Generative AI and Firm-level Productivity: Evidence from Startup Funding Dynamics*

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This paper provides new evidence on the impact of Generative AI on startup productivity: We argue that valuable but non-exclusive technological innovations *can* be a source of competitive advantage if entrepreneurs leverage them as complementary assets to their existing skill set. To show this, we exploit the release of GitHub Copilot as a quasi-natural experiment affecting software-developing startups. We find a significant reduction in the time-to-initial-funding by about 20% relative to comparable startups, while funding sizes remain unchanged. These effects are strongest when founders have more technological or managerial experience. Importantly, startups secure these initial deals with 22% fewer employed software developers. Our analysis highlights the considerable implications of GenAI as a new resource available to decision-makers, shaping the trajectories of new ventures.

JEL Classification: G24, O31, O33, D24
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1 Introduction

Technological resources play an increasingly important role in the knowledge-based economy (Arora and Nandkumar, 2012; Giustiziero *et al.*, 2023; Krakowski *et al.*, 2023). They are highly relevant for entrepreneurial startups, which are typically more flexible than established companies in adopting innovations but also operate under greater resource constraints (e.g., Holtz-Eakin *et al.*, 1994; Aghion *et al.*, 2007; Kerr and Nanda, 2011; Kerr *et al.*, 2014; Weiblen and Chesbrough, 2015). Therefore, founders and managers of new ventures seek to exploit technological innovations to accelerate scaling and eventually overcome the liabilities of newness and smallness.

The arrival of Generative Artificial Intelligence (GenAI) in the early 2020s marks a fundamental technological change. As a new general-purpose technology, GenAI is anticipated to significantly enhance overall firm-level productivity, potentially even transforming organizational structures as a whole (Brynjolfsson *et al.*, 2023; Eisfeldt *et al.*, 2023).[1] However, a priori, its actual implications for individual startup productivity are unclear. On the one hand, GenAI may boost productivity by complementing or even substituting human cognitive labor (Noy and Zhang, 2023). This effect may particularly benefit startups as they rely on the iterative exploration of new product and business ideas but often struggle to access the necessary resources (Gilbert *et al.*, 2006; Ko and McKelvie, 2018). On the other hand, like many other technological innovations, GenAI solutions are intangible, non-rival, and often free-of-charge assets that are available to all market participants (Brynjolfsson and McAfee, 2014). In other words, they are neither unique, imperfectly imitable, nor controlled by a specific firm. Hence, they do not yield startups a competitive advantage in the spirit of the resource-based view (Barney, 1991), per se.

In this paper, we argue that the spread of valuable but non-rival technological innovations *can* introduce a new source of competitive advantage for startups once complemented with appropriate human resources. To show this, we analyze the emergence of new GenAI technologies on startup productivity. We measure productivity in terms of startups' funding dynamics, such as the time-to-funding, which is one of the earliest quantifiable indicators of firm-level operational efficiency (e.g., Hsu, 2007). Moreover, we assess the human capital input employed to realize respective funding outcomes. Our empirical anal-

[1] The classification of AI as a general-purpose technology is well-established, with pervasive application across many sectors, considerable potential for technical improvements, and triggering further innovation through spillover effects (e.g., Brynjolfsson *et al.*, 2018; Goldfarb *et al.*, 2023). While AI developments at the beginning of the 21^{st} century were mainly "predictive", the "generative" form of AI has attracted most of the attention only recently (see also Section 5). According to Sam Altman (2023), CEO of OpenAI, the company developing ChatGPT, the emergence of GenAI can provoke "*economic shocks* [...] *at a level far beyond anything we are prepared for*".

ysis explores the funding activities, firm characteristics, and employment patterns of a large sample of 21,834 startups that secured their first funding round between Q1 2020 and Q3 2023.

For identification, we exploit the release of GitHub Copilot, a GenAI-based coding assistant, as a positive shock to the productivity of startups. Initially released in 2021, GitHub Copilot represents one of the pioneering GenAI applications and has since experienced rapid adoption (GitHub, 2023a). It entails significant productivity effects for software programmers, with an average reduction of 56% in the time-to-completion of development tasks (Peng *et al.*, 2023). We posit that these efficiency gains have transformative effects on nascent software firms. Our empirical strategy thus considers the release of GitHub Copilot as exogenous variation in the productivity of software development over time.

Moreover, the GitHub Copilot release has well-suited properties for a quasi-natural experiment. The propensity to respond to the release provides a natural delineation of treatment and control groups that we can explore using a difference-in-differences (DID) framework.[2] Unlike other (GenAI-related) technology shocks, GitHub Copilot is likely to have varying effects on startups' productivity, depending on how central software development is for generating their main products or services. Specifically, we distinguish between startups that develop new software solutions and comparable startups that do not. This propensity of benefiting from GitHub Copilot serves as identifying cross-sectional variation. Additionally, we investigate differences in startup founding teams to carve out the role of human resources as complementary assets to GenAI. We focus on technological and managerial experience as two important pre-entry categories of founder characteristics (Colombo and Grilli, 2005; Dencker and Gruber, 2015).

Within this setting, we test three main hypotheses regarding the potential impact of GenAI technologies on startup productivity. Technological innovations can augment the capabilities of existing resources within a startup. In our empirical framework, this means that software-developing startups should benefit disproportionally from the productivity increase triggered by the release of GitHub Copilot. With the time-to-funding as an early-stage indicator of startup productivity, we first hypothesize that GitHub Copilot accelerates funding activities of software-developing startups relative to other startups. Moreover, our second hypothesis posits that the productivity effects of GitHub Copilot are most pronounced at the earliest stages of a startup's lifecycle, i.e., when the liabilities of newness and smallness

[2]Notably, the setup also moderates concerns about simultaneous supply-sided funding dynamics. First, it is not plausible that investors would use GitHub Copilot for their own business activities. Second, the general GenAI boom that was mainly triggered by the release of ChatGPT and which fueled investors' expectations in GenAI-related returns had not yet broken out at the time of the GitHub Copilot release in 2021.

are most binding. Resource constraints can significantly impede hiring activities and product development at these early stages. Third, we hypothesize that the release of GitHub Copilot coincides with fewer software developers employed by the focal startup at the time of initial funding. That is, fewer software programmers would be needed to achieve a given level of output if GenAI indeed increased their individual efficiency. Fourth, we argue that only the integration of GitHub Copilot with existing human capital can constitute a new source of competitive advantage for software-developing firms. This reflects the idea that new technologies typically do not fully substitute human capital but serve as a complement (e.g., Gaessler and Piezunka, 2023). Accordingly, we hypothesize that the productivity effects of GitHub Copilot are most pronounced for startups whose founders possess complementary skills in terms of technological or entrepreneurial experience.

The empirical findings support our main hypotheses. Prior to the release of GitHub Copilot, software-developing and other software startups have similar funding dynamics. After the release, software-developing startups experience a 4.8-month acceleration in the time-to-funding relative to the control group. This effect is economically significant, translating to a relative acceleration of obtaining funding by about 20%. The results hold controlling for country-, sector-, and time-specific characteristics, as well as startup-level covariates. The observed effects diminish for the time to the second funding round and vanish in later funding rounds. This pattern highlights the crucial role of technological innovation in mitigating resource constraints during the early stages of a startup. In this context, we also show that software-developing startups raise similar amounts of funding, despite receiving it earlier. A series of robustness tests underscores the validity of these findings. We demonstrate that the main results are unlikely to be driven by alternative channels, including fluctuation in aggregate VC market sentiment, COVID-19-related effects associated with remote work, or the launch of ChatGPT.

Importantly, we find that software-developing startups employ significantly fewer programmers throughout the early phases of their lifecycle. Our estimates show a 22% decrease in software developers employed at treated startups at time of funding, comparing pre- and post GitHub Copilot periods. This suggests that startups impacted by the new GenAI technology benefit from higher operational efficiency: They secure similar amounts of funding in less time and with fewer employees.

Furthermore, the release of GitHub Copilot disproportionally benefits more experienced entrepreneurs. The main effects are most pronounced for software-developing startups led by founders with computer

science degrees and older founders, reflecting academic and practical experience. The benefits are also larger for founders with more entrepreneurial experience, such as serial founders. Our findings corroborate the view that GitHub Copilot enhances existing resources by replacing less efficient ones. Human capital complemented with GenAI can substitute human capital without GenAI. These insights indicate that GitHub Copilot *can* provide a new source of competitive advantage, enabling experienced entrepreneurs to replace resources that are no longer rare or imperfectly imitable, such as formerly hired software programmers.

Overall, this paper offers novel insights into how technological change impacts firm-level productivity by analyzing the effects of GenAI on startup dynamics. Gaining a better understanding of the role of new general-purpose technologies in the entrepreneurial ecosystem is of first-order importance. Technological resources are a crucial driver of firms' competitive advantage, such that shifts in their availability directly affect growth patterns. This is especially true in the context of GenAI, given its potential to disrupt a wide range of tasks and occupations (Felten *et al.*, 2021, 2023). Related studies at the individual level show greatest efficiency gains for low skilled or unexperienced users (Noy and Zhang, 2023; Peng *et al.*, 2023; Dell'Acqua *et al.*, 2023b; Brynjolfsson *et al.*, 2023). In contrast, we show that founder experience is an essential complement to realizing firm-level productivity gains from GenAI. This insight echoes studies examining complex organizational settings similar to ours (Otis *et al.*, 2023; Toner-Rodgers, 2024). Consequently, our analysis is of highest managerial relevance, revealing new findings on the interplay of GenAI and human capital, and their effects on startup productivity.

From a theoretical perspective, our analysis speaks to the literature that studies how decision-makers use strategic resources, particularly new technologies, to gain a competitive advantage (Polidoro and Toh, 2011; Dencker and Gruber, 2015; Krakowski *et al.*, 2023). Entrepreneurial activities inherently involve the (re-)combination of existing resources to develop new, unique, and sometimes disruptive capabilities that cannot be substituted by larger companies (Alvarez and Barney 2001). This agility provides startups with strategic advantages, for example in adopting new technologies. At the same time, due to their newness and smallness, startups typically control fewer resources and face tighter constraints in financial and human capital (e.g., Cooper *et al.* 1994; Gilbert *et al.* 2006; Ko and McKelvie 2018). As a result, startups frequently rely on the resources of other market participants to access a broader range of missing assets (e.g., Kor and Mahoney 2005; Nason *et al.* 2019).

We argue that new technologies, such as GitHub Copilot, can also alleviate these constraints, reducing startups' dependence on acquiring additional human resources to generate competitive advantage. In the spirit of the resource-based view, technological innovation can enable the creation of valuable resources once it complements humans' cognitive capabilities. Our findings show that GenAI can serve as a new source of competitive advantage that substitutes more traditional and costly resources even if it fails to fulfill the criteria of rare and non-imitable assets. For these benefits to materialize, entrepreneurs must be able to integrate their own capabilities with new technological resources to effectively mitigate the liabilities of newness and smallness. Overall, these considerations contribute to the discussion of how new technologies can substitute or complement existing resources (e.g., Powell and Dent-Micallef, 1997; Krakowski *et al.*, 2023).

From a practical perspective, our analysis improves the understanding of changing startup dynamics caused by new technologies as highly complementary and scalable but non-rival resources. More explicitly, we shed light on the workings and implications of GenAI, arguably one of the most significant technological innovations in the 21^{st} century. Given the recent advancements of popular GenAI applications, initial evidence on their economic impact is emerging (e.g., Brynjolfsson *et al.*, 2023; Eisfeldt *et al.*, 2023; Noy and Zhang, 2023; Hui *et al.*, 2023; Demirci *et al.*, 2025). Unlike related studies, our analysis investigates the impact of GenAI on firm-level productivity by estimating its effects on startup funding dynamics. We can estimate productivity gains for entrepreneurial ventures by exploring the release of GitHub Copilot as an identifying event, with funding and employment dynamics serving as a measures of startup productivity. Thereby, we contribute to the early efforts to study the economics of GenAI. We offer new and valuable insights that help founders and managers anticipate its potential effects on entrepreneurial ventures' productivity and growth dynamics.

The remainder of this paper is structured as follows: Section 2 discusses related literature and derives the main hypotheses. Section 3 describes the institutional setting, the data, and introduces the empirical framework. Section 4 presents the main results, including several robustness tests and extensions of the main analyses. Section 5 provides additional evidence on the underlying mechanisms. Section 6 discusses the implications, generalizability, and limitations of our analysis. Section 7 concludes.

2 Theoretical background and hypotheses

2.1 Related literature

Our analysis mainly contributes to three central strands of the literature. Foremost, we speak to the management and entrepreneurship literature by providing new insights into whether and how the arrival of GenAI provides firms with a new source of competitive advantage. A central body of research studies the importance of strategic assets as a driver of competitive dynamics and firm strategies (Barney, 1991; Porter, 1991; Rothaermel, 2001; Christensen, 2013). Since the onset, this literature stream has considered technology-based resources to yield firms a competitive advantage moving beyond a mere cost reduction or product differentiation (Mata *et al.*, 1995; Arora and Nandkumar, 2012; Giustiziero *et al.*, 2023). A complementary literature stream has been investigating the role of founders' human capital as a key for new venture development and growth (Colombo and Grilli, 2005; Unger *et al.*, 2011). Experience and cognitive capabilities play an essential role in enabling founders to exploit new opportunities (Dencker and Gruber, 2015; Helfat and Peteraf, 2015). We combine these two central streams of the literature by providing new evidence on the actual growth implications of GenAI as a new resource available for decision-makers in nascent firms. Our analyses thus integrate the roles of technological innovations and founders' expertise in accelerating business scaling, highlighting the importance of entrepreneurial experience.

Further, we contribute to the strategic management literature that studies managerial implications of new technology adoption (e.g., Powell and Dent-Micallef, 1997; Choudhury *et al.*, 2020; Felten *et al.*, 2021; Krakowski *et al.*, 2023). Recent studies show that AI can help managers to enhance their productivity by facilitating learning and decision-making (Shrestha *et al.*, 2019; Gaessler and Piezunka, 2023). Most broadly, prior research provides survey-based insights into firms' self-reported productivity gains related to AI (Czarnitzki *et al.*, 2023). Others suggest that AI can substitute or complement human capital in organizations (e.g., Agrawal *et al.*, 2019; Felten *et al.*, 2021), an effect that substantially varies across specific tasks (Dell'Acqua, 2022; Gaessler and Piezunka, 2023). In a similar vein, the literature points out that AI adoption in organizations requires caution as it may come along with coordination failures and ethical considerations (Cowgill *et al.*, 2020; Dell'Acqua *et al.*, 2023a). Closely related to our work, Krakowski *et al.* (2023) show that AI adoption, in the form of chess competitions, has the potential

to render humans' traditional competitive capabilities obsolete. In contrast to them, we assess how the likely most impactful technological development in recent history, GenAI, affects productivity at the firm level.

