.*	*SE*		*Coef.*	*SE*		*Coef.*	*SE*		*Coef.*	*SE*	
Mass-media expense ratio	-.011	(.014)		.003	(.005)		-.002	(.014)		.008	(.004)	**
Personal sales expense ratio	.030	(.015)	**	.003	(.004)		.025	(.015)	*	-.002	(.004)	
Venture age	1.347	(1.243)		.960	(.549)	*	1.164	(1.296)		.862	(.527)	
Mass-media × Venture age							**.004**	**(.004)**		**.006**	**(.002)**	**
Personal sales × Venture age							**-.012**	**(.006)**	**	**-.005**	**(.002)**	**
Product devel. focus	-.113	(.198)		-.036	(.076)		-.068	(.222)		-.022	(.072)	
Liquidity	.136	(.179)		-.075	(.074)		.164	(.184)		-.073	(.071)	
Number of investors	.035	(.082)		-.007	(.028)		.047	(.084)		-.005	(.027)	
Change founder team	.361	(.971)		.371	(.484)		.498	(1.024)		.470	(.474)	
Prizes won	.690	(1.257)		.222	(.245)		.684	(1.304)		.244	(.234)	
Industry start-up entries	.007	(.014)		.000	(.005)		.008	(.016)		.001	(.005)	
Ind. SU closes-to-entries	-.004	(.104)		.016	(.041)		.002	(.105)		.012	(.039)	
Industry concentration	.163	(.199)		-.009	(.071)		.171	(.209)		-.013	(.068)	
Industry growth	-.121	(.142)		.039	(.057)		-.148	(.147)		.034	(.055)	
$IMR_{Nonresponse}$	-.731	(1.767)					-.451	(1.767)				
$IMR_{Attrition}$	.597	(.214)	***	-.004	(.087)		.624	(.219)	***	.003	(.083)	
Cf mass-media. exp. ratio	.109	(.215)		.019	(.076)		.108	(.234)		.022	(.074)	
Cf personal sales exp. ratio	.042	(.108)		-.081	(.044)	*	.061	(.127)		-.070	(.043)	
Wave dummies	Yes			Yes			Yes			Yes		
Start-up dummies	Yes			Yes			Yes			Yes		
Obs.	405			597			405			597		
Log-likelihood	-1,204.56						-1,195.44					

*** $p < .01$; ** $p < .05$; * $p < .10$ (two-tailed tests). *Notes:* This table presents unstandardized coefficients. SE = bootstrap standard errors derived from 500 bootstrap replications. The models are estimated using multiple equation CMP in Stata. The models account for item nonresponse on “sales revenue” with an IMR. All models contain IMRs to control for panel attrition and control function corrections (CF) for mass-media and personal sales expense ratios.

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