How Do Employees Generate Firm Value With Generative AI? Evidence From Open-Source Software

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Abstract

This paper investigates which employees create firm value with Generative AI and how they do so in the context of open-source software (OSS) projects by U.S. public firms. I construct a novel AI exposure measure for developers and exploit the introduction of GitHub Copilot, a code autocompletion tool powered by OpenAI's large language models. By comparing productivity and innovation outcomes between developers with high and low exposure to the tool, I find that Generative AI boosts productivity and multitasking capabilities, with the effects stronger for firm-owned projects, for activities more relevant to coding, and for men or senior developers. Generative AI does not affect probability of innovation, but new projects initiated by innovators with high AI exposure receive more community interest and are valued 6.2% higher by the stock market. These effects concentrate on innovator teams with women or junior innovators. Overall, these findings highlight how Generative AI may create firm value by complementing firm labor differently based on employees' gender and experience.

Keywords: Generative AI, Productivity, Innovation, Firm value
JEL Classification: G10, J24, O33, O36

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1 Introduction

The public release of ChatGPT has led to a burst of discussion and debate over the potential implications of generative artificial intelligence (AI) on labor and business. Previous research have shown that AI can contribute to firm value and growth via labor inputs, product innovation, and managers' decision making (Eisfeldt, Schubert and Zhang, 2023; Babina, Fedyk, He and Hodson, 2023, 2024; Berger, Cai, Qiu and Shen, 2024; Otis, Clarke, Delecourt, Holtz and Koning, 2024). However, disruptive technologies often result in heterogenous responses of employees with different characteristics, such as gender, skill level, and experience (Kogan, Papanikolaou, Schmidt and Seegmiller, 2023; Carvajal, Franco and Isaksson, 2024; Otis et al., 2024). Therefore, it is important for firms to identify which employees generate value with Generative AI and through which channels, as this informs decisions on human capital investment, technology investment, and resource allocation.

In this paper, I investigate which employees contribute to firm value through their use of generative AI. In particular, I explore how Generative AI enhance labor productivity and foster product innovation of firms. I use open-source software (OSS) projects made available by U.S. public firms on GitHub, the most popular open-source platform, as my empirical laboratory. I identify firms' developers by linking GitHub organization accounts with Compustat firms through various procedures. This empirical setting is relevant, as generative AI pronouncedly affects software development[1] and OSS, software that is made publicly available with no or little cost and a practice increasingly used by firms, can bring both substantial externality (Hoffmann, Nagle and Zhou, 2024a)

[1]For example, surveys done by the Census Bureau show that the share of firms adopting AI is the highest in the information industry (See https://www.economist.com/business/2024/02/29/how-businesses-are-actually-using-generative-ai). A report published by the Burning Glass Institute and SHRM (https://shrm-res.cloudinary.com/image/upload/v1706729099/AI/CPR-230956_Research_Gen-AI-Workplace_FINAL_1.pdf suggests Generative AI's biggest impact will be in banking and tech.

and private value for firms, which further predicts future firm growth (Emery, Lim and Ye, 2024). Moreover, with the detailed individual-level timestamped records of activities linked with firms, I am able to observe long-term impact in a real-world work collaboration environment and establish a direct linkage between labor activities and firm value. This paper therefore departs from many prior studies, which often look at short-term impact on well-defined discrete tasks using experiments or single-firm settings.

I use the generalized difference-in-differences (DID) approach to study the causal effects of Generative AI on labor outcomes of developers working for firms. Specifically, I exploit the official launch of GitHub Copilot, a coding tool powered by OpenAI's large language models and widely adopted since then, on June 21st, 2022.[2] I constructed a novel developer-level measure of Generative AI exposure based on the programming languages developers use, as some languages, such as Python, benefit more from Generative AI than others, such as Stata, because there is more training data in certain languages available for LLMs.[3] I then compare developers with high and low *ex ante* AI exposure before and after the introduction of Generative AI.

I start by investigating Generative AI's impact on labor productivity. I find that Generative AI improves productivity and multitasking abilities. Specifically, I find developers at firms with high AI exposure are 1.2% more likely to contribute code to firm-owned projects per month, and the number of projects they work concurrently on

[2]The tool is integrated seamlessly into development environments and assists developers by suggesting code snippets in real time as they type code or natural language instructions. In addition, it later offered a GPT-4-powered chat feature in March 2023, allowing developers to interact with the AI assistant within their codebase. Since its introduction, developers have quickly adopted the tool, with over one million paid subscribers in 2023 and one third Fortune 500 adopters as of December 2022. See https://github.com/features/copilot (September 2024).

[3]For example, A GitHub post during the technical preview of GitHub Copilot says that "GitHub Copilot works with a broad set of frameworks and languages, but this technical preview works especially well for Python, JavaScript, TypeScript, Ruby and Go." See https://github.blog/2021-06-29-introducing-github-copilot-ai-pair-programmer/.

increases by 0.07, or about 6.5% of the mean. The effects are stronger for firm-owned projects and for activities more relevant to coding. This is likely, as GitHub Copilot was released about five months before the general availability of ChatGPT. Therefore, any immediate impact on labor outcomes observed is more likely to be attributed to Generative AI complementing coding tasks rather than other activities of software developers, such as writing emails. Dynamic effects observed from event-study analysis show that firms' developers immediately react to the introduction of Generative AI, that the effects persist over time, and that there is no evidence violating the parallel trend assumption.