To the best of our knowledge, this study is among the first to examine the general impact of GenAI adoption in organizations. First evidence on the implications of GenAI focuses on the productivity gains of individuals. For example, studies document efficiency gains for customer support agents (Brynjolfsson *et al.*, 2023), consultants (Dell'Acqua *et al.*, 2023b), and simple writing tasks of other professionals (Noy and Zhang, 2023).[3] So far, there is only limited firm-level evidence on the implications of GenAI. As a notable exception, Eisfeldt *et al.* (2023) establish the link between GenAI, labor inputs, and firm values; They study firms' exposure to GenAI and show that it positively relates to excess daily stock-market returns in response to the launch of ChatGPT. Unlike these studies, we provide new empirical and theoretical insights on the impact of GenAI on firm-level productivity. Our empirical setting analyzes the launch of GitHub Copilot as a quasi-natural experiment. Further, we shed light on the theoretical considerations of how non-rival and imitable technologies can serve firms by enhancing productivity. Thereby, our work provides new perspectives regarding the early implications of GenAI for economic actors, highlighting its potential to speed up the business development of startups.

Finally, our paper also provides new evidence to the entrepreneurial finance literature by assessing the implications of technology shocks for the financing dynamics of startups. Specifically, we extend the literature that studies general shifts in market conditions on startup financing activities. A growing body of research investigates the role of policy (e.g., Cumming and Li 2013; Giraudo *et al.* 2019; Edwards and Todtenhaupt 2020; Denes *et al.* 2023) and market-based changes, such as the emergence of new technologies, on startup performance (e.g., Fairlie and Chatterji 2013; Ewens *et al.* 2018; Dushnitsky and Stroube 2021). Two related studies examine the effects arising from the introduction of cloud computing (Ewens *et al.*, 2018) and low-code platforms (Dushnitsky and Stroube, 2021) on startups' funding demands and venture capitalists' investment strategies. The technologies examined in these studies represent direct shocks to the infrastructure cost of startups, whereas GitHub Copilot affects financial expenditures only indirectly but instead enhances startup productivity. Our work extends prior contributions by exploiting a different, though crucially important technology shock as we reveal the

[3] In addition to this, some preliminary work states a potentially strong effect of large language model technologies on the US labor market (Eloundou *et al.*, 2023; Felten *et al.*, 2023; Hui *et al.*, 2023; Demirci *et al.*, 2025).

implications of the spread of GenAI on startup funding dynamics.

2.2 Hypothesis development

Entrepreneurial activities require the recombination of existing resources to achieve a desirable outcome (e.g., Arora and Nandkumar, 2012). These activities are typically constrained by a lack of resources, most notably in terms of financial and human capital (e.g., Cooper *et al.*, 1994; Gilbert *et al.*, 2006). Unlike established companies that have already accumulated sufficient resources, entrepreneurial startups often lack the market power to negotiate the terms of trade when acquiring resources externally (Zahra, 2021). These liabilities of newness and smallness induce startups to be particularly dependent on external resources held by other market participants, slowing down business development (e.g., Kor and Mahoney, 2005; Nason *et al.*, 2019).

Entrepreneurial startups must focus on assembling value-relevant resources to overcome these liabilities and enable growth. In traditional software-developing startups, skilled human resources often comprise a considerable portion of operational and non-monetary costs (Blatter *et al.*, 2012). Preliminary research indicates significant productivity gains for individuals who use GitHub Copilot (Peng *et al.*, 2023; Cui *et al.*, 2024). Conceptually, the release of GitHub Copilot represents a technology-driven productivity shock that reduces startups' operational costs, enabling them to reach milestones, such as securing external funding, significantly faster.

Moreover, we propose that the release of GitHub Copilot has differential effects on funding dynamics across startups, depending on the field of their business activity. The non-rival nature of GitHub Copilot certainly triggers spillovers across business fields. Still, the propensity to benefit from GitHub Copilot should be higher, on average, for startups whose operations rely more heavily on software development tools. In contrast, the introduction of GitHub Copilot should have fewer direct implications for startups that offer products and services which do not require new software development. For example, many entrepreneurial startups use modular software solutions in a plug-and-play mode, such as mobile apps or digital platforms, without actually developing new software solutions.[4] These considerations are consistent with prior literature on different but related technology shocks that benefited specific groups of firms (Mata *et al.* 1995; Ewens *et al.* 2018). Based on this, we hypothesize that:

[4] We refer to Section 3.2 for more details on this classification.

Hypothesis 1: *After the release of GitHub Copilot, the time-to-funding of software-developing startups decreases relative to other (software) startups.*

Furthermore, we argue that new technologies disproportionately affect startups at the beginning of their lifecycle, as they shift firms' cost of experimentation (Ewens *et al.*, 2018). Especially during the early stages, experimentation is a central element in entrepreneurship and resource constraints are particularly binding (e.g., Zahra, 2021). For example, demonstrating a functional prototype as a proof of concept is essential for startups to convince (prospective) stakeholders about the viability and potential of their business idea. By definition, more mature startups already have more advanced products and business models. Hence, relaxing resource constraints should be most beneficial for young startups.

These considerations are highly relevant in the context of GitHub Copilot. Limited availability of resources can significantly slow down experimentation in the form of the programming activities of software-developing startups. Therefore, resource constraints make it more difficult for startups to reach their initial milestones, such as developing first functional prototypes. We propose that GitHub Copilot is most impactful when these constraints are most severe - during the early phases of experimenting. Following this, we hypothesize that:

Hypothesis 2: *The effect of GitHub Copilot on the time-to-funding of software-developing startups is strongest at earlier funding rounds.*

Moreover, we argue that GenAI productivity gains should be reflected in the composition of labor inputs. Technological innovation may raise the efficiency of experimentation by both lowering costs and reducing required inputs (Kerr *et al.*, 2014). This implies that startups able to effectively leverage the new technology should need fewer inputs to achieve a given level of output.

Again, this aspect is particularly important in the context of GitHub Copilot. Software development traditionally involves trained personnel as key input for programming tasks. As such, startups face resource constraints not only in financial terms but also in human capital. The individual productivity gains of GitHub Copilot are well documented (QUOTE!). Software-developing startups should benefit from this new technology not only by relaxing financial constraints but also by serving as a potential substitute for labor inputs. Startups startups that successfully exploit these efficiency gains should require fewer software developers to reach first milestones. For these reasons, we propose that new technologies like GitHub Copilot can considerably reduce the demand for skilled personnel:

Hypothesis 3: *After the release of GitHub Copilot, the average number of software developers at the time of funding decreases for software-developing startups relative to other (software) startups.*

Central to our analysis, we also posit that GenAI has differential effects on startups depending on their founders' capacity to exploit the new technological resources. The adoption of innovation and especially AI-based technologies can vary substantially across specific tasks (Dell'Acqua, 2022; Gaessler and Piezunka, 2023). Early studies on the productivity effects of GenAI primarily assess individual-level performance, mostly using experimental settings (Brynjolfsson *et al.*, 2023; Noy and Zhang, 2023). These studies commonly find greater productivity improvements for less experienced or less skilled individuals in the context of relatively simple tasks. In contrast, we investigate productivity effects of GenAI in more complex organizational settings. Here, pioneering work comes to contrasting conclusions, suggesting that highly skilled or more experienced individuals within organizations are best able to capture value from GenAI (Otis *et al.*, 2023; Toner-Rodgers, 2024).[5]

These insights indicate that firm-level productivity effects likely differ from those at the individual level and require distinct theoretical considerations. We derive a theory-based prediction about which types of founders are best equipped to create a competitive advantage through technology adoption. As a starting point, it is essential to emphasize that GitHub Copilot does not directly yield a competitive advantage for startups. According to the resource-based view (Barney, 1991), all imperfectly imitable and non-substitutable tangible and intangible assets controlled by a firm are considered value-relevant resources. Technological innovations are intangible assets that lack physical presence and, thus, require a medium that stores its value (Crouzet *et al.*, 2022). However, as a non-rival and principally non-excludable good, GitHub Copilot can be acquired by anyone without substantial transfer and adoption costs.[6] It thus does not classify as a rare or inimitable resource from the perspective of the resource-based view. As such, it is unlikely to create a competitive advantage for nascent firms by itself.

However, organizations can gain a competitive advantage by adopting new technology whenever they are capable of integrating it with existing resources into uniquely complementary bundles (Sirmon *et al.*, 2008). For example, in the context of information technology and AI adoption, this factor has proven to

[5] Anecdotal evidence supports these views. For example, a serial entrepreneur, Chang Kim, described a startup founder who laid off junior software programmers and coded more himself in response to recent GenAI progress. He notes that "*product development is much faster now* [...]. *It seems like AI is making experienced, senior professionals more effective at their jobs, reducing the need for junior employees*" (Kim, 2023). Similarly, a recent article in the Wall Street Journal (2024) reports that computer science graduates struggle to find jobs as tech companies require less entry-level hires.

[6] Note that GitHub Copilot is not free of charge. However, the fees of ten USD per month or 100 USD per year (for individuals, as of June 2024) are negligible compared to other operating expenses of startups.

yield competitive advantage despite the underlying technology not being rare or inimitable (Mata *et al.*, 1995; Krakowski *et al.*, 2023). Following these considerations, decision-makers *can* gain competitive advantage, conditional on integrating existing resources and GenAI technologies into uniquely complementary resource bundles. Thus, we argue that GitHub Copilot classifies as a technological innovation that requires skilled human capital as a complement to become a value-relevant resource.

In the context of startups, the capability to integrate GenAI should strongly rely on their founders' characteristics. As such, the decision-making processes as well as product development in startups are typically concentrated on the founding team members, especially before external investors step in. In general, more experienced decision-makers are better positioned to estimate the future value of newly available resources (Kraaijenbrink *et al.*, 2010). Prior experience endows founders with stronger operational expertise and network ties (Colombo and Grilli, 2005; Hsu, 2007), both of which are also conducive to exploiting new opportunities arising from technological innovation. Hence, we propose that more experienced founders can better exploit GenAI to accelerate business development and, thus, the acquisition of funds.[7] We formally state this as the following hypothesis:

Hypothesis 4: *The effect of GitHub Copilot on the time-to-funding of software-developing startups is stronger for startups with more experienced founders.*

3 Institutional background, data, and estimation strategy

3.1 The empirical setting: the rollout of GitHub Copilot

GitHub Copilot is an AI-powered coding assistant developed collaboratively by GitHub and OpenAI.[8] It leverages recent advancements in large language models (LLMs) by utilizing a modified version of GPT-3 and assists software developers by suggesting code and snippets in real-time within the coding environment. Its capabilities extend from completing simple lines of code to providing more complex algorithmic solutions across various programming languages, making it a significant innovation for software developers.

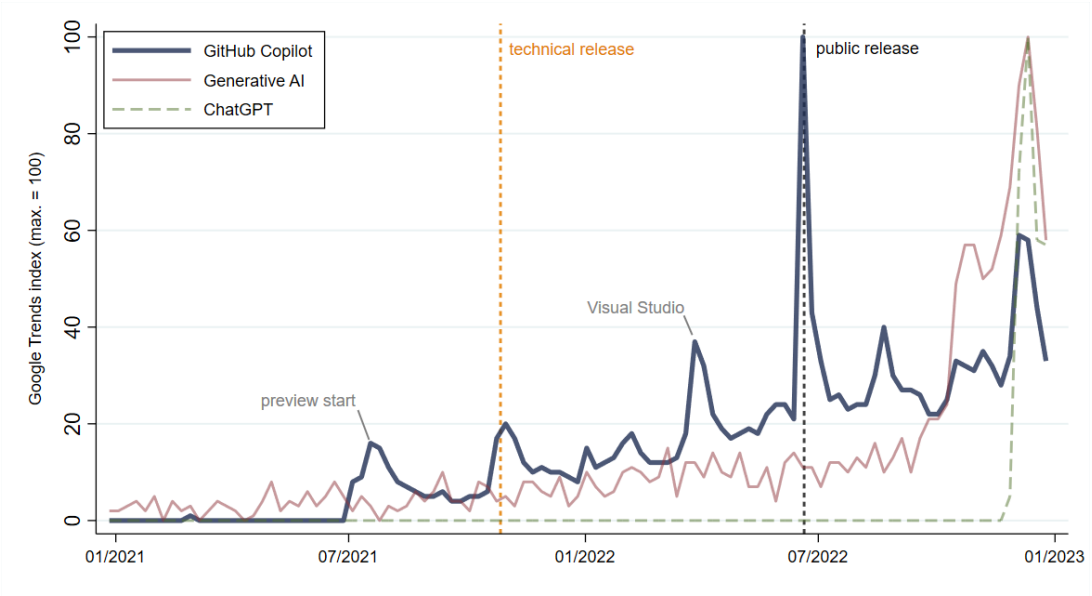
[7] Note that this assumption does not preclude that less experienced programmers may benefit from GenAI applications by accelerating coding performance. Instead, it suggests that more experienced founders have a higher propensity to draw a competitive advantage from the arrival of the new resource.

[8] GitHub is a leading open-source software development platform. It also serves as a valuable data source for empirical research, e.g., on the role of open-source software in product development and startup financing (Fisch, 2019; Conti *et al.*, 2021; Wright *et al.*, 2023). Unlike them, we exploit the release of a specific GitHub product as quasi-natural experiment.

GitHub Copilot was released in distinct stages. As of June 2021, a technical preview offered access for a limited amount of specialized users. The first relevant launch of GitHub Copilot occurred in October 2021 (henceforth "technical release"). Unlike the initial preview phase, this technical release allowed developers to use GitHub Copilot in their preferred development environment. Specifically, a plugin release on a popular developer platform, JetBrains marketplace, granted a broad audience of programmers access to GitHub Copilot. GitHub further expanded Copilot's availability within the IDE '*Visual Studio*' in March 2022. During this introductory phase, GitHub Copilot generated 27% of code in popular coding languages, such as Python (GitHub, 2023a). In June 2022, GitHub Copilot was officially released to all developers, marking the end of the introductory phase (henceforth "public release"). Figure 1 displays Google Search Trends, illustrating the timeline of the aforementioned events.