I then explore the heterogeneity in employees' responses along gender and seniority dimensions. Employees' responses to Generative AI can vary based on adoption, usage, and adaptation. For instance, female and junior employees may benefit from AI-driven interactive chat support tools, as they are less likely to ask for or receive feedback from colleagues (Emanuel, Harrington and Pallais, 2023). However, female employees are often found to be reluctant to adopt technologies, partially due to "AI shame" (Carvajal et al., 2024) and lower confidence (Humlum and Vestergaard, 2024). In terms of seniority, while senior workers may have been better equipped to unleash Generative AI's potential due to their experience, Kogan et al. (2023) find that older workers are negatively affected by labor-augmenting technologies because they lack the ability to adapt. Thus, it remains an empirical question as to which employees, in terms of gender and seniority, improve productivity and engage in innovation process, which ultimately contribute to firm value and growth in the Generative AI era.

I compare Generative AI's effects on productivity outcomes between senior and junior developers and between female and male developers. I find that Generative AI's effects on productivity and multitasking are stronger for senior developers, who might be experienced enough to fully unleash the potential of Generative AI. Generative AI increases productivity more for men, but the gender difference disappears when it comes to multitasking. A possible explanation is that while Generative AI improve both time and cognitive capacity for women, they tend to use the extra time capacity outside work.

I further study how Generative AI affects innovation outcomes. While Generative AI does not affect the probability of innovation on average, it increases community interest in new projects, as proxied by the number of stars received by repositories (projects) as of February 2024. By distinguishing the AI exposure of the projects themselves from that of the innovator teams, I show that the increase in community interest is mainly driven by innovators' AI exposure. Exploiting the heterogeneity of team composition in gender and seniority, I find that the effects are stronger for new projects led by innovator teams consisting of more female or junior members. The results suggest that women and junior innovators may benefit from the additional time and cognitive capacity, quick feedback, and faster learning enabled by by Generative AI, and they may also become more confident in the success of novel ideas with the help of Generative AI.

As Generative AI increases labor productivity and demand for new innovation, potentially reducing costs and increasing revenue, one would expect AI-exposed projects to generate more firm value. To test this, I estimate the private value for firms' open-source projects based on the methodology introduced in our other paper (Emery et al., 2024). Specifically, the value is calculated based on stock market reaction within three days after the public release of the repository. This value has been shown to predict future sales growth, profitability, employment growth, and patent innovation. I find that projects that with greater exposure to Generative AI themselves experience a 9.9% increase in value, showing greater interest from investors. In addition to that, projects led by innovator teams with high AI exposure are valued 6.2% higher. Similar to the results for community interest, I find Generative AI's effects on repository value are stronger for innovator teams composed of women or junior developers. For an AI-exposed team of five senior male innovators, replacing one man with a woman increases Generative AI's effect on value by 12.8 percentage points, and replacing one senior with a junior increases the effect by 5.3 percentage points.

Literature. This study makes several contributions to the literature. First, I add to the growing body of research on the impact of Generative AI on labor outcomes. Previous research has studied the short-term impact of Generative AI on individual-level productivity and creativity across different types of discrete tasks, usually in experimental or single-firm settings (Brynjolfsson, Li and Raymond, 2023; Dell'Acqua, McFowland, Mollick, Lifshitz-Assaf, Kellogg, Rajendran, Krayer, Candelon and Lakhani, 2023; Noy and Zhang, 2023; Doshi and Hauser, 2024; Zheng, Wong, Zhou and Koh, 2024). Only a few studies have used large observational data, which allows researchers to examine longer-term impact and improve external validity (Song, Agarwal and Wen, 2023; Zhou and Lee, 2023; Hoffmann, Boysel, Nagle, Peng and Xu, 2024b; Yeverechyahu, Mayya and Oestreicher-Singer, 2024). While my empirical setting is closely related to Song et al. (2023),Hoffmann et al. (2024b), and Yeverechyahu et al. (2024), who study the effects of GitHub Copilot on GitHub activities, their identification strategies induced selection issues or restricted their sample to top maintainers or specific programming languages. Instead, the novel AI exposure score implemented at the developer level in this paper expands the sample to include general developers. More importantly, my paper focuses more on *firms* rather than on pure productivity outcomes. By using high-frequency, long-term observational data linked to firms, I am able to study detailed individual behavior in a collaborative work environment across all U.S. public firms that engage in open-source innovation. This allows me to provide more concrete evidence on the interaction between labor and firm performance through both labor productivity and innovation channels. Also, by comparing firm-related and non-firm-related activities, I show that AI-boosted productivity gains are more relevant for firm projects.

Secondly, this paper speaks to the literature on the role of AI in firm value and growth. Several studies have examined how AI may affect firm value through labor productivity (Eisfeldt et al., 2023; Kogan et al., 2023), labor composition (Babina et al., 2023; Berger et al., 2024), product innovation (Babina et al., 2024), and entrepreneur decision making (Otis et al., 2024). This paper offers individual-level evidence supporting some of these previous findings, particularly through the labor productivity and innovation channels. Additionally, I identify the potential role of AI in augmenting labor's cognitive capacity for multitasking. Moreover, this study also exploits heterogeneous employee responses to disruptive technologies along gender and seniority dimensions, identifying which employees can contribute to firm value with Generative AI.

Methodologically, this study also contributes to the literature that uses Generative AI to generate new data and construct measurements to overcome various data challenges in academic research. For example, researchers have leveraged large language models (LLMs) to summarize or classify unstructured data (Cheng, Lee and Tambe, 2022; Beckmann, Beckmeyer, Filippou, Menze and Zhou, 2024; Chen and Wang, 2024; Kim, Muhn and Nikolaev, 2024) and generate synthetic data for variables that require less subjective evaluation, such as occupational AI exposure scores (Eisfeldt et al., 2023; Eloundou, Manning, Mishkin and Rock, 2023; Kogan et al., 2023). This paper uses novel LLM-based AI exposure scores for programming languages and applies LLM-inferred gender and task classification to overcome data challenges and improve research efficiency.

2 Institutional Background

2.1 Open Source Software and Commercial Engagement

Systems granting excludability, such as patents, have been seen to be important to incentivize innovation (Arrow, 1962; Crouzet, Eberly, Eisfeldt and Papanikolaou, 2022). Yet, there has been an increasing trend in open-source innovations, particularly in the software industry. Based on the definition of the Open Source Initiative, "open source" means not only access to the source code but also allowing free redistribution and modification under terms defined by open-source licenses. Therefore, when an innovation is "open-sourced," it is made publicly available to all parties at little or no cost. Because of potential knowledge spillovers and the reduction of replacement costs for OSS adopters, open-source software can generate large externalities and facilitate innovation in society as a whole (Fershtman and Gandal, 2011; Nagle, 2019; Hoffmann et al., 2024a; Chen, Shi and Srinivasan, 2024). The recent debates over open-source large language models further show the increasing importance and impact of open-source innovation.

While open-source innovations contribute to social welfare, they can also generate private value for firms.[4] Indeed, many firms choose to make their innovation open source. A recent survey finds that 90% of Fortune 100 companies use GitHub, the largest platform for developing open-source innovation.[5] Emery et al. (2024) document an increasing trend of open-source activity by U.S. public firms, with these firms representing 68% of the stock market by market capitalization by the end of 2023. They show open-source

[4]There is a broad literature studying the incentives for commercial firms to reveal their innovations in an open-source way, see Allen (1983), Lerner and Tirole (2002), Harhoff, Henkel and von Hippel (2003), Dahlander and Gann (2010), Henkel, Schöberl and Alexy (2014), Parker, Van Alstyne and Jiang (2017), Alexy, West, Klapper and Reitzig (2018), Nagle (2018), Teece (2018) and Lin and Maruping (2022). For reviews of the open-source literature, see von Hippel and von Krogh (2003), Goldfarb and Tucker (2019), and Dahlander, Gann and Wallin (2021).

[5]See https://octoverse.github.com/2022/.

innovation can generate private value for firms, and this value is a predictor of future sales growth, profitability, employment growth, and patent innovation.

2.2 Software Development Activities on GitHub

GitHub operates on the Git system, which supports a distributed and collaborative framework for software development. Although not all open-source projects are developed on GitHub, it remains the largest platform for such efforts and is closely associated with the concept of open-source software. This section will outline key terms and activities related to software development on GitHub.

To share their innovations on GitHub, firms begin by setting up organization accounts. Within these accounts, they can establish repositories (projects), with administrators determining whether these will be publicly accessible or restricted to selected organization or project members with appropriate permissions. The creation and maintenance of public repositories incur minimal costs, whereas managing private repositories may require GitHub Team or GitHub Enterprise subscriptions for additional support and features. Importantly, despite previous charges for private repositories before GitHub's 2015 shift from a repository-based to a user-based pricing model, public repository hosting has been free since GitHub's launch.

The development process starts with developers making modifications to the codebase, committing these changes locally with concise descriptions. These "commits" are then "pushed" to remote branches, making the updates accessible to other contributors and users.

Users who want to follow a repository's progress can "star" a repository, essentially bookmarking it for future reference. Those who have questions or suggestions can also "open issues," which are addressed by the development team and the broader community.

Additionally, users can contribute by "forking" the repository, creating a personal copy to work on independently. If the changes made in the fork are considered beneficial to the original project, users can submit "pull requests." These pull requests are formal proposals to merge their changes back into the original repository. These pull requests are reviewed, and if accepted, the modifications are integrated into the main codebase, further advancing the open-source project.

2.3 GitHub Copilot

GitHub Copilot is a cloud-based AI-powered code completion tool developed by GitHub in collaboration with OpenAI. Specifically, it is built on OpenAI's Codex model, a large language model trained on vast datasets of public code repositories. The tool integrates seamlessly into popular Integrated Development Environments (IDEs), and is designed to assist developers by suggesting code snippets and entire functions in real-time as they write code. Initially, it was launched in June 2021 in preview, available with a limited number of spots. It has later become generally available to all developers since June 21st, 2022. While GitHub Copilot is freely available for verified students and maintainers of popular open-source projects, for most individual developers it is priced at $10 per month. There is also an Enterprise option for business. The tool is widely adopted since then. There are over one million paid subscribers in 2023, and one third of Fortune 500 companies use GitHub Copilot as of December 2022.[6]

Developers use GitHub Copilot by installing it as an extension in supported IDEs. As they type, Copilot analyzes the code context and offers autocomplete suggestions. It can also generate code based on natural language descriptions, allowing users to input

[6] See https://github.com/features/copilot (September 2024).

comments describing desired functions or algorithms, and Copilot will output the corresponding code. Therefore, it significantly enhances developer productivity by reducing the time spent on routine coding tasks, lowering the cognitive load, and minimizing common errors. In addition, by offering creative coding solutions and suggesting best practices, it enables developers to learn new coding techniques and languages. In March 2023, GitHub Copilot further offers GPT-4-powered chat feature, which allows developers to engage in a dialogue with the AI assistant to get feedback and suggestions.