Upon inception, GitHub Copilot attracted a large user base. Already in February 2023, the share of code generated by GitHub Copilot ranged between 46 and 61% depending on the programming language (GitHub, 2023a). Further, its availability as a generally accessible tool worldwide has profound implications for software programmers. According to a GitHub survey (2022), 90% of users reported a significant productivity increase, and 87% stated that GitHub Copilot helps them invest less mental effort on repetitive tasks. Experimental evidence reports that GitHub Copilot leads to an average reduction of 56% in time-to-completion for development tasks (Peng *et al.*, 2023).

Figure 1: Google Search Trends for GitHub Copilot



The release of GitHub Copilot has well-suited properties for an empirical assessment. It represents one

of the pioneering LLM-based tools released to the public. Other examples include applicable chatbots, image synthesis platforms, and multimedia generators, such as ChatGPT, Midjourney, and Synthesia. However, the temporal precedence of GitHub Copilot in the aftermath of its technical release allows us to examine the effect of GenAI without confounding influences from subsequent or preceding technological advancements in the domain (see again Figure 1). Furthermore, GitHub Copilot's rapid and encompassing adoption marks a sudden and significant productivity shift for software developers. The release of GitHub Copilot, therefore, constitutes a suitable quasi-experimental setting to examine the causal effect of GenAI as a technology shock on startup productivity.

3.2 Data source and structure of the sample

To systematically analyze the effect of GitHub Copilot as a technology shock on early-stage funding dynamics, we leverage data on startups and their funding activities from Crunchbase. Crunchbase is widely used by scholars as a source of information on entrepreneurial activities across countries and industries (Dalle *et al.*, 2017). It offers detailed information on firms' funding and other business activities. A benchmark analysis places Crunchbase among the startup databases with the best coverage and highest accuracy, with key dimensions being the size, timing, and type of funding events (Retterath and Braun, 2020). Appendix B describes the data in more detail, including an assessment of potential truncation issues in Crunchbase data.[9]

We augment this data by adding employment data on founders and the employees of respective startups, using data from Revelio Labs. These information allow us to elicit the mechanisms behind the financial outcomes at the employee level. Revelio Labs provides granular information on workforce dynamics, including employee roles, job types, tenure, and previous experiences. Revelio extracts its data from publicly available professional profiles, such as LinkedIn. In the context of our study, this source seems appropriate because employees and founders the startups in our sample arguably have a high propensity to use online platforms for signaling purposes (see **??**). Using this data, we compute employee counts and characteristics on a quarterly frequence for our sample startups.

Our sample is based on repeated cross-sectional data extracted from Crunchbase in March 2024. It includes startups headquartered in the US, Canada, and Europe that have successfully raised an initial

[9]The analysis of recent events, such as the popularization of GenAI software, requires contemporary data. Crunchbase relies on crowdsourcing as its primary data collection method, which may introduce inaccuracies in the most recent funding data. In Appendix B, we show that our analysis is not prone to such truncation issues.

funding round between Q1 2020 and Q3 2023, a symmetrical time window around the rollout phase of GitHub Copilot. We aggregate the daily data on a monthly level and winsorize observations below the 5^{th} percentile and above the 95^{th} percentile to address outliers in the main variables. We use a relatively flexible specification on the round type since Crunchbase labels may be prone to mislabelling; We only consider investments related to early-stage grants and equity investments. Further, we apply a common strategy to remove erroneous reporting about financing rounds (see Lerner, 1995; Townsend, 2015). Following Townsend (2015), we remove firms with rounds raised no fewer than 30 days and no more than six years apart, either from their founding date (for the first round) or from the preceding round (for all subsequent rounds).

The final sample comprises 21,834 startups with at least one funding round between Q1 2020 and Q3 2023. Table A2 (Appendix) lists all variables used in the analysis. Table 1 presents the summary statistics on the key variables employed in this sample. Consistent with our sampling strategy, startups are relatively young when they first receive external funding. On average, it takes startups about two years after incorporation to receive their first deal. Half of the startups obtain initial funding within 20 months, while the initial deals covered in the sample are fairly evenly spread across the sample period (see Figure A1, Appendix A). The median deal size is one million USD and about one out of every three startups secures follow-on funding. Table A1 (Appendix A) contains statistics that further detail the sample regarding country, firm size, and funding type distributions.

3.3 Classifying treatment and control groups

In Section 2.2, we propose that startups' propensity to respond to the GitHub Copilot release depends on their business fields. To classify them, we follow related literature (e.g., Edwards and Todtenhaupt, 2020) and use the Crunchbase business field categories to assign each startup to a specific sector. We distinguish three main categories: 1) software-developing startups, 2) other software startups, and 3) non-software startups. Importantly, our empirical strategy does not require this classification to perfectly delineate startups that benefit from the introduction of GitHub Copilot and those that are immune to it. Instead, we compare firms that have, on average, a higher or lower propensity to utilize the technology. If non-software or other software startups indeed benefit from GitHub Copilot, our estimations are biased downwards. Hence, the approach is a conservative way of classifying firms.

Table 1: Summary statistics

	Obs.	Mean	SD	p10	p25	Median	p75	p90
Time-to-funding	21,834	24.468	17.452	5.033	10.833	20.267	35.533	51.700
log(*DealSize*)	14,699	13.586	2.030	10.898	12.206	13.816	15.060	16.002
DealSize (in TUSD)	14,699	3,412	6,307	54	200	1,000	3,470	8,900
Follow-on investment	21,834	0.317	0.466	0	0	0	1	1
Total *DealSize* (in TUSD)	16,402	12,732	87,260	100	300	2,000	6,583	22,401
Developers	21,834	0.165	0.371	0	0	0	0	1
OtherSoftware	21,834	0.776	0.417	0	1	1	1	1
# investors	21,834	2.423	2.932	1	1	1	3	6
Syndicate	18,826	0.305	0.460	0	0	0	1	1
US investors	21,834	0.644	0.479	0	0	1	1	1
European investors	21,834	0.380	0.485	0	0	0	1	1
Remote	21,834	0.615	0.487	0	0	1	1	1
LowPropensity	21,834	0.300	0.458	0	0	0	1	1
Computer Science degree	6,143	0.222	0.415	0	0	0	0	1
Founder rank	10,970	435,486	478,176	49,992	132,923	321,120	648,826	1,008,532
Founder age (since grad.)	4,750	14.760	9.076	4.332	8.006	13.011	20.014	28.019
Founder with exit	10,970	0.084	0.278	0	0	0	0	0
Serial founder	10,970	0.319	0.466	0	0	0	1	1
Founding team size	10,970	1.801	0.909	1	1	2	2	3
Time-to-funding; 2^{nd} round	12,234	32.085	16.755	11.800	18.700	29.667	43.600	56.933
log(*DealSize*); 2^{nd} round	8,519	14.473	2.021	11.562	13.182	14.734	15.847	16.907
Time-to-funding; 3^{rd} round	5,701	38.629	15.749	18.233	26.433	37.700	50.467	61.300
log(*DealSize*); 3^{rd} round	4,126	13.922	2.089	11.842	13.764	15.187	16.497	17.453
# employees	18,542	12.162	12.248	2	4	8	16	30
# employed software developers	18,542	1.888	2.814	0	0	1	3	6

Notes: The table provides statistics on the main variables. For variable definitions, see Table A2 (Appendix).

Specifically, we define firms as software-developing startups if they operate in sectors in which the main product or service primarily requires them to generate new software solutions (henceforth referred to as *software-developing* startups). For these firms, software development constitutes their core value proposition to their customers. Examples are business fields labeled in Crunchbase as software-as-a-service (SaaS), software development kits, machine learning, or programming. Unlike startups in these fields, others incorporate existing software solutions in their business model, such as apps or online platforms, but do not develop new solutions (henceforth *other software* startups). These firms leverage software for their main product or service without explicitly focusing on commercializing self-programmed software. Examples include the Crunchbase labels customer relationship management, user interface, data visualization, and digital platforms. Lastly, all startups that do not operate in software-related business fields are henceforth referred to as *non-software* startups. Table A3 (Appendix A) comprises a detailed list of these three categories, including examples of business activity descriptions

from Crunchbase.

To support our classification approach, we assess the number of software developers employed at the focal startups at the time of initial funding. Descriptive statistics in Table A4 (Appendix) confirm that software-developing startups employ, on average, significantly more software developers (2.9) compared to other software startups (1.9), and non-software startups (0.9).These figures are consistent with the objective to distinguish firms in terms of the focus of their business operations on software development, and their corresponding responsiveness to the release of GitHub Copilot.

In our sample, 16.5% of startups are software-developing startups, 71.1% are other software startups, and 12.4% are non-software startups. This distribution is consistent with the focus of VC investors on high-growth technology startups. Table A4 reports summary statistics similar to Table 1, distinguishing the startup categories.

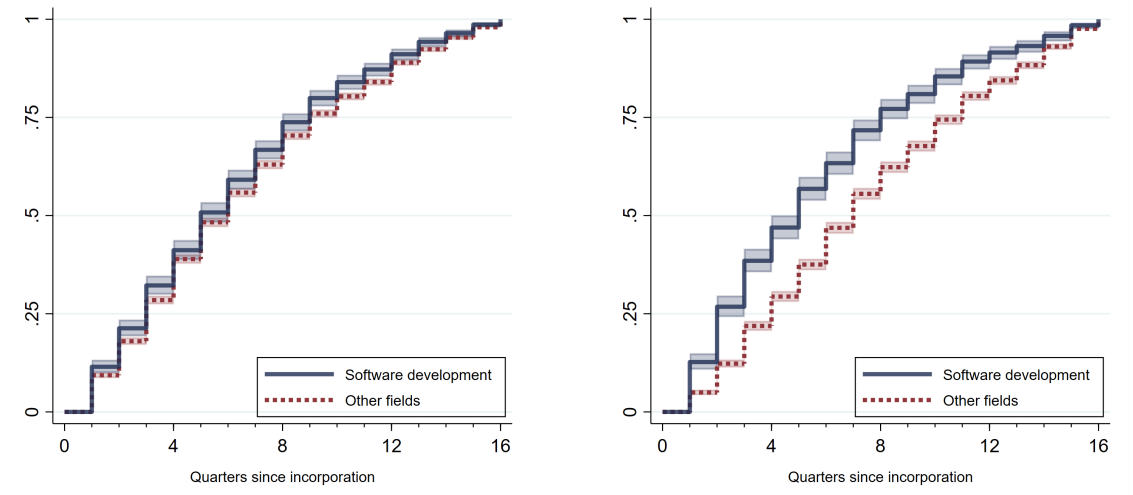
Moreover, univariate statistics on startups' time-to-funding across these industry classes already indicate a potential change in startup funding dynamics after the GitHub Copilot release. The Nelson-Aalen failure estimates ("hazard rates") in Figure 2 display the speed of securing initial funding after incorporation. We estimate the hazard rates for software-developing startups and all other startups before the technical release of GitHub Copilot (Panel A) and after its public release in June 2022 (Panel B). Overall, about 60% of the startups receive their initial funding round within the first two years after incorporation. Before the initial release, the time-to-funding does not differ between software-developing startups and other startups. Afterwards, the time-to-funding of software-developing startups is significantly shorter than for startups operating in other business fields. For example, after five quarters (about 15 months), 50% of software-developing startups receive their initial funding round (see Panel A). Meanwhile, it takes about six more months (i.e., seven quarters) until 50% of startups from other business fields secure their initial funding round (see Panel B). Figures A2 and A3 (Appendix) confirm that these funding patterns also apply when comparing software-developing and other software startups.

3.4 Defining the baseline model

The impact of GitHub Copilot as a technology shock on startup productivity can be measured as the differential effect on the time-to-funding, comparing software-developing startups with startups in other business fields. The empirical setting allows a differences-in-differences (DID) type analysis in which

Figure 2: Nelson-Aalen estimates: the time-to-funding of software development and other startups

Panel A: *Before* the GitHub Copilot preview phase **Panel B:** *After* the public GitHub Copilot release



Notes: This graph displays Nelson-Aalen failure estimates (hazard rates) of the timing of the first funding event, using a panel-structured dataset on the startup-quarter level. The hazard rate is conditional on having a funding event within the first five years after incorporation and is estimated for software-developing startups (solid blue line) and startups operating in other business fields (dashed red line). Panels A and B display the probability of receiving the first funding before the GitHub Copilot initial release and after its public release, respectively. The shaded areas around the hazard rates mark the 95% confidence intervals.

software-developing startups serve as the treatment group and other startups are control group firms. Formally, we estimate the following fixed effect specification:

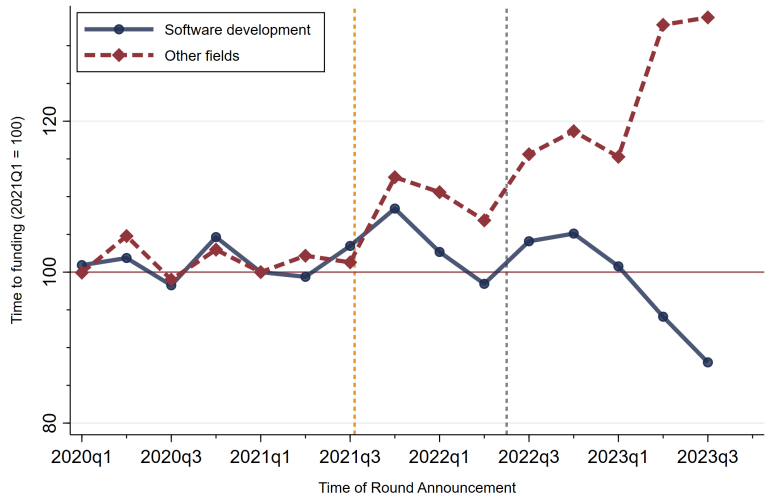
$$Y_{ijct} = \beta_1(Developer_i \times Post_t) + \beta X_i + \gamma_t + \delta_c + \mu_j + \epsilon_{ijct}, \tag{1}$$

with, the dependent variable, Y_{ijct}. In the baseline specifications, Y_{ijct} represents the time-to-initial-funding for a startup i, in industry j, in country c, and at time t. Time is a continuous measure of months reflecting the funding round announcement date. $Developer_i$ is a dummy that equals one for software-developing startups, as defined in Section 3.3, and zero otherwise. $Post_t$ is a dummy variable that equals one for startups that raised their initial funding round in any month after the release of GitHub Copilot and zero otherwise. We use two specifications for this date: i) the public release in June 2022 and ii) the technical release in October 2021. Hence, the interaction term $Developer_i \times Post_t$ captures the difference in funding dynamics between software-developing startups and other startups after the release of GitHub Copilot, relative to the difference before the release. The coefficient of interest, β_1, captures this average treatment effect. A negative significant coefficient implies that GitHub Copilot reduces the time-to-funding for software-developing startups relative to other startups, confirming Hypothesis 1. A vector of control variables (X) controls for firm-specific investor characteristics and the base variables

of the DID estimator. The model includes time fixed effects (γ_t) that control for business cycle trends or the general investment climate across time. We also control for country- and industry-specific, time-invariant factors by including country fixed effects (δ_c) and industry fixed effects (μ_j). Standard errors are clustered at the startup level, with ϵ_{ijct} representing the error term.