3 Data and Methodology

3.1 Data

3.1.1 GitHub Activity of U.S. Public Firms' Developers

To construct the dataset on GitHub activity of developers working for U.S. public firms, I begin by linking GitHub organization accounts with firms. Following the methodology of Conti, Peukert and Roche (2021), I first collect websites of organization accounts via the GHTorrent project and the GitHub API. I then match these domains with the web URLs of U.S. public firms and their subsidiaries from Compustat or Orbis. Accounts whose domains are indicative of hosting or social media services, such as "github.com" and "facebook.com.", are not considered as matched. I then manually search for firms' open-source organization accounts to complement the domain-based matching. Specifically, I query the firm names together with the term "open source" via Google to locate official web pages that list their open source projects, and search the firm names on GitHub to identify associated organization accounts. Following this, I compile a comprehensive list of public repositories owned by the identified organization accounts through the GHArchive database, which records and archives timestamped public activity of GitHub repositories. In total, I match 1,281 firms with 3,314 organization accounts and 168,085 public repositories up to the year 2023.

Upon establishing a link between U.S. public firms and their respective GitHub organization accounts and public repositories, I use the GHArchive database to gather additional information on the public footprints of these repositories. Most importantly, I identify individuals who are internal contributors (i.e., those who push commits to firm-owned repositories) as firms' developers. I also obtain activity records of these developers in non-firm repositories. However, the panel used for analysis only includes periods when a developer actively contribute code to firm-owned projects. Therefore, activity records of non-firm-related repositories outside this period are excluded from analysis. Overall, my sample spans from January 1st, 2021 to December 31st, 2023, 18 months before and after the introduction of GitHub Copilot.

Finally, I classify GitHub activities based on skills required. In addition to coding, an activity requiring core skills for programmers, GHArchive also records activities that require general skills like communication and collaboration. I ask ChatGPT to classify Github activities into four categories based on relevant skills: core, general , mixed, and no skill related. Combining the large language model's response with subjective evaluation, I classify "PushEvent", "PullRequestEvent", and "PullRequestReviewEvent" as core skill-related events, "IssueCommentEvent" and "IssueEvent" as general skill-related events, and "CommitCommentEvent" and "PullRequestReviewCommentEvent" as mixed skill-related events. See Section B.1 for prompt and classification details.

3.1.2 Developer and Repository Characteristics

I use the GitHub API to collect static characteristics of developers as of March 2024. In particular, I obtain the account create date and self-reported names. I use the user account create date to calculate tenure and proxy for seniority. Figure 2 illustrates the distribution of account create month in my data. For self-reported names, I use OpenAI's API to interact with the GPT-3.5 turbo model and ask it to guess developers' gender based on their names. Then I infer developers' gender when the score is above 0.5 (0-1 scale). See Section B.2 for prompt and example response. In addition, I exclude users with account name containing "bot" or with "bot" account type to ensure bot accounts will not contaminate my sample. By leveraging LLMs, I am able to not only overcome name-based gender inference challenges, such as names from non-English speaking countries, but also identify other information sometimes included in self-reported names, such as bot type and company, without sacrificing accuracy. For instance, Alexopoulos, Lyons, Mahetaji, Barnes and Gutwillinger (2023) show that ChatGPT perform as well or outperform common commercial tools.

Similarly, I collect static characteristics of firm-owned and non-firm-related repositories extant as of February 2024. This includes an array of attributes from descriptive repository metadata, such as programming languages and their corresponding byte sizes, to quantitative measures of community engagement, including the number of stars, watchers, and forks.

3.1.3 Repository Value and Firm Characteristics

I estimate the forward-looking value of repositories using a stock market-based approach. Specifically, the value is calculated based on the stock market reaction within three days after a project is made public. Our other paper (Emery et al., 2024) provides methodology details and validation of the value measure. Stock return data comes from CRSP and other firm financial characteristics are obtained from Compustat.

3.2 Generative AI Exposure Measure

To compare users with relatively higher *ex ante* exposure to Generative AI with users with lower exposure, I leverage the programming languages used by a user from June 2019 to June 2021, which ends right before the Copilot preview and one year before the introduction of GitHub Copilot to ensure that the AI exposure score does not reflect selection effects. The idea is that some languages (such as Python) benefit more from Generative AI than others (such as Stata) because there are more training data in certain languages available for LLMs. For each language, I assign an exposure score (0-1) to Generative AI coding tools based on ChatGPT's suggestions. Section B.3 provides prompt details. While this paper is among the first to use ChatGPT to assign AI exposure score to programming languages, LLM-based AI exposure score has been largely implemented for occupations (Eisfeldt et al., 2023; Eloundou et al., 2023; Kogan et al., 2023). Table 1 lists selected languages and their AI exposure scores, with Python ranked first with a score of 1 and Stata and TeX ranked among the lowest with a score of 0.5. Other languages irrelevant for coding, such as CSV, do not have an AI exposure score.

Because there is no directly available information on language usage over time at user-level, I take two steps to approximately measure user-level AI exposure. First, I calculate the total language byte size for each user (b_i^l) based on user activities in firm-owned repositories and the byte size of languages in each repository (b_r^l) between June 2019 and June 2021. For each repository, I calculate user's fraction of contribution of each language in terms of the user's share of "PushEvent" and then sum it up to user-language level. Specifically, I calculate:

$$b_i^l = \sum_r \frac{a_{i,r}}{\sum_j a_{j,r}} b_r^l,$$

where b_i^l is the byte size of language l contributed by user i, $a_{i,r}$ is the total number of PushEvent activity of user i in repository r, and b_r^l is byte size of language l used in repository r.

Then for each user, I calculate the weighted AI exposure score, where the weight is the byte size of a given language to the byte size of all code contribution by user i among the two-year period one year prior to the introduction of GitHub Copilot. Specifically, I construct the user-level AI exposure score as follows:

$$s_i = \sum_l \frac{b_i^l}{\sum_l b_i^l} s^l,$$

where s_i is the weighted AI exposure score of user i, b_i^l is the byte size of language l contributed by user i, and s^l is AI exposure score of language l provided by ChatGPT. Lastly, I define users with s_i in the 4th quartile as having high exposure to Generative AI.