A central identifying assumption of DID approaches revolves around the concept of pre-treatment parallel trends. In our setup, this implies that software-developing and other startups can serve as appropriate treatment and control groups if their funding patterns are similar before the release of GitHub Copilot. While the parallel trends assumption cannot be definitively proven, descriptive analyses can provide a degree of validation. Figure 3 visually supports that the parallel trends assumption is not violated. This result is consistent with the pre-GitHub Copilot pattern in the hazard rates of the time-to-funding (see, e.g., Figure 2).[10]

Figure 3: Average time-to-funding, by quarter (indexed)



Notes: This graph displays the mean dependent variable, the time to initial funding, on a quarterly level for software-developing startups (blue solid line) and other startups (red dashed line). The quarterly averages are measured at the end of each quarter. The vertical dashed orange line indicates GitHub Copilot's technical release in October 2021 and the vertical dashed black line indicates the public release in June 2022.

[10] As a second assumption, DID estimations require the absence of other systematic changes that affected the treatment group, during the same period, and in ways that might confound the observed results. In Section 4.3, we present a series of robustness checks that mitigate concerns about potential confounding events.

4 Empirical Analysis

4.1 Baseline results

We start by estimating the effect of the GitHub Copilot release on startups' funding dynamics. Table 2 displays the results from estimating Equation (1). In Column I, the coefficient of the interaction term *Developer* × *Post* is large, negative, and significant at the one percent level, consistent with Hypothesis 1. The coefficient size (-4.793) suggests that software-developing startups experience an average reduction of about five months to initial funding relative to other startups. The size of this effect is economically significant, implying a 19.6% decrease in the relative time-to-funding (compared to the mean of 24.468 months, displayed in Table 1). Column II shows that this effect is similar but slightly smaller (-3.815) when considering the technical release as the initial treatment period. This finding likely reflects that fewer firms were subject to the technical release than to the full release (see Section 3.1).

Table 2: Baseline results: The effect of the GitHub Copilot on startups' time-to-funding

Dependent variable:	Time-to-funding			
	(I)	(II)	(III)	(IV)
Developer × Post	-4.793***	-3.815***	-5.754***	-5.099***
	(0.669)	(0.629)	(0.849)	(0.803)
Sample:	Full		Excluding other software startups	
Post definition (release):	Public	Technical	Public	Technical
Additional controls:				
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
N	21,834	21,834	8,521	8,521
R^2	0.19	0.19	0.23	0.23

Notes: This table displays DID estimation results on the effect of GitHub Copilot on the time-to-funding of software-developing startups relative to control group startups. Column I displays the results of the main specification, as defined in Equation (1). Column II is similar to before, only here, the Post variable is equal to one for all quarters after the technical release in June 2021. The next two specifications are similar to Columns I and II but exclude all other software startups that are not software-developing startups. The base variables of the DID estimator are omitted in the output. Table A5 (Appendix A) displays the full output, including estimates on the control variables and DID base variables. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

These results are robust to a series of tests. First, Columns III and IV show that the observed effects become larger when comparing software-developing and non-software startups. Second, Table A6

(Appendix A) shows that the baseline results are not affected when using alternative (i.e., more narrow) classifications of software-developing and other software startups. Third, controlling more rigorously for the type of startup investments, i.e., pre-seed, seed, and VC financing, does not qualitatively affect the main findings (Tables A7). Fourth, we run a plausibility test that repeats the analyses for a subset of distinct business fields with a low propensity to respond to GenAI technologies due to regulatory hurdles. Intuitively, regulatory scrutiny varies across industries, with particularly tight regulation in sensitive fields such as healthcare, governmental (e.g., military), or energy sectors. Consistently, the interaction term for these subsectors is insignificant across fields (see Table A8, Appendix A).

So far, our analysis compares the effects of GitHub Copilot, distinguishing software-developing and all other startups. Next, we turn to a more specific comparison that singles out other software startups among the control group firms that are not developing software (i.e., *other software* startups, as defined in Section 3.3). As Figure A3 (Appendix A) illustrates, the time-to-funding of software startups is closely aligned before the initial release of GitHub Copilot, whereas software-developing startups have a significantly shorter time-to-funding than other software startups afterwards.

To examine this correlation in greater detail, Table 3 summarizes estimates on the differential effects of GitHub Copilot within software startups using the DID framework. Specifically, Columns I and II repeat the estimations from the baseline model (i.e., Columns I and II of Table 2) but exclude all non-software startups. Thus, the DID estimator captures the differential change in the time-to-funding comparing software-developing to other software startups. The corresponding coefficient is negative and significant at the one percent level. The average effect size is slightly smaller than before but remains economically significant: The coefficient (3.843) suggests a relative decline of the time-to-funding by about 18.5% of software-developing startups relative to other software startups (see the mean dependent variable of these subgroups in Table A4, Appendix). Column II shows that this effect is again slightly weaker when considering the technical release of GitHub Copilot as the treatment event.

For robustness, we analyze these patterns in two alternative ways. Estimates in Columns III and IV are similar to before, but *exclude* software-developing startups from the estimation sample. Instead of using the *Developer*-dummy variable, these regressions use a dummy equal to one for all other software startups and zero otherwise ($OtherSoftware$). In these specifications, the coefficients of interest remain negative and statistically significant. However, the average treatment effect for other software startups

Table 3: Baseline effects of GitHub Copilot within software startups

Dependent variable:	Time-to-funding					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Developer × Post	-3.843***	-3.073***			-6.189***	-5.360***
	(0.690)	(0.648)			(0.836)	(0.791)
OtherSoftware× Post			-2.020***	-2.107***	-2.107***	-2.178***
			(0.665)	(0.626)	(0.626)	(0.627)
Sample:	Software startups		Excluding software-developing startups		Full	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	16,754	16,754	18,127	18,127	21,834	21,834
R^2	0.18	0.18	0.19	0.19	0.19	0.19

Notes: This table displays DID estimations similar to the baseline estimations. Columns I and II are specified equivalent to Columns I and II of Table 2 but exclude startups that are not active in software-related fields. Columns III and IV exclude all software-developing startups. Here, the DID estimator consists of the two Post-indicators and the dummy *OtherSoftware*, which is equal to one for all software startups, and zero otherwise. Columns V and VI use the full sample and include both DID terms as defined before. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

relative to non-software startups is much smaller. The coefficient (-2.020) implies a reduction of 8.6% to the average mean dependent variable for other software startups (see Table A4, Appendix). Columns V and VI confirm the previous results using a specification that includes both DID estimator specifications simultaneously. Overall, these estimates reinforce Hypothesis 1. Notably, the findings also mitigate concerns that observable differences between software-developing and other startups drive our main results.

4.2 The effect of GitHub Copilot in subsequent rounds and deal sizes

Next, we analyze a set of alternative dependent variables. First, we examine the effect of GitHub Copilot on startups' time to the second and third funding rounds, thereby testing Hypothesis 2. To this end, we repeat the previous analysis from Section 4.1 for a subset of firms that receive follow-on funding within the sample timeframe, which applies to 31.7% of startups in the main sample. Again, the time-to-funding is calculated as the time between incorporation and the respective funding rounds.

The results displayed in Table 8 show a statistically significant reduction in the time to the second

funding round for software-developing startups relative to other startups after the public release of GitHub Copilot. The coefficient in Column I indicates an economically rather small reduction in the time-to-funding of about 2.354 months, equivalent to a relative acceleration by 7.3% (with the mean dependent variable 32.085, see Table 1). This effect is notably smaller than the reduction in the time to the first funding round (19.6%, Table 2). It also applies when comparing software-developing and other software startups (Column III), but the coefficients turn insignificant when considering the technical release of GitHub Copilot (Columns II and IV). Further, the coefficients of the DID estimators are insignificant across all specifications when considering the third funding round. These results suggest that the accelerating effect of GitHub Copilot is strongest in the earliest lifecycle stages of startups.[11] Overall, this finding supports Hypothesis 2 and emphasizes the crucial role of technological innovation in mitigating resource constraints, especially for young startups.

Table 4: The effect of GitHub Copilot on the time-to-funding of subsequent funding rounds

Dependent variable:	Time-to-funding							
	2nd round				3rd round			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII	(VIII)
Developer × Post	-2.354***	-1.200	-2.312**	-1.276	0.753	1.029	0.453	1.054
	(0.877)	(0.799)	(0.910)	(0.828)	(1.222)	(1.124)	(1.269)	(1.167)
Sample:	Full		Software startups		Full		Software startups	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical
Additional controls:								
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,234	12,234	10,003	10,003	5,701	5,701	4,732	4,732
R^2	0.18	0.18	0.19	0.19	0.21	0.21	0.23	0.23

Notes: This table displays DID estimations similar to the baseline estimations. Columns I-IV (Columns V-VIII) repeat Columns I and II from Tables 2 and 3 but use the time to the second (third) funding round as the dependent variable. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Second, we assess the size of respective deals as an alternative outcome variable. A priori, the effects of GitHub Copilot on changes in the amounts of funding are unclear. On the one hand, GitHub Copilot increases productivity and enables startups to raise funding earlier on, both of which imply a lower funding demand. On the other hand, efficiency gains from GitHub Copilot allow firms to reach product

[11] For robustness, we test the timing of the main effects on the first, second, and third funding rounds using estimations that apply the two treatment indicators (Post) simultaneously. The results displayed in Table A9 (Appendix) reconfirm that the main effects are mainly attributed to the earliest funding rounds.

and business development targets faster, raising startup valuation and corresponding deal sizes. Testing the size-related effects, therefore, remains an empirical task.

We repeat the main analyses using the total amount of funding per round (in logs of USD) as the dependent variable. Table A10 (Appendix A) displays the results. Panel A shows no differential effect on the initial deal size obtained by software-developing startups after the release of GitHub Copilot relative to other startups. If anything, we find a moderate positive effect when comparing software-developing startups to non-software startups. Consistently, Panel B shows no effect on the subsequent rounds either. These findings suggest that the GitHub Copilot-induced effects on startup valuation and capital demand offset each other.

4.3 Potential Confounding Events and Alternative Mechanisms

This section addresses potential concerns about other factors that may impact software-developing startups' funding dynamics during the treatment period. We examine the three arguably most influential contemporaneous events during the early 2020s: the shift towards remote work triggered by the COVID-19 pandemic, changes in the VC sentiment at the time, and the launch of ChatGPT, the most popular GenAI tool to date.

Remote labor and COVID-19 We start by estimating the potential role of the COVID-19 pandemic and the accompanying policy restrictions on startup funding dynamics in our sample. The idea behind this approach is that the pandemic-related policies and the corresponding rise in remote work might be an alternative factor that systematically affected funding patterns of software-developing startups. This consideration is crucial in our setup because software startups are generally more adaptable to remote operations. Hence, they likely experienced fewer disruptions in their business operations compared to other startups that may rely heavily on on-site activities, such as specific hardware startups.

To demonstrate that such a differential impact is unlikely to drive the main results, we distinguish firms that operate in business fields with a higher or lower ability to support remote work. For classification, we rely on the "*ability to work from home*" metrics provided by Adams-Prassl *et al.* (2022). Fields with high remote work scores include financial services, content publishing, or internet services. Fields with a low propensity to remote work are, amongst others, the food and beverage sectors. Table A11 (Appendix) contains the full list of business fields with a high or low propensity to offer remote work.

Using this classification, we deploy a *Remote*-indicator that flags startups active in business fields with a high propensity to offer remote work as an alternative treatment measure instead of the *Developer* dummy in Equation (1). Panel A of Table 5 (Columns I and II) shows that the remote indicator is generally not able to explain the main results for a subsample of software startups. The coefficients of the interaction terms are smaller and statistically insignificant. As an alternative test, we use a different treatment indicator, *Covid*, which is equal to one for all periods after the first lockdown in March 2020. Again, the coefficient of the interaction term is insignificant, reflecting the homogeneous impact of the pandemic on all market participants (see Column III). We repeat these estimations using non-software startups only (see Columns IV-VI). Intuitively, if a COVID-19-driven increase in remote work represents an alternative mechanism, such an effect would emerge as differences in time to initial funding between the non-software industries based on their remote work capacities. Again, the estimates are qualitatively similar to before. Overall, we find that changes in the availability of remote work in the context of the COVID-19 pandemic are unlikely to confound the main findings.

VC sentiment: The general VC investment climate is a second potential factor that may confound the effect of GitHub Copilot on the time-to-funding. In the main specifications, we account for general time-specific trends by controlling for time fixed effects. This approach captures variation arising from general changes in the funding environment. However, shifts in VC sentiment could have differential effects across specific types of startups. For example, Ewens *et al.* (2018) show that hot markets favor specific, more experimental ("high-risk") startups. Arguably, software-developing startups may be more experimental than the average startup, thus benefiting disproportionately from hot markets by receiving initial funding at earlier stages. Hence, we investigate the role of the VC market sentiment as an alternative mechanism behind the main results.