3.3 Identification Strategy

I use a generalized difference-in-differences (DID) approach to study the reactions of labor productivity and innovation outcomes of firms' developers to the introduction of GitHub Copilot, a code autocompletion and chat tool powered by OpenAI's GPT models. Using the shock of GitHub Copilot's public release has several advantages. First, GitHub Copilot is designed for coding tasks and is seamlessly integrated with major IDEs (integrated development environments), making it particularly relevant and easy to use for software developers. Second, the tool was officially launched for individual developers on June 21st, 2022,[7] five months before the release of ChatGPT on November 30th, 2022. Therefore, any initial reaction observed is likely to be driven by Generative AI powering job-specific coding tasks of developers rather than changes in activities of other tasks unobservable in the software development context. Third, while there was a period of technical preview since June 29th, 2021[8], the preview was strictly limited to a number of spots with relatively poor performance. The general availability of the tool can therefore serve as an ideal shock for the main purpose of this paper.

For baseline regressions, I use the following specification:

$$Y_{i,t} = \beta_1 Post_t \times AI\ Exposure_i + \mu_i + \theta_t + \epsilon_{i,t}, \tag{1}$$

where $Post_t$ indicates periods after the introduction of GitHub Copilot. Specifically, it equals one since July 2022 for monthly analysis or the third quarter of 2022 for quarterly analysis. $AI\ Exposure_i$ equals one for the group with relatively high Generative AI exposure, i.e., the user's *ex ante* AI exposure score is in the fourth quartile. In addition, I include individual (μ_i) and time (θ_t) fixed effects to control for time-invariant individual characteristics and common time trends. The outcomes of interest $Y_{i,t}$, include individual-level labor productivity measures, such as the likelihood and intensity of different types of activity in firm and non-firm projects, and innovation measures, such as the likelihood of initiating new firm-owned projects.

I further explore the heterogenous effects of Generative AI on employees along the gender and seniority dimensions. To do this, I conduct a triple difference-in-differences

[7] For official announcement, see https://github.blog/news-insights/product-news/github-copilot-is-generally-available-to-all-developers/

[8] See https://github.blog/news-insights/product-news/introducing-github-copilot-ai-pair-programmer/.

(DDD) analysis using the following specification:

$$
\begin{aligned}
Y_{i,t} =& \beta_1 Post_t \times AI\ Exposure_i + \beta_2 Post_t \times Char_i \\
&+ \beta_3 Post_t \times AI\ Exposure_i \times Char_i + \mu_i + \theta_t + \epsilon_{i,t},
\end{aligned} \tag{2}
$$

where $Char_i$ is a dummy indicating the inferred gender or seniority of developer i. For seniority, the dummy equals one if the tenure of the developer on the GitHub platform, approximated based on the account's create date, is in the fourth quartile. The coefficient of interest is therefore β_3.

Additionally, I conduct an event-study analysis for individual-level reactions to the introduction of the Generative AI. While the generalized DID approach gives an estimate of the average impact over the time horizon after the AI shock, the event-study approach allows for examining dynamic effects and checking whether the parallel trend assumption is violated or not. The event-study specification is as follows:

$$
Y_{i,t} = \sum_{l=\underline{l}+1}^{\bar{l}-1} \gamma_l D_{i,t}^{l} + \gamma_{\underline{l}} D_{i,t}^{\underline{l}} + \gamma_{\bar{l}} D_{i,t}^{\bar{l}} + \mu_i + \theta_t + \epsilon_{i,t}, \tag{3}
$$

where D_l are leads and lags of treatment for short-run effects, and $D^{\underline{l}}$ ($D^{\bar{l}}$) accounts for periods before $\underline{l}$ (after $\bar{l}$) periods relative to treatment for all longer-run effects. D^{-1} is omitted for normalization, that is, one month or one quarter before the introduction of GitHub Copilot based on the panel frequency. For monthly analysis, I set $\underline{l} = -7$ and $\bar{l} = 13$, and for quarterly analysis, I set $\underline{l} = -6$ and $\bar{l} = 5$.

Lastly, I conduct DID analysis in repeated cross-sections for project-level innovation outcomes in terms of community interest and value. Specifically, I estimate the following:

$$\begin{aligned} Y_{r,f,t} =& \beta_1 Innovator\ AI\ Exposure_r + \beta_2 Post_t \times Innovator\ AI\ Exposure_r \\ & + \beta_3 Repo\ AI\ Exposure_r + \beta_2 Post_t \times Repo\ AI\ Exposure_r \\ & + Controls_{r,f,t-1} + \alpha_{industry} + \theta_t + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $Y_{r,f,t}$ is the dependent variable for community interest (number of stars received) and repository value estimated based on stock market reaction. I include both repository-level AI exposure ($Repo\ AI\ Exposure_r$) based on the repository language compositionand team-level AI exposure ($Innovator\ AI\ Exposure_r$) if one of the initiators is with high AI exposure. I include lagged firm-year level controls, including the natural logarithms of one plus cumulative number of firm-owned repository, market capitalization, volatility, number of employees, and one plus value of patent portfolio. I also control for return on assets, R&D expenditure as a share of assets, whether R&D expenditure is missing, and innovator team size, and include industry (defined at SIC 3-digit level) and time fixed effects.[9] Similar to developer-level analysis described above, I further exploit the heterogeneity of team composition in terms of gender and seniority.

4 Empirical Results

4.1 Summary Statistics

I provide an overview of monthly open-source activities of firm's developers before the introduction of GitHub Copilot in Table 2. First, Panel (a) shows that the average AI

[9]These controls have been shown to be significant determinants of repository value as documented in Emery et al. (2024).

exposure score in my sample is around 0.81, with little difference between women and men or between junior and senior developers. Core skill events, which are related to coding activities, account for the majority of activity records. Specifically, 69% developers at least contribute code once, and an average developer contributes code around 30 times per month, showing that these developers are active contributors. Developers on average contribute to 2.6 projects per month, although they show active public footprint in 3.8 projects. Firms' developers work mostly for firm-owned projects (1.6 projects per month), but they are also active for individual projects (1.3 projects per month) and projects owned by non-firm organizations (0.7 projects per month). Exploiting heterogeneity in developer's characteristics, I show that before the introduction of the Generative AI coding tool, women or junior developers contribute less in terms of intensity and frequency than men or senior developers across all types of activities, and they work on less number of projects concurrently.

Panel (b) of Table 2 compares activities and characteristics between developers with high and low exposure to Generative AI. Developers with high exposure tend to be slightly more junior, contribute less code, less active and work on less number of projects concurrently. However, there is no difference in terms of gender ratio.

Before moving to empirical analysis, the raw changes of outcomes might already tell the impact of the Generative AI shock. Figure 3 plots firm-related coding activities over time between developers with high and low exposure to Generative AI. Similar to what has been shown in the summary statistics above, developers with lower AI exposure are more active in general. Both groups see declining trends of activity in the pre-treatment period, and the trends are generally parallel. This might be because developers in my sample code less as they become more senior over time, or it can be because teams grow larger over time that there is less work for a single developer. However, after the introduction of Generative AI, the slope of the decrease becomes more flat for developers with low AI exposure, and developers with high exposure become increasingly more active. This shows that while the productivity of all developers are positively affected by Generative AI, the effect is much stronger for developers with high AI exposure. In addition, comparing the share of contribution to firm-owned versus non-firm-related projects, both groups have identical firm-contribution ratio prior to treatment. However, in the post-treatment period, developers with high AI exposure contribute more to firm-owned projects.[10]

4.2 Labor Productivity

In this section, I examine the impact of Generative AI on labor productivity outcomes in a more rigorous way. I start by investigating the extensive margin, i.e., whether a developer has any open-source activity in a given month. Table 3 provides results estimated from equation 1 and 2. Panel (a) shows GitHub activity changes after the introduction of Generative AI for firm-owned projects. Intuitively, the coding tool powered by Generative AI significantly increases the likelihood of coding-related events (i.e., core-skill and mixed-skill related activities). Specifically, developers with high AI exposure are 1.22% more likely to contribute code to firm-owned projects. On the contrary, the effect is minimal for activities unrelated to coding in general. Exploiting the inferred gender and tenure of developers, I find the effect on core-skill related activity is stronger for men and senior developers, albeit the difference is insignificant for seniority. Panel (b) shows results for activity of non-firm-related projects. Similarly, developers more exposed to Generative AI become more active in core coding tasks, particularly for men. However, they are not more active in mixed-skill activities, which is consistent with the fact

[10]Note that the sample is restricted to developers active in at least one firm-related project within a given quarter. Thus, the difference between firm and non-firm contribution cannot be explained by developers with low AI exposure being more likely to experience layoff.

that most non-firm-related projects are individual projects that require little external communication or collaboration that is involved in mixed-skill related events.

Figure 4 and Figure 5 show the event study results for activity engagement associated with firm-owned and non-firm-related projects, respectively. The coefficients are estimated from equation 3. First, the coefficients prior to the launch of GitHub Copilot show that the parallel trend assumption is not violated. Second, for coding activities, particularly core-skill related events, there is an immediate jump after the introduction of Generative AI. The short-term effects show that right after the introduction, developers with high exposure are 2-4% more likely to contribute code to firm-owned projects. In addition, the effects persist until 10 months later. Similar to DID results, the effects are weaker for activities unrelated to coding or non-firm-related projects.

Next, I compare the intensity of different activities between developers with high and low AI exposure before and after the introduction of Generative AI. For this analysis, I aggregate activities by quarter as there are many zeros in the monthly panel. Results are shown in Table 4. Similarly, Generative AI boosts productivity for both firm-owned and non-firm-related projects. The effects are stronger for firm-owned projects, for activities more relevant for coding, and for men or senior developers.

Figure 6 and Figure 7 plot the event study results for activity intensity associated with firm-owned and non-firm-related projects, respectively. Similarly, I do not observe significant evidence rejecting the parallel trend assumption. Generative AI enhances developers' productivity immediately. The effects are stronger for firm-owned projects and coding related activities. Different from the results for extensive margin, as shown above, AI's impact on activity intensity persists and is increasing over time.

If Generative AI enhances labor productivity, developers may find they have more time capacity than the work demand of a given project. In addition, as the Generative AI coding tool can largely save time for routine tasks, developers may have more cognitive capacity to multitask. In this case, they may be able to work on multiple projects at the same time. To test this, I regress number of repositories in which a developer is active per month on the post and treatment indicators. Table (5) reports the results. Consistent with the prediction, developers with higher AI exposure work on more firm-owned repository across all types of activity, as shown in Panel (a). Once again, the effects are stronger for senior developers. Yet the gender differences disappear: both men and women work on more projects concurrently. In addition, when the AI-exposed developers multitask, they work more on firm-owned projects rather than non-firm-related projects. The coefficients for non-firm-related projects, as shown in Panel (b), are statistically insignificant and nearly zero.

I plot the event study results for number of active firm-owned and non-firm-related projects in Figure 8 and Figure 9, respectively. Again, coefficients prior to treatment are insignificant and nearly zero, showing that the parallel trend assumption is not violated. Focusing on the dynamic effects, there is an immediate jump in number of active firm-related projects to which an average developer contribute code concurrently each month. The effects generally persists, with the highest short-term effect estimated around 0.1, or about 10% of the mean (1.02). However, there is even a slight reduction in number of active non-firm-related projects.