To quantify VC sentiment, we extract data on the FTSE Venture Capital Index (TRVCI). The TRCVI represents the sentiment in the VC industry by measuring its gross performance. It aggregates venture-funded private company values and replicates these through a combination of publicly listed assets. We construct three alternative treatment indicators based on this VC Index. First, we generate a continuous variable aggregating the daily VC market sentiment data on a monthly average. Second, we flag months in the top decile of the VC sentiment distribution as "hot markets", i.e., months during which the market

Table 5: Robustness test: Testing alternative mechanisms

Panel A: Remote work and COVID-19 as alternative mechanism

Dependent variable:	Time-to-funding					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Remote × Post	-1.012	-0.859		0.603	-0.863	
	(0.684)	(0.624)		(1.388)	(1.328)	
Remote × Covid			0.694			0.250
			(1.197)			(2.392)
Sample:	Software startups			Non-software startups		
Post definition:	Public	Technical	-	Public	Technical	-
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	16,754	16,754	16,754	4,662	4,662	4,662
R^2	0.18	0.18	0.18	0.20	0.20	0.20

Panel B: VC market sentiment as alternative mechanism

Dependent variable:	Time-to-funding					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Developer × VC sentiment	0.200***	2.373**	-0.133	0.168***	2.380*	-0.801
	(0.039)	(1.206)	(1.005)	(0.041)	(1.247)	(1.045)
Sample:	Full			Software startups		
VC sentiment definition:	Continuous	Hot market	Cold market	Continuous	Hot market	Cold market
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	18,295	18,295	18,295	13,986	13,986	13,986
R^2	0.19	0.19	0.19	0.19	0.19	0.19

Notes: This table displays DID estimations testing the effects of remote working environments and VC market sentiment as alternative mechanisms affecting startups' time-to-funding. Panel A tests the effect of the treatment on business fields with a high propensity to allow employees to work remotely. Columns I and II are similar to Columns I and II of Table 3. Only here instead the *Developer* indicator is exchanged with a remote indicator that is equal to one for all business fields with a high propensity to offer remote work as defined in Adams-Prassl *et al.* (2022), and zero otherwise. Column III uses an alternative treatment indicator, *Covid*, which is equal to one for all months after the initial lockdown in the US and Europe in March 2020. Columns I-III use the sample of software startups. Columns IV-VI repeat these specifications using the sample of non-software startups. Panel B tests the effects of the market sentiment in the VC industry as an alternative mechanism. Columns I-III are similar to the baseline estimation (Column I of Table 2). Instead of the *Post* indicator, the estimations use a continuous VC sentiment measure (Column I), a binary indicator equal to one for particularly favorable (Column II), or unfavorable (Column III) VC market conditions, and zero otherwise. Favorable (unfavorable) market conditions are the ten percent of all months in the sample during which the VC market sentiment was highest (lowest). Columns IV-VI repeat these estimation using a sample of software startups only. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

sentiment was particularly high. Third, conversely, we also classify months in the bottom decile of the distribution, indicating months in which the sentiment was particularly low ("cold markets").

Panel B of Table 5 displays regressions that repeat the baseline estimates from Table 2, but replace the treatment indicators (*Post*) with the three VC market sentiment dummies. The idea is that if VC market sentiment could equally (or better) explain the main findings, this setup should yield similar results to the baseline estimates. However, we generally find a *positive* association between VC market sentiment scores and the time-to-funding of software-developing startups. This finding is robust to using all three VC sentiment measures (Columns II and III) and excluding non-software startups (Columns IV-VI), suggesting that the general investment climate is rather a moderator in the baseline specifications. Hence, VC market sentiment is unlikely to be an omitted factor driving the main results.

ChatGPT launch: As another alternative mechanism, we analyze potentially confounding effects arising from the successive rollout of ChatGPT. ChatGPT is a general-purpose chatbot that mimics human conversations with its users. Its ability to write and debug computer programs is a functionality comparable to the core purpose of GitHub Copilot. It is, therefore, natural to consider the role of ChatGPT as an alternative mechanism in our empirical context.

However, the mere fact that both GitHub Copilot and ChatGPT are GenAI-based software applications does not imply that the two technologies are equally likely to drive the baseline results. First, GitHub Copilot and ChatGPT are two conceptually different tools. GitHub Copilot is a specialist tool that benefits software programmers by completing and generating codes. In contrast, ChatGPT is a generalistic application designed to assist a broad audience in a variety of conversation-like tasks. Thus, the introduction of GitHub Copilot represents a differential technology shock, whereas ChatGPT triggered a homogeneous shock across the economy. Second, the timing of the ChatGPT rollout only marginally overlaps with the main effects of the GitHub Copilot release that emerge already in 2022 (see again Figure 1). Despite ChatGPT's initial launch in November 2022, developers were able to utilize APIs for programming tasks only after the launch of ChatGPT-4 in mid-March 2023. Moreover, anecdotal evidence suggests that even this release did not immediately enhance user productivity.[12] Similarly, a comprehensive evaluation study shows that inaccuracies of ChatGPT responses were still dominating by

[12] Lucas Dunker, software developer at Harvard Medical School software engineering co-op, stated in May 2023: "*We use* [ChatGPT] *just for general creative advice, maybe for naming a project or naming variables. We don't really use it for a lot of our actual code [...]. They're usually a little too complex for ChatGPT to add to or do much to.*" (Weldon, 2023).

August 2023 (Kabir *et al.*, 2024). In line with these arguments, Figure 4 shows that the general interest in GenAI reached its highest levels in the second half of 2023, i.e., well after the release of GPT-4 in March 2023. Overall, these aspects question that ChatGPT's release affects confound our main results.

Figure 4: Google Trends: Predictive versus Generative AI



Nevertheless, to address remaining concerns about ChatGPT being a potentially confounding factor, we test the robustness of our baseline regressions regarding its rollout. First, we exclude startups that received their initial funding after the release of GPT-4 on March 24, 2023. This step removes all startups that could have used ChatGPT as an alternative GenAI tool for programming tasks. Table 6 shows that the baseline estimates do not qualitatively change when excluding these startups (Columns I-IV). As an alternative approach, we remove all startups that received their initial funding round after the official introduction of ChatGPT on November 30, 2022. This way, we also exclude firms that potentially benefited from the rising interest in GenAI technologies, for example, from potential investors. This approach results in a very narrow treatment time window but still yields a statistically significant negative differential effect of GitHub Copilot on software-developing startups' time-to-funding. These findings are consistent with the observation that the effect of GitHub Copilot on the funding dynamics of software-developing startups has already unfolded in early 2022. Importantly, these results mitigate concerns that the launch of ChatGPT was an alternative technology shock underlying the main results.

The tests in this section offer strong support for the validity of the estimation approach and the main findings. Results hold for different potential alternative mechanisms, including the introduction of ChatGPT, COVID-19-induced shifts towards remote work, and changes in VC market sentiment. These insights underscore the link between the release of GitHub Copilot and the productivity increase of software-developing startups.

Table 6: Robustness test: excluding startups with funding post-ChatGPT

Dependent variable:	Time-to-funding					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Developer × Post	-2.169***	-2.093***	-2.094**	-1.869**	-2.023***	-1.785**
	(0.836)	(0.661)	(0.865)	(0.712)	(0.743)	(0.767)
Sample (timeframe):	Pre ChatGPT 4.0				Pre initial ChatGPT release	
Sample (firms):	Full		Software startups		Full	Software startups
Post definition (release):	Public	Technical	Public	Technical	Technical	Technical
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	18,768	18,768	14,511	14,511	17,092	13,235
R^2	0.18	0.18	0.18	0.18	0.18	0.18

Notes: This table displays DID estimations similar to the baseline estimations. Only here, the estimations exclude months during which ChatGPT was available. Specifically, Columns I-IV repeat Columns I and II from Tables 2 and 3 but exclude any observations after the launch of ChatGPT 4.0 in March 2023. Columns V and VI are similar to Columns II and IV but exclude all observations after the first release of ChatGPT on November 30, 2022. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

5 Underlying mechanisms and heterogeneous treatment effects

The previous analyses provide robust evidence that software developing startups raise similar amounts of funding significantly earlier in their lifecycle To detail on these findings, this section answers two main questions. First, are the observed patterns indeed related to productivity gains? To answer this question, we examine changes in startups' hiring of software developers. The underlying premise is that firm-level productivity gains result from increased individual efficiency among software developers employed by our sample startups. Second, which types of startups are best positioned to capture productivity gains from GenAI? To this end, we assess differences in treatment effects regarding startup founders' prior technological and entrepreneurial experience. This allows us to identify key characteristics that enable startups to gain a competitive advantage through new technology adoption.

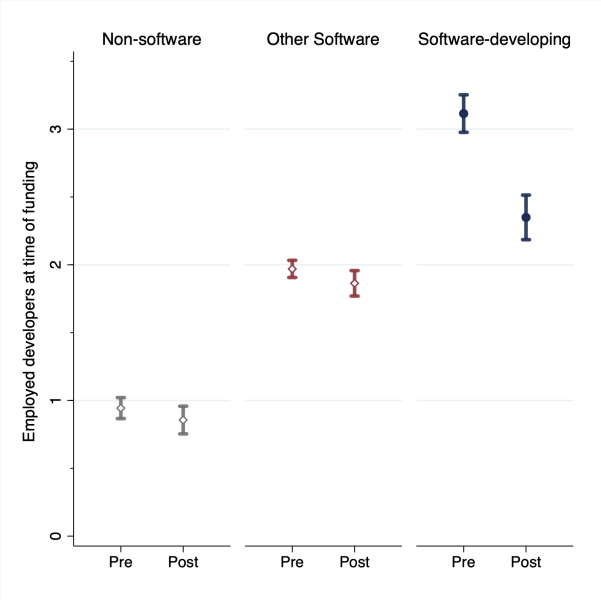
5.1 Startup hiring of junior software developers

We first examine changes in startups' hiring of junior software programmers. Again, the underlying idea is that the release of GitHub Copilot should coincide with a lower demand for new programmers, if the productivity gains boost individual developer efficiency: Fewer software programmers would be needed to achieve a given level of output. Hiring skilled developers is typically one of the first and most

resource-intensive steps in scaling a software startup (Blatter *et al.*, 2012; Roach and Sauermann, 2024), and GitHub Copilot may alleviate this burden. We leverage data from Revelio to compute the number of software developers at sample startups in each quarter. Specifically, we identify software developers based on their job titles and count them over time, excluding startup founders.

Figure 5 displays the average number of employed software developers at the time of initial funding. Further, it compares startups before and after the release of GitHub Copilot, distinguishing software-developing startups, other software startups, and non-software startups. Intuitively, the average number of software developers employed across these subgroups varies significantly. More importantly, the graph reveals a striking pattern: software-developing startups employ a significantly lower average number of programmers at the time of initial funding when comparing pre- and post GitHub Copilot periods. This pattern does not apply for other startups in the sample.

Figure 5: Software developers at time of funding



Next, we detail on these descriptive patterns, re-estimating the baseline specification as defined in Equation (1). We use the number of software developers at time of funding as dependent variable. Hence, the coefficient on the interaction term of *Developer* and *Post* now captures the differential change in the number of software developers at the time of initial funding before and after the release of GitHub Copilot, comparing software-developing and other startups.

The results in Table 7 show that software-developing startups employ significantly fewer developers at the time of their initial funding compared to other software startups (Columns I and II) and non-software

startups (Columns V and VI) after the release of GitHub Copilot. By contrast, no significant change is observed for other software startups relative to non-software startups (Columns III and IV). The DID estimators are negative and statistically significant at the one percent level. The treatment effects are economically meaningful. For example, the DID estimator in Column V (-0.630) implies a decrease in software team size by 22% relative to the mean dependent variable (see Table A4, Appendix). These findings do not qualitatively change when using the number of software developers employed at startups at fixed time intervals of 1, 3, and 6 quarters after incorporation (see Table A12, Appendix).

Table 7: The effect of GitHub Copilot on the number of software employees

Dependent variable:	Number of Software Developers					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Developer × Post	-0.568***	-0.427***			-0.630***	-0.436***
	(0.139)	(0.136)			(0.142)	(0.141)
OtherSoftware× Post			-0.050	0.001	-0.052	-0.008
			(0.090)	(0.086)	(0.090)	(0.086)
Sample:	Software startups		Excluding software-developing startups		Full	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	14,139	14,139	15,137	15,137	18,295	18,295
R^2	0.24	0.24	0.24	0.24	0.25	0.25

Notes: This table displays DID estimations in line with the baseline estimations, but for a new dependent variable: The number of employed software developers at time of initial funding. Columns I and II estimate the effect within software startups only for both *Post* definitions. Columns III and IV compare *OtherSoftware* startups with non-software startups. Columns V and VI use the full sample and include both DID terms as defined before. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

These findings resonate with anecdotal evidence. For instance, the Wall Street Journal (2024) describes that computer science graduates increasingly struggle to find jobs due to a significant decline in the demand for entry-level hires at tech companies since late 2022.[13] Similarly, preliminary evidence of a substitution effect of GenAI on labor finds a significant negative relationship between the introduction of GenAI technologies on jobs and earnings of freelancers (Hui *et al.*, 2023; Demirci *et al.*, 2025).

[13]Further, the findings mirror aggregate statistics on job announcements. Table **??** (Appendix) displays postings on the job platform *Indeed* between February 2020 and July 2023, distinguishing job announcements for software programmers and any other position. It shows a steady rise in job announcements that applies to both the number of job postings of software developers and other job types until June 2022. As of this date the index starts to declines for software development jobs, eventually converging to its initial level in early 2023. In contrast, for all other jobs the index remains constant.

Overall, the results in this section confirm Hypothesis 3. They consistently show that software-developing startups hire significantly fewer programmers during the early phases of their lifecycle before and after the release of GitHub Copilot. These findings reinforce the idea that startups affected by the new GenAI technology increase their operational efficiency: They secure the same amount of funding in less time and with fewer employees than before.

5.2 Founder experience as a strategic complement

Another central question in the literature on technological innovation and emerging studies on GenAI concerns how users' experience influences who benefits most from new technologies. This link is especially relevant in our setting, as competitive dynamics directly depend on these outcomes. Experimental studies at the individual level show that low-skilled or inexperienced users benefit most from GenAI (Brynjolfsson *et al.*, 2023; Noy and Zhang, 2023; Peng *et al.*, 2023). In our more complex organizational setting, this conceptually suggests that GenAI reduces performance variation among software teams in our sample startups. At the margin, having superior software employees provides less competitive advantage in the new GenAI regime. In contrast, the relative importance of founders' ability to strategically leverage this technological resource increases. To test this relation systematically, we analyze the differential effects of GitHub Copilot on software-developing startups, depending on the experience of the founding team upon the incorporation of the focal startup. We follow prior research and distinguish founders' technological and managerial (i.e., entrepreneurial) experience (Colombo and Grilli, 2005; Dencker and Gruber, 2015), assuming that the capability of integrating GitHub Copilot should strongly rely on the founders' capabilities. To measure experience, we draw on detailed information in the Crunchbase data available to subsets of the main sample.[14] Specifically, we consider the founders' educational background as well as the time since obtaining a university degree as a proxy for their technological experience. The education degree is a direct measure of the technological know-how obtained in an academic context; the time since graduation should positively correlate with the founders' technological experience gained on the job. Moreover, we use two measures for entrepreneurial experience. First, we consider the founders' Crunchbase rank score, which is a dynamic ranking for all people in the Crunchbase dataset. This score has been used in previous literature (e.g., Edwards and Todtenhaupt, 2020) and captures the prominence of respective persons, amongst others, based on the number of connections, funding

[14] The main results also apply to the subsamples for which supplementary data on founders is available (undisplayed).

events, or news articles in Crunchbase. The Crunchbase rank score thus reflects startup founders' prior entrepreneurial experience. As a second, more direct measure, we consider whether founders have previously launched other startups. We utilize the founder information to construct binary indicators that distinguish founders with and without high levels of experience.

Based on these classifications, we deploy split sample regressions. The results displayed in Table 8 show that the main effects of the GitHub Copilot release on startups' funding dynamics are more pronounced for startups with more experienced founder teams. Columns I and II re-estimate the baseline effect for software-developing startups with at least one founder or no founder with a computer science degree, respectively. While both coefficients of the DID estimator are negative, only the coefficient in the subsample of startups with computer scientists as founders is statistically significant. Further, the effect size is about four times larger for startups whose founders hold a computer science degree (34.9%) than for startups without (8.9%).[15] These results remain qualitatively similar when comparing startups whose average founder age is above the median (Column III) with those below the median (Column IV). Here, the effect size is about three times larger for more experienced founder teams.

Table 8: Founder experience and the effect of GitHub Copilot on the funding dynamics of startups

Dependent variable:	Time-to-funding							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Developer × Post	-6.796***	-2.040	-6.057**	-1.828	-2.763**	0.605	-4.711**	-2.367
	(2.624)	(1.878)	(2.459)	(2.598)	(1.319)	(2.567)	(2.033)	(1.497)
Experience measure:	Computer degree		Founder age		Crunchbase rank		Serial founder	
Experience (1/0)	= 1	= 0	= 1	= 0	= 1	= 0	= 1	= 0
Additional controls:								
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. variable:	19.495	22.879	22.643	22.164	19.617	25.496	20.171	23.443
N	958	4,073	1,922	1,699	4,829	4,773	2,855	6,775
R^2	0.34	0.25	0.28	0.33	0.23	0.22	0.25	0.22

Notes: This table displays DID estimations that are similar to Column I of Table 3 but use sample splits of software-developing startups regarding high and low technological and entrepreneurial experience. Columns I and II distinguish startups with and without founding team members that have an educational background in computer science. As an alternative measures of technological experience, we consider a median split of the founders' age at the first funding round in years since graduation (Columns III-IV). Columns V-VIII distinguish startups with at least one (= 1) or no (= 0) founder with previous entrepreneurial experience, defined as the Crunchbase rank (Columns V and VI) and prior experience as a startup founder (Columns VII and VIII). Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

These patterns are very similar when considering the founders' managerial experience at the time they

[15]The effect size is obtained by dividing the DID coefficient by the mean of the dependent variable as indicated at the bottom of Table 8: For startups whose founders hold a computer science degree, the effect size is $0.34860 = -6.796/-19.495$.

launched the focal startup. Estimates in Columns V-VIII show that the startups with more experienced founders in terms of the Crunchbase rank and previous founding activities (i.e., serial founders) exhibit a much larger reduction in the time-to-funding after the release of GitHub Copilot compared to relatively less experienced ones. For example, the reduction in time-to-funding is more than twice as large for startups in which founders have prior experience to start their own business (see Columns VII and VIII).

In sum, these results consistently show that software-developing startups with more experienced founders disproportionally benefit from the introduction of GitHub Copilot. This finding applies to technical and entrepreneurial experience while being slightly more pronounced in the former case. More experienced founders are able to better exploit GitHub Copilot as a new technology, accelerating their business development and, in particular, the acquisition of funds. Hence, the successful integration of GenAI depends on the capabilities of the founding team, confirming Hypothesis 4.

6 Discussion

6.1 Theoretical implications

Our research contributes new insights to a central question in the strategic management literature: Can new general-purpose technologies, as non-rare and imitable resources, provide a source for competitive advantage? Traditional resource-based view literature posits that resources leading to competitive advantage are valuable, rare, inimitable, and non-substitutable (Barney, 1991). While GenAI technologies are certainly valuable, they do not fulfill the criteria of rare and inimitable resources due to their broad availability and general-purpose functionality. Despite these properties, GenAI can still significantly impact competitive dynamics, as our results demonstrate. In particular, we show how GenAI can provide a source for competitive advantage once combined with human capabilities to form complementary resource bundles. Thereby, we offer a more nuanced understanding of the resource-based view, emphasizing that also non-rare and imitable resources can drive competitive advantage when they are effectively integrated with firm-specific assets.

The necessity of integrating GenAI with human capabilities speaks to a strand of the resource-based view, which focuses on the importance of bundling complementary resources (Sirmon *et al.*, 2008). Our findings show that it is the founders' capabilities that determine the ultimate productivity effect of

GenAI for their startup. In particular, the complementarity between the entrepreneurs' educational background (computer science), practical experience, and the nature of the new technology (GenAI for software development) supports the view that only the unique bundling of resources allows firms to create a competitive advantage in an increasingly dynamic and technology-driven environment.

Consequently, our findings also add to the discourse on the role of managerial capabilities in adapting, integrating, and reconfiguring internal and external resources (e.g., Teece *et al.*, 1997; Helfat and Peteraf, 2015). Existing studies suggest that experienced decision-makers are well-positioned to predict the future value of technological innovation (see Kraaijenbrink *et al.*, 2010). We show that prior technological and entrepreneurial experience enables startup founders to implement GenAI technologies more effectively than their competitors. These results extend the findings on AI as a source of competitive advantage from isolated settings, such as chess (Gaessler and Piezunka, 2023; Krakowski *et al.*, 2023), suggesting that neither humans nor AI alone create performance differences.

6.2 Generalizability

The spread of GenAI technologies during the early 2020s marks an extraordinary period that fundamentally affects firm dynamics. Our empirical setting focuses on one specific GenAI application and one specific set of firms – GitHub Copilot and software-developing startups. However, despite having natural limits to their uniform applicability (see Section 6.3), the implications of our findings are likely generalizable to other technological innovations and other types of firms.

While GitHub Copilot is designed specifically for software developers, its basic functionality and value proposition are closely comparable to other GenAI tools. As a common denominator, these tools aim to augment human work by generating or improving content, such as text, images, or sound. Accordingly, the observed effects are likely indicative for other GenAI applications targeted towards different consumer groups. Additionally, our theoretical considerations on new technology adoption are likewise transferable to all other technological innovations that are valuable but non-rare and imitable.

Moreover, the benefits observed for startups can also be relevant to other firm types. While our analysis focuses on growth-oriented entrepreneurial startups, all companies, regardless of size or age, should be able to experience operational benefits similar to those observed in our setting. As such, the basic principles of GenAI are the same for any firm as they enable productivity gains by enhancing

employees' efficiency. Further, the importance of complementary human capital should be relevant across firms as it is usually the managers who decisively determine the successful adoption of new technologies (e.g., Teece *et al.*, 1997; Helfat and Peteraf, 2015). Decision-makers with more managerial and technological expertise can be expected to accelerate the adoption and maximize the value-added delivered through GenAI. These aspects are particularly relevant since GenAI will affect the entire economy and not just subsets of specific firms.

Relatedly, our findings from the software sector can be indicative of how GenAI impacts other fields. Due to the general-purpose nature, managers in other sectors should be able to achieve similar competitive advantages once they can identify and implement new GenAI technologies. The skills and knowledge gained from using GenAI in one business field can likely be transferred to other fields. In fact, GitHub Copilot serves as a role model for a number of similar products developed for other sectors, which led to a boom in VC financing for "*AI Copilots*" (Sraders, 2023).

6.3 Limitations and future research

Our analysis remains subject to certain limitations. First, our empirical strategy assumes that the business field of startups represents their propensity to use GitHub Copilot. This assumption is consistent with survey evidence, suggesting that most developers who could benefit from GitHub Copilot are indeed using it (GitHub, 2023b). Still, we cannot claim with certainty whether startups will use GitHub Copilot or not. Hence, it is important to note that our classification of treated startups is likely a conservative measurement approach and, if anything, underestimates the actual effects.

Second, our results have natural boundaries to their general applicability across firms. For example, large incumbent firms usually have different technology adoption patterns than startups as their organizational structure is more complex and hierarchical, and their (perceived) need to increase resource-efficiency may be relatively smaller. Similarly, the different regulatory and competitive structures of industries may curtail a more general applicability of our findings, especially regarding the transfer of individual productivity effects to the firm level. For instance, as our results show, startups in heavily regulated industries such as healthcare and biotech might face challenges in accelerating their operations. These factors can affect the implementation and utilization of new technologies, potentially leading to different outcomes than those suggested in our analysis. While there are limits to the generalizability of

our results, it is important to note that our approach allows us to capture the effects on the likely most relevant set of firms, given entrepreneurial startups' relatively high absorptive capacity of technological innovation. Still, future work should consider alternative sets of firms when investigating the productivity effects of GenAI.

Third, our study represents a first step towards understanding the impact of GenAI on firm-level productivity and, in particular, startup funding dynamics. The topicality of our analysis limits us from exploring some important performance indicators that will only be measurable over time, such as firm survival, successful exits, or inventive outputs. By definition, our results provide insights regarding the immediately measurable productivity implications of GenAI. It will thus be valuable to assess firm-level productivity and competitive dynamics using different outcome measures. Given GenAI's large disruptive potential, we encourage further research to evaluate the long-term implications of the economy-wide adoption.

6.4 Practical implications

Our analysis has important implications for managers, who increasingly face the task of evaluating and defining the role of AI in their organizations. Most notably, the findings suggest that entrepreneurs and decision-makers should carefully consider whether GenAI technologies can serve as a strategic complement to existing resources in their business operations. As such, we show that technological and entrepreneurial experience is vital for effectively leveraging GenAI, which could motivate investment in complementary human capital, for instance, by adjusting hiring criteria or upskilling the existing workforce. These insights are especially relevant in the context of entrepreneurial ventures, whose liabilities but also capabilities of newness and smallness (i.e., flexibility) make them particularly adaptive to new technologies.

Conversely, our study also informs managers about the limitations of GenAI adoption, as it may not *per se* yield a competitive advantage. We show that the success of integrating GenAI into organizations depends on the capabilities of the founding teams. This finding is particularly noteworthy in the context of early research on GenAI's productivity effects. While experimental studies at the individual level often show greater benefits for less-skilled or less-experienced users (Noy and Zhang, 2023; Peng *et al.*, 2023; Dell'Acqua *et al.*, 2023b; Brynjolfsson *et al.*, 2023), early research in more complex organizational

settings suggests that skilled or experienced users gain more (Otis *et al.*, 2023; Toner-Rodgers, 2024). Our results align with the latter, identifying founder experience as a key complement to realizing firm-level productivity gains from GenAI.

7 Conclusion

We examine the effects of new general-purpose technologies on startup productivity. Our empirical analysis explores the release of GitHub Copilot as a quasi-natural experiment that exogenously affected the funding dynamics of these firms. For them, securing initial funding is among the first measurable productivity indicators. As we show, studying the release of GitHub Copilot as a pioneering GenAI-enabled application has the key advantage of estimating the impact of GenAI without confounding subsequent technological advancements in the field. Following the release of GitHub Copilot, software-developing startups secure the same level of funding 20% faster and with 22% fewer software employees, relative to comparable peer startups. Furthermore, these novel empirical findings allow us to provide new theoretical perspectives on how valuable, but ultimately non-exclusive, technological innovation can yield firms a competitive advantage. Intuitively, GenAI does not *per se* constitute a unique resource to entrepreneurs and managers since it is a non-rival technology available to most market participants at low cost. Consistent with this idea, our findings show that GenAI can lead to productivity gains only if it is used as a strategic complement to existing resources: It is the complementary human capital, in other words, the people who are decisive in determining the productive potential of GenAI in firms.

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FOR ONLINE PUBLICATION – Internet Appendix

Appendix A: Tables and Figures from the Appendix

Table A1: Summary statistics

Panel A: Country distribution

	Obs.	Share (in %)	Cumul. share (in %)
USA	12,217	56.0	56.0
Great Britain	2,540	11.6	67.6
Canada	1,153	5.3	72.9
Germany	1,123	5.1	78.0
France	983	4.5	82.5
Spain	485	2.2	84.7
Switzerland	417	1.9	86.6
Netherlands	400	1.8	88.5
Sweden	365	1.7	90.1
Italy	269	1.2	91.4
Other	1,882	8.6	100.0
Total	21,834	100.0	

Panel B: Firm size distribution, number of employees (measured in 03/2024)

	Obs.	Share (in %)	Cumul. share (in %)
1 - 10	12,188	55.8	55.8
11 - 50	7,097	32.5	88.3
51 - 100	726	3.3	91.7
101 - 250	451	2.1	93.7
251 - 500	101	0.5	94.2
501 - 1,000	44	0.2	94.4
$>$ 1,000	42	0.2	94.6
Unkown	1,185	5.4	100.0
Total	21,834	100.0	

Panel C: Investment types of first deal

	Obs.	Share (in %)	Cumul. share (in %)
Seed	8,438	38.6	38.6
Pre-Seed	6,959	31.9	70.5
VC (series A)	3,060	14.0	84.5
Grants	2,700	12.4	96.9
Angel	460	2.1	99.0
Crowdfunding	217	1.0	100.0
Total	21,834	100.0	

Table A2: List of variables

Key variables	
Time-to-funding	The main dependent variable; Time from date of incorporation to the date of initial funding round announcement. The total number of days is divided by 30 resembling the time-to-funding counted as a continuous measure of months.
Post Public	Dummy equals one if the funding round was announced after the public release of GitHub Copilot in June 2022 and zero otherwise
Post Technical	Dummy equals one if the funding round was announced after the technical release of GitHub Copilot in October 2021 and zero otherwise
Developers	Dummy equal to one if the firm is a software-developing startup as defined in Table A3 (Appendix A), and zero otherwise
OtherSoftware	Dummy equal to one if the firm is any software startup as defined in Table A3 (Appendix A), and zero otherwise
Other variables	
# investors	Number of external investors that participated in any funding round
Computer Science degree	Dummy equals one if at least one founder in the founding team has a computer science degree and zero otherwise
Covid	Dummy equal to one for all months after March 2020 and zero otherwise
DealSize	Amount of funding (in thousand USD) raised in the firm's initial funding round
European Investors	Dummy equal to one if any of a firm's funding rounds involved a European investor and zero otherwise
Follow-on investment	Dummy equals one if a firm received a follow-on funding round, conditional on receiving an initial funding round, and zero otherwise
Founder age	Average age (in continuous years) of the founding team based on the first graduation of each founder
Founder rank	Relative ranking variable for founders in the Crunchbase dataset indicating prominence based on various signals (e.g. connections, engagement, funding events, news mentions), see, e.g., Edwards and Todtenhaupt (2020)
Founder with exit	Dummy equals on if any founder in the founding team previously had a successful exit
Founding team size	Number of individual founders in a firm's founding team
log(DealSize)	Logarithm of the amount of funding raised in the firm's initial funding round