Overall, I find that after the introduction of GitHub Copilot, a coding tool powered by Generative AI model, developers with high AI exposure show higher productivity and multitasking capability. The effects are stronger for firm-owned projects, for activities more relevant to coding, and for senior developers who might be able to leverage Generative AI's potential better as they are more experienced. While prior research finds that junior and low-skill workers often benefit more from Generative AI (Brynjolfsson et al., 2023; Dell'Acqua et al., 2023; Kogan et al., 2023; Gambacorta, Qiu, Shan and Rees, 2024), the different effects I observed here could be attributed to two factors. First, senior developers, as defined in this paper, are not necessarily older, therefore they may not lack the ability to adapt, as often argued by other research. Second, experience is a benefit with AI in coding tasks because seniors can easily spot bugs and understand the broader context of a project. Generative AI's capability to assist with lower-level coding allows them to focus more on these strategic areas, thus improving their overall efficiency.

In terms of gender heterogeneity, I find Generative AI boosts productivity more for men, but the gender difference disappears in terms of multitasking. Therefore, the gender difference in AI-induced productivity is less likely to be explained by lower technology adoption or higher tendency to choose to work on side projects among female developers. A more possible explanation is that while Generative AI improve both time and cognitive capacities for women, they implement the extra time capacity outside work.

In addition, these findings provide explanations for the increase of coding activity of firm-owned projects as a share of total coding activity, as shown in Figure 3. First, while the productivity gain is evident across all repositories, it is stronger for firm-owned projects. Second, when AI-exposed developers have extra capacity for working on multiple projects, they tend to work on firm-owned projects. Overall, it shows that employees augmented with Generative AI do not choose to work more for side projects. Instead, it is mainly firm projects that benefit Generative AI.

4.3 Product Innovation

In addition to improving labor productivity, Generative AI may contribute to firm value and growth by stimulating new ideas and products (Babina et al., 2024). With extra time and cognitive capacities, humans augmented by AI are freed from routine tasks and may shift to focus on creative activities. Furthermore, since GitHub Copilot provides interactive chat support over the code base, developers can receive quick feedback, facilitating faster learning and ideation. This might be particularly true for developers underrepresented in the profession, such as women, who are less likely to ask for and receive feedback from their colleagues (Emanuel et al., 2023).

I study the impact of Generative AI on firms' open-source innovation, focusing on the likelihood of developers becoming innovators, the community's interest in the innovation, and the value of the innovation. I define innovators as those who initiate new projects owned by the firm. Specifically, I identify innovators who publicly contribute code to newly created projects within two weeks of their initiation.[11]

My analysis starts with the likelihood of producing innovation and the number of new projects initiated each quarter. Table 6 reports the results. In general, the introduction of Generative AI does not have an effect on either the likelihood of producing innovation or the number of innovations. If anything, junior developers at firms with high AI exposure appear to be 0.6% less likely to create firm-owned new projects post-treatment. One potential explanation is that junior innovators are more likely to leave public firms, resulting in their exclusion from the sample after the introduction of Generative AI.

Next, I move to the project-level outcomes. Specifically, I look at the community interest, proxied by the number of stars received as of February 2024, and the repository

[11] This definition is conservative as some projects are made public several months after creation, and, as a result, no innovators are identified for these projects.

value (in 2023 dollars), which is estimated based on stock market reaction to the public release of the project. One may be concerned that project composition could shift after the AI breakthrough in this repeated cross-sectional analysis. For example, there may be more AI-related Python-based projects that are naturally contributed by Python developers. To address such concerns, I also control for the project-level AI exposure score based on the project's language profile.

Table 7 reports the results. In Panel (a), I show that Generative AI does not necessarily help projects with greater AI exposure attract more community interest. However, projects initiated by innovators with high AI exposure do receive significantly more stars, indicating greater recognition. Exploiting team-level characteristics such as gender and seniority, I find that the effects are much stronger for projects led by teams with higher female or junior ratios, showing that Generative AI benefits women and junior innovators more in the product innovation context.

So far, my results show that Generative AI has the potential to reduce labor costs by increasing labor productivity and to increase revenue by driving higher product demand. Therefore, one would expect AI-exposed projects to create more firm value. For firms, open-source innovation has been shown to generate private value, and this value is a predictor of future sales growth, profitability, employment growth, and patent innovation (Emery et al., 2024). From a social welfare perspective, open-source innovation largely benefits society by reducing replacement costs (Hoffmann et al., 2024a) and increasing overall patent values (Chen et al., 2024).

I estimate the value of the new innovation based on the methodology documented in Emery et al. (2024), a stock-market based approach, and investigate the impact of Generative AI on the private value of open-source innovation for firms. I control for innovator team size and firm-year characteristics that have been shown to be determinants of repository value. The results are shown in Panel (b) of Table 7. First, I find that projects that are themselves more exposed to Generative AI see an increase in value by 9.9%. Additionally, projects contributed by innovators with high AI exposure are valued 6.2% higher. Again, the effects are stronger for projects led by teams composed of women or junior developers. For an AI-exposed team of five senior male innovators, replacing one man with a woman increases AI's effect on value by 12.8 percentage points, and replacing one senior with a junior increases the effect by 5.3 percentage points, *ceteris paribus*.