(*Continued on next page*)

Table IA2: List of variables (*continued*)

log(DealSize); 2nd round	Logarithm of the amount of funding raised in the firm's second funding round
log(DealSize); 3rd round	Logarithm of the amount of funding raised in the firm's third funding round
LowPropensity	Dummy equal to one for firms operating in business fields with low propensity to respond to GenAI technologies due to regulatory hurdles, as listed in Table A8 (Appendix) and zero otherwise
Remote	Dummy equal to one if a firm has a high propensity to offer remote work as defined in Table A11 (Appendix) and zero otherwise
Serial founder	Dummy equals on if any founder in the founding team previously founded another company
Syndicate	Dummy equal to one if any of a firm's funding rounds involved a syndicate of investors and zero otherwise
Total DealSize	Total funding amounts (in thousand USD) received by a firm in all funding rounds as of March 2024
Time-to-funding; 2nd round	Time (in continuous months as for *Time-to-funding*) from the incorporation date to the announcement date of the second funding round
Time-to-funding; 3rd round	Time (in continuous months as for *Time-to-funding*) from the incorporation date to the announcement date of the third funding round
US Investors	Dummy equal to one if any of a firm's funding rounds involved a US investor and zero otherwise
VC Market Sentiment	Numeric indicator of VC market sentiment based on the FTSE Venture Capital Index, aggregated to a monthly average
Hot Market	Dummy equals one if the month of funding round announcement belongs to the top decile of the VC market sentiment distribution and zero otherwise
Cold Market	Dummy equals one if the month of funding round announcement belongs to the bottom decile of the VC market sentiment distribution and zero otherwise

Table A3: Crunchbase business fields classifying startups

Software-developing startups	"artificial intelligence" "machine learning" "neural network" "deep learning" "algorithm" "saas" "software as a service" "software development kit" "coding" "programming" "script" "natural language processing"
Examples	"focused on simplifying banking by leveraging advanced artificial intelligence techniques"; "world's fastest and most optimal route optimization engine"; "a cloud-based ai platform that helps real estate developers to plan in the early stage of development."
Other software startups (non-developers)	"platform" "software" "application" "application programming interface" "digital" "cloud" "tech" "online" "e-commerce" "database" "webapp" "website" "frontend" "backend" "full-stack" "devops" "paas" "platform as a service" "iaas" "infrastructure as a service" "faas" "function as a service" "virtualization" "automation" "chatbot" "virtual assistant" "analytics" "big data" "data science" "internet of things" "augmented reality" "virtual reality" "mixed reality" "blockchain" "cryptocurrency" "crypto" "smart contract" "server" "microservices" "firmware" "content management system" "customer relationship management" "enterprise resource planning" "integration" "browser extension" "plugin" "interface" "user experience" "user interface" "framework" "library" "version control" "repository" "data visualization" "dashboards" "business intelligence" "virtual machine" "streaming" "encryption" "security" "cybersecurity" "firewall" "virtual private network" "digital transformation" "digital solution"
Examples	"a civic matchmaking tool that matches retirees and those who are about to retire with worthwhile volunteer initiatives"; "an on-demand mobile application that allows consumers to book event vendors for their social events in minutes"; "car rental app platform designed to bring down car ownership and move the full transition to e-mobility forward"
Non-software startups	*all other*
Examples	"selling of human-grade dog food that is rich in vitamins and minerals"; "clinical trial advisory and support services that are founded on a future-ready, flexible, and people-first culture"; "organization of the printing and distribution of 3d printed models for people who are blind"

Notes: This table lists all business fields used to classify startups as software-developing, other software, and other (non-software) startups, respectively. The fields are displayed as provided in the Crunchbase data. Below each category, we provide examples for corresponding business activity descriptions that are also provided in the Crunchbase data.

Table A4: Summary statistics, by industry groups

	Developers		*OtherSoftware*		Non-Software		Differences in means
	Mean	Median	Mean	Median	Mean	Median	Colums I-III
Time-to-funding	20.768	16.6	23.434	19.133	30.017	26.767	-2.666***
log(*DealSize*)	13.650	13.843	13.744	13.931	13.086	13.196	-0.094**
DealSize (in TUSD)	2,854	1,028	3,697	1,122	3,042	538	-842***
Follow-on investment	0.365	0	0.330	0	0.248	0	0.035***
Total *DealSize* (in TUSD)	12,706	2,144	13,807	2,192	9,607	1,152	-1,101
# investors	2.464	1	2.594	1	1.926	1	-0.130**
Syndicate	0.343	0	0.332	0	0.207	0	0.011
US investors	0.647	1	0.645	1	0.640	1	0.002
European investors	0.364	0	0.389	0	0.368	0	-0.024***
Remote	0.994	1	0.649	1	0.242	1	0.345***
LowPropensity	0.164	0	0.285	0	0.441	0	0.121***
Computer Science degree	0.331	0	0.220	0	0.097	0	0.111***
Founder rank	354,462	245,532	428,271	316,614	547,230	446,515	73,809***
Founder age (since grad.)	14.069	12.799	14.872	13.216	15.166	13,674	0.804**
Founder with exit	0.089	0	0.087	0	0.068	0	0.003
Serial founder	0.328	0	0.327	0	0.282	0	0.001
Founding team size	1.921	2	1.792	2	1.708	2	0.129***
Number of employees	12.665	8	12.115	8	11.857	7	-0.550**
Number of software employees	2.856	2	1.938	1	0.912	0	-0.918***

Notes: This table displays mean and median values of statistics similar to Table 1. The table distinguished software-developing startups (Columns I-II), other software startups (Columns III-IV), and non-software startups (Columns V-VI). The last column displays differences in means between software-developing and other software startups (Column I versus III). *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A5: Baseline results – full coefficient table

Dependent variable:	Time-to-funding			
	(I)	(II)	(III)	(IV)
Developer × Post	-4.793***	-3.815***	-5.754***	-5.099***
	(0.669)	(0.629)	(0.849)	(0.803)
Developer	1.835***	2.317***	-0.014	0.660
	(0.692)	(0.734)	(1.774)	(1.802)
# investors	-0.401***	-0.402***	-0.383***	-0.380***
	(0.039)	(0.039)	(0.079)	(0.079)
US-based investors	3.550***	3.562***	4.029***	4.006***
	(0.542)	(0.542)	(0.910)	(0.908)
European-based investors	3.384***	3.365***	4.130***	4.044***
	(0.483)	(0.483)	(0.820)	(0.818)
Constant	22.338***	22.334***	23.841***	23.926***
	(0.454)	(0.454)	(1.039)	(1.039)
Sample:	Full		Excluding other software	
Post definition (release):	Public	Technical	Public	Technical
Additional controls:				
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	21,834	21,834	8,521	8,521
R^2	0.19	0.19	0.23	0.23

Notes: This table is equivalent to Table 2, but displays the coefficients of control variables, except of time (deal-month) fixed effects and country fixed effects. Further, the output of the industry classifications are omitted. In total, there are 2,139 unique business field combinations for each startup as defined in the Crunchbase data, typically comprising multiple overlapping business fields. Only here, we use alternative indicators of whether firms belong to the treatment group. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A6: Robustness tests on the baseline results: Alternative treated group definition

Dependent variable:	Time-to-funding							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII	(VIII)
Developer^{profile} × Post	-4.219***	-3.086***	-5.230***	-4.471***				
	(0.642)	(0.605)	(0.846)	(0.802)				
Software^{broad} × Post					-2.434***	-1.573***	-5.747***	-5.135***
					(0.543)	(0.507)	(0.849)	(0.802)
Sample:	Full		Excluding other software		Full		Excluding other software	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical
Additional controls:								
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,834	21,834	8,521	8,521	21,834	21,834	8,521	8,521
R^2	0.19	0.19	0.24	0.23	0.19	0.19	0.23	0.23

Notes: This table displays DID estimations similar to Columns I-IV of Table 2. Only here, we use alternative indicators of whether firms belong to the treatment group. Specifically it deploys an indicator that classifies software-developing startups using the companies self-description on Crunchbase (Columns I-IV) and an indicator that simply uses the overarching "software" category in Crunchbase (Columns V-VIII), as defined in Table A3 (Appendix). Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A7: Robustness tests on the baseline results: Controlling for investment types

Dependent variable:	Time-to-funding							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII	(VIII)
Developer^{profile} × Post	-3.720***	-2.955***	-3.265***	-2.606***	-3.008***	-2.359***	-3.120***	-2.468***
	(0.644)	(0.599)	(0.664)	(0.617)	(0.674)	(0.575)	(0.697)	(0.643)
Investment types:	All early-stage investment types				Seed and venture capital rounds			
Sample:	Full		Software startups		Full		Software startups	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical
Additional controls:								
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,834	21,834	16,754	16,754	18,238	18,238	14,661	14,661
R^2	0.25	0.25	0.24	0.24	0.26	0.26	0.25	0.25

Notes: This table displays DID estimations similar to Columns I-II and V-VI of Table 2, but additionally controls for investment type fixed effects (Columns I-IV). Estimations in Columns V-VIII are equivalent to before but only include those investment types that refer to seed (and pre-seed) investments and VC deals. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A8: Placebo tests on the baseline results: Regulated industries and GitHub Copilot

Dependent variable:	Time-to-funding					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Biotech × Post	-0.228					
	(1.057)					
Healthcare × Post		0.992				
		(0.830)				
Governmental × Post			4.045			
			(6.534)			
Energy × Post				-2.569		
				(2.329)		
Transportation × Post					2.114	
					(1.560)	
LowPropensity × Post						0.788
						(0.710)
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	16,754	16,754	16,754	16,754	16,754	16,754
R^2	0.18	0.18	0.18	0.18	0.18	0.18

Notes: This table displays DID estimations similar to Column I of Table 2. Here the main regressor (*Developer*) is exchanged with industries that have a low propensity to the introduction of GitHub Copilot as they are highly regulated. The industries are biotechnology (Column I), healthcare (Column II), government & military services (Column III), energy (Column IV), transportation (Column V), and an indicator that is equal to one for all startups that are active in either one of these sectors (Column VI). Standard errors (in parentheses below coefficients) are clustered at the startup-level. As treatment indicator (*Post*), the regression use the date of the the public release of GitHub Copilot. However, the results remain qualitatively unchanged when using the technical release date (undisplayed). *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A9: GitHub Copilot: The timing of effects

Dependent variable:	Time-to-funding					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Developer × $\text{Post}^{\text{Full}}$	-3.770***	-2.596**	0.095	-2.983***	-2.416**	-0.416
	(0.881)	(1.135)	(1.516)	(0.908)	(1.176)	(1.576)
Developer × $\text{Post}^{\text{Tech.}}$	-1.475*	0.336	0.975	-1.242	0.145	1.289
	(0.827)	(1.034)	(1.395)	(0.853)	(1.070)	(1.449)
Sample:	Full			Software startups		
Funding round:	1st round	2nd round	3rd round	1st round	2nd round	3rd round
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	21,834	12,234	5,701	16,754	10,003	4,732
R^2	0.19	0.18	0.21	0.18	0.19	0.23

Notes: This table displays estimations on the time-to-funding of software-developing startups relative to other startups both before and after the release of GitHub Copilot. All estimations are structured as in the baseline estimation in Equation (1). The specification in Column I includes both DID estimators, i.e., the two post-dummies that indicate the post treatment period as defined by the technical release and the public release of GitHub Copilot as used in Columns I and II of Table 2. Columns II and III are similar to before but use the time to the second and third round as the dependent variable. Columns IV-VI are similar to the first three but here the sample includes only software startups. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A10: GitHub Copilot and startup funding size

Panel A: First funding round

Dependent variable:	log(*DealSize*)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Developer × Post	0.097	0.015	0.273**	0.124	-0.046	-0.077
	(0.085)	(0.080)	(0.114)	(0.108)	(0.088)	(0.082)
Sample:	Full		Excluding other software		Software startups	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	14,175	14,175	5,457	5,457	10,936	10,936
R^2	0.33	0.33	0.36	0.36	0.34	0.34

Panel B: Second and third funding rounds

Dependent variable:	log(*DealSize*)							
	2nd round				3rd round			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII	(VIII)
Developer × Post	-0.119	-0.005	-0.091	0.018	-0.052	-0.052	-0.096	-0.085
	(0.113)	(0.104)	(0.117)	(0.107)	(0.164)	(0.148)	(0.172)	(0.155)
Sample:	Full		Software startups		Full		Software startups	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical
Additional controls:								
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,194	8,194	6,750	6,750	3,943	3,943	3,291	3,291
R^2	0.35	0.35	0.37	0.37	0.44	0.44	0.45	0.45

Notes: This table displays DID estimations similar Table 2, only here, the dependent variable is the logarithm of the deal size (in USD). Panel A display estimates on the size of the first round. Panel B is similar to Columns I-II and V-VI of Table 2 and uses the size of the second (Columns I-IV) and third funding round (Columns V-VIII) as the dependent variable. Note that there is many missing observations on this variable, which is why the number of observations is smaller than in the baseline regressions. Still, if we re-estimate the baseline estimation using the sample for which funding size data is also available, the baseline effects remain qualitatively the same (undisplayed). Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A11: Business fields and their propensity to offer remote work

Unlikely remote	"agriculture and farming"; "biotechnology"; "clothing and apparel"; "commerce and shopping"; "community and lifestyle"; "consumer electronics"; "consumer goods"; "education"; "events"; "food and beverages"; "hardware"; "healthcare"; "manufacturing"; "media and entertainment"; "natural resources"; "real estate"; "sports"; "transportation"; "travel and tourism"
Likely remote	"artificial intelligence"; "data analytics"; "information technology"; "internet services"; "software"; "advertising"; "apps"; "content and publishing"; "design"; "financial services"; "gaming"; "lending and investments"; "messaging and telecommunications"; "mobile"; "music and audio"; "platforms"; "professional services"; "sales and marketing"; "video"; "cloud"

Notes: This table provides a the set of keywords applied to identify firms operating in business fields that have a high or low propensity to offer remote work for their employees. For classification, we follow Adams-Prassl *et al.* (2022).

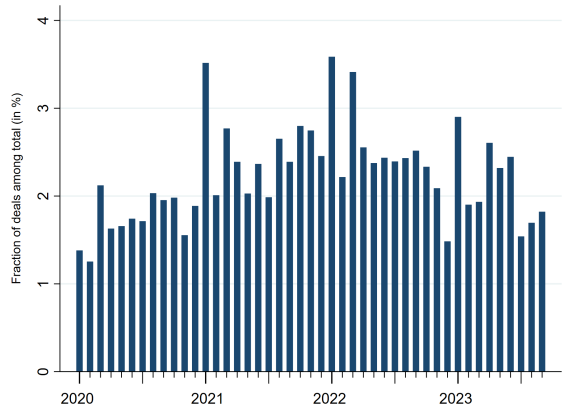
Table A12: The effect of GitHub Copilot on software employees at fixed times after incorporation

	Number of Software Developers					
	(I)	(II)	(III)	(IV)	(V)	(VI)
Developer × Post	-0.311**	-0.275*	-0.545***	-0.394**	-0.352*	-0.356*
	(0.130)	(0.150)	(0.165)	(0.180)	(0.188)	(0.187)
$OtherSoftware$× Post	-0.132*	-0.117	-0.311***	-0.251**	-0.282***	-0.220*
	(0.078)	(0.092)	(0.099)	(0.115)	(0.108)	(0.116)
Time after incorporation:	1 quarter		3 quarters		6 quarters	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10,617	10,617	10,648	10,648	13,250	13,250
R^2	0.22	0.22	0.25	0.25	0.28	0.28

Notes: This table displays DID estimations similar to the estimations in Table 7 Columns I-VI repeat Columns V-VI from Table 7 but at fixed time intervals after incorporation instead of at the time of funding. The first row shows DID estimates for software-developing startups, while the second row displays these estimates for $OtherSoftware$ startups. Standard errors (in parentheses below coefficients) are clustered at the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Figure A1: Summary statistics

Panel A: Distribution of initial funding round, Q1 2020 – Q3 2023



Panel B: Kernel density distribution of time-to-funding

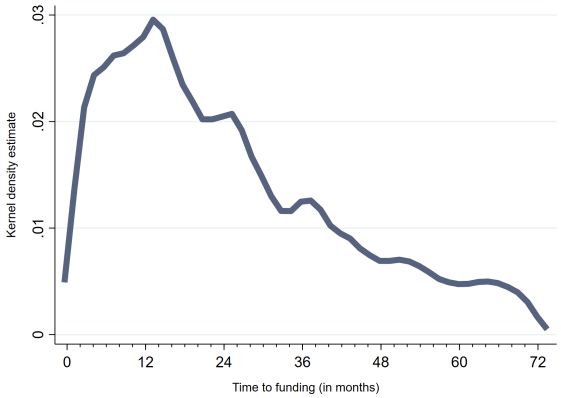
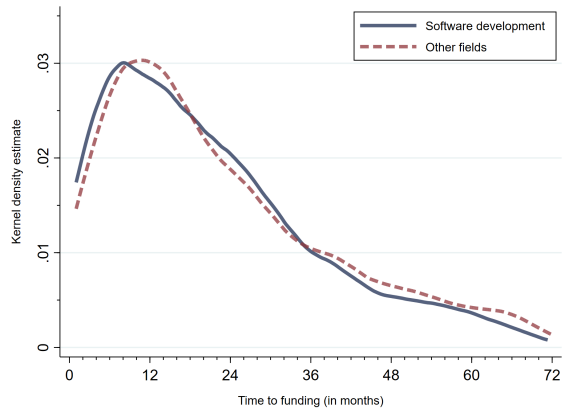


Figure A2: Kernel density estimates, time-to-funding of software-developing and other startups

Panel A: *Before* the GitHub Copilot preview phase



Panel B: *After* the public GitHub Copilot release

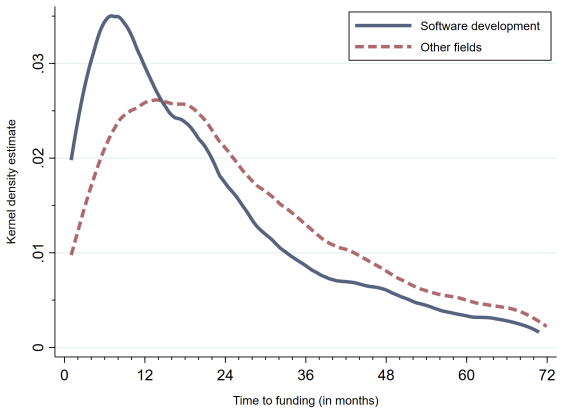
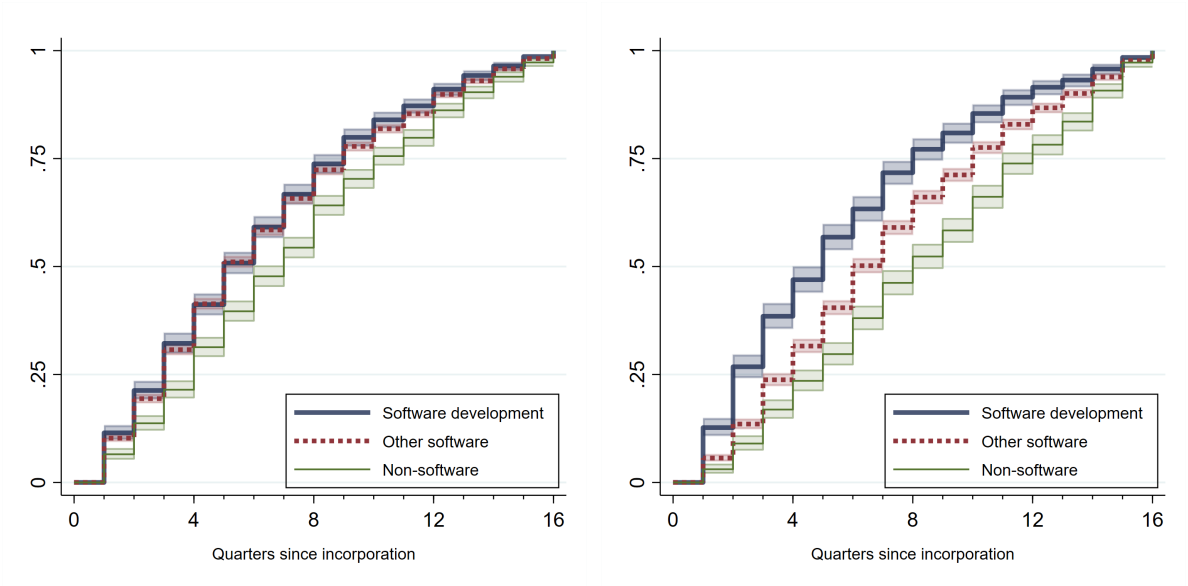


Figure A3: Nelson-Aalen cumulative hazard rates on the time-to-funding, by industries

Panel A: *Before* the GitHub Copilot preview phase **Panel B:** *After* the public GitHub Copilot release



Notes: This graph displays Nelson-Aalen failure estimates (hazard rates) of the timing of the first funding event, similar to Figure 2. Only here, among the non-software-developing startups, we distinguish those active in software fields and those that are not active in any software-related fields. Again, Panels A and B display the probability of receiving the first funding for the pre- and post-treatment periods, respectively. The shaded areas around the hazard rates mark the 95% confidence intervals.

Appendix B

Examining possibile truncation issues in the Crunchbase data

Our analyses leverage data that became available only relatively recently after the focal events. For our main sample, we use a Crunchbase snapshot extracted in March 2024. Crunchbase sources its data from official statements and from (mostly young) firms voluntarily disclosing information. Hence, this setup potentially introduces some recency-biases that we investigate in the following. As we show, the Crunchbase data can indeed be associated with a certain bias towards larger first round investments for the final two quarters before extraction. Consistent with this finding, we excluded the final two quarters from our analyses. In the following, we detail on our data validation approach.

Crunchbase sources their data mainly through two channels: a network of over 4,000 global investment firms, which contribute monthly portfolio updates in exchange for complimentary platform access, and a community of contributors, consisting of more than 500,000 executives, founders, and investors who actively add and revise company profiles. Additionally, community-sourced data are augmented by continual algorithmic web search of news and publicly available information. These large data sets are processed using machine learning algorithms to ensure data accuracy and identify anomalies. Finally, the Crunchbase data team engages in manual validation and curation to ensure data integrity and quality.[16]

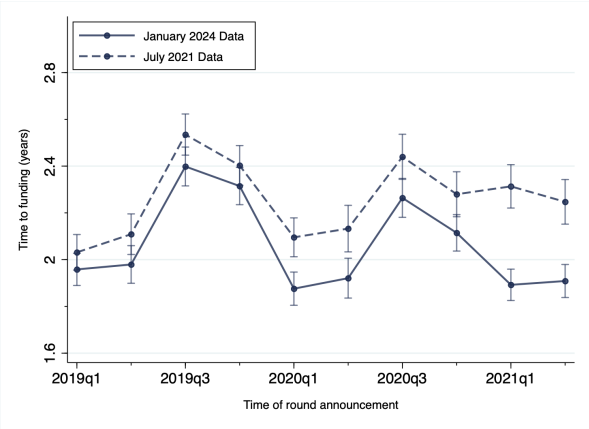
To address recency concerns and rule out a biased sample, a comparative analysis is conducted using a second cross-sectional dataset from Crunchbase, retrieved in July 2021. This comparison spans the period from Q1 2020 to Q2 2021, juxtaposing data collected immediately after the observed period (July 2021) against data retrieved at a later point in time (January 2024). Should biases exist in the most recent Crunchbase data, noteworthy discrepancies between the two datasets can be observed.

Figure A4 displays the average time to initial funding and average (log) initial funding size for the datasets retrieved in July 2021 and in January 2024. While the dataset retrieved in July 2021 consistently shows both a higher average time to initial funding and higher initial funding sizes compared to its counterpart, the overarching trends and the relative progressions align closely between the two datasets for the first quarters. Notably, the most recent quarters reveal a greater variance in both time-to-funding and funding size, which points to a biased reporting of the latest financing rounds.

[16] Based on information from Crunchbase, see "Where does Crunchbase get their data?"

Figure A4: Average time to Initial Funding - January '24 vs. July '21 Data

Panel A: Time to Initial Funding



Panel B: Log Initial Funding Size

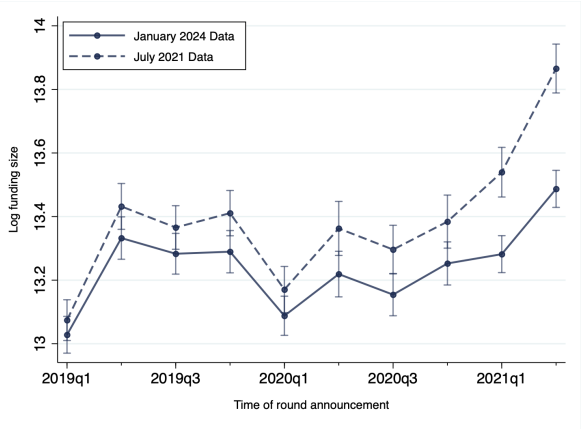


Table A12 displays an examination of the quarterly funding data and supports the previous observation. In the July 2021 vintage, the last reported quarters exhibit a notably lower number of rounds, and both the average and median sizes of funding, as well as the average number of investors per deal, are notably larger compared to the data from January 2024. Additionally, a significant decline in the number of reported funding rounds is observed in the final two quarters of the January 2024 dataset. This pattern indicates an initial over-representation of larger funding rounds, which gradually becomes more balanced as additional, smaller rounds are documented.

Table A12: Quarterly Breakdown of Initial Funding Round Data

Quarter	# of Rounds		Avg. Size		Median Size		Avg. Time		Avg. Investors	
	Jul'21	Jan'24	Jul'21	Jan'24	Jul'21	Jan'24	Jul'21	Jan'24	Jul'21	Jan'24
2019q1	2479	2862	1.84	1.67	0.48	0.43	2.26	2.20	1.75	1.71
2019q2	2115	2414	2.43	2.22	0.80	0.70	2.30	2.16	2.01	1.95
2019q3	2192	2442	2.32	2.17	0.65	0.60	2.62	2.51	2.00	1.92
2019q4	2137	2421	2.43	2.23	0.76	0.65	2.56	2.48	2.11	2.07
2020q1	2065	2602	2.16	1.93	0.54	0.50	2.31	2.14	2.02	1.97
2020q2	1569	2039	2.37	2.05	0.68	0.53	2.36	2.16	2.16	1.95
2020q3	1724	2278	2.09	1.91	0.62	0.50	2.53	2.37	2.41	2.26
2020q4	1615	2267	2.39	2.03	0.75	0.60	2.42	2.26	2.56	2.42
2021q1	1791	2964	2.74	2.17	1.00	0.60	2.50	2.13	2.68	2.53
2021q2	1655	2922	3.04	2.36	1.26	0.76	2.43	2.10	3.31	2.72
2021q3	185	2983	3.72	2.24	1.82	0.70	3.00	2.45	3.44	2.72
2021q4		3445		2.74		1.00		2.57		3.03
2022q1		3663		2.69		1.00		2.34		2.91
2022q2		3186		2.66		1.00		2.27		3.04
2022q3		2596		2.72		1.00		2.80		3.00
2022q4		2515		2.70		1.00		2.76		3.00
2023q1		2308		2.79		1.00		2.64		2.57
2023q2		2499		2.47		0.60		2.57		2.42
2023q3		1914		2.81		1.00		3.11		2.68
2023q4		1636		3.11		1.31		3.07		2.78

Notes: This table provides a comparison between the Crunchbase data retrieved in July 2021 and the data retrieved in January 2024. Both datasets are compared via a quarterly breakdown of funding information for all initial funding rounds included in the final sample. Time is expressed in years and size in millions. Time refers to the duration from incorporation to the announcement of the initial funding round. Investors refers to the numbers of investors participating in the initial funding round. Jul'21 refers to the dataset retrieved in July 2021. Jan'24 refers to the dataset retrieved in January 2024.