In summary, I do not find evidence that Generative AI encourages firms' developers to be innovators. However, projects led by teams with high AI exposure do see an increase in community recognition and are valued more highly by the stock market. The effects are stronger for projects led by teams with more women or junior innovators, showing that Generative AI benefits women and junior innovators more in the product innovation context. This contradicts the findings related to labor productivity, where the results reveal that Generative AI benefits men and senior developers more. There are several potential explanations. From the employees' perspective, the extra time and cognitive capacities, quick feedback, and faster learning brought about by Generative AI may help women and junior innovators generate ideas. They may also become more confident in the success of novel ideas with the help of Generative AI. From the investors' perspective, investors may consider AI adoption a signal of quality for women and therefore value such projects more highly. For example, Carvajal et al. (2024) find that there is a value premium in hiring decisions for female candidates with Generative AI knowledge, while the value premium is nearly zero for men.

5 Conclusion

In this paper, I explore which employees with Generative AI contribute to firm value in the context of open-source softwares made available by U.S. public firms. By constructing a novel developer-level measure of AI exposure and exploiting the official launch of GitHub Copilot, I show the effects of Generative AI on labor productivity and innovation and explore the heterogeneous employee responses along gender and seniority dimensions.

For labor productivity, I find that Generative AI boosts productivity and multitasking ability. Developers at firms with high AI exposure are 1.2% more likely to contribute code to firm-owned projects monthly, and work on 0.07 more concurrent projects, a 6.5% increase from the mean. These effects are stronger for firm-owned projects, for activities more relevant to coding, and for senior developers who might be experienced enough to fully leverage AI's potential. While men experience higher productivity gains, gender differences in multitasking disappear, implying that women may allocate the additional time capacity outside work. Event-study analysis reveals that the productivity gains persist over time, with no evidence of parallel trend violations.

I also investigate Generative AI's influence on innovation. While it does not significantly affect the probability of innovation, it increases community interest in new projects, as indicated by the number of repository stars in February 2024. The rise in interest is mainly driven by innovators' AI exposure rather than project's AI exposure. Projects led by teams with more female or junior members see stronger effects, suggesting that Generative AI could benefit women and junior innovators through time and cognitive capacity, feedback, learning, and higher confidence.

Consistent with the increase in labor productivity, which may reduce costs, and the increase in demand for new innovation, which may increase revenue, I find that Generative AI creates firm value. Using stock market reactions within three days of a repository's release to estimate value, I find that AI-exposed projects see a 9.9% increase in value. Additionally, projects led by teams with high AI exposure are valued 6.2% higher. Notably, AI's impact on value is greater for teams with women or junior developers. Replacing one male with a female in an AI-exposed team consisting five senior male innovators raises Generative AI's effect on innovation value by 12.8 percentage points, while replacing a senior with a junior increases it by 5.3 percentage points.

The study could have implications for both firms and policymakers. Firms may need to reassess resource allocation and training programs to maximize the benefits of Generative AI tools, especially by addressing disparities in usage and outcomes across gender and experience levels and fostering more inclusive innovation environments. For policymakers, my results offer insights on the debates over AI regulation and policies facilitating access to AI.

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A Appendix

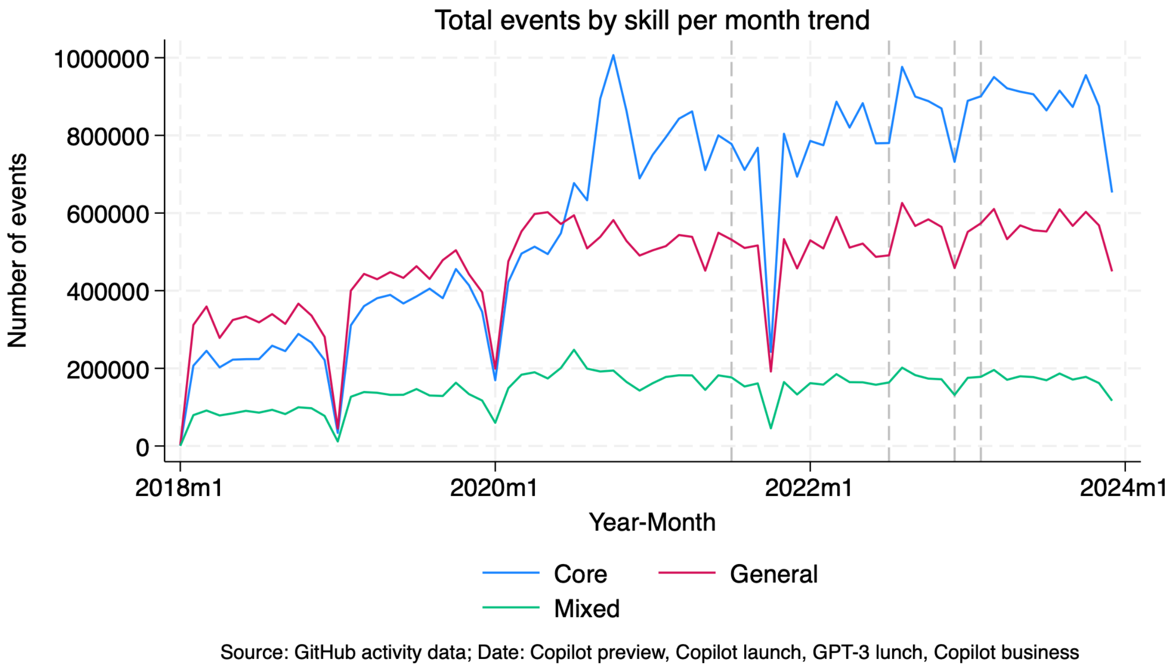

Figure 1. Monthly Aggregated Github Activities Over Time

This figure plots the monthly open-source activities within public firm-owned repositories on the GitHub platform from 2018 to 2023. Activities are grouped based on their related skill requirements. See Section B.1 for classification details.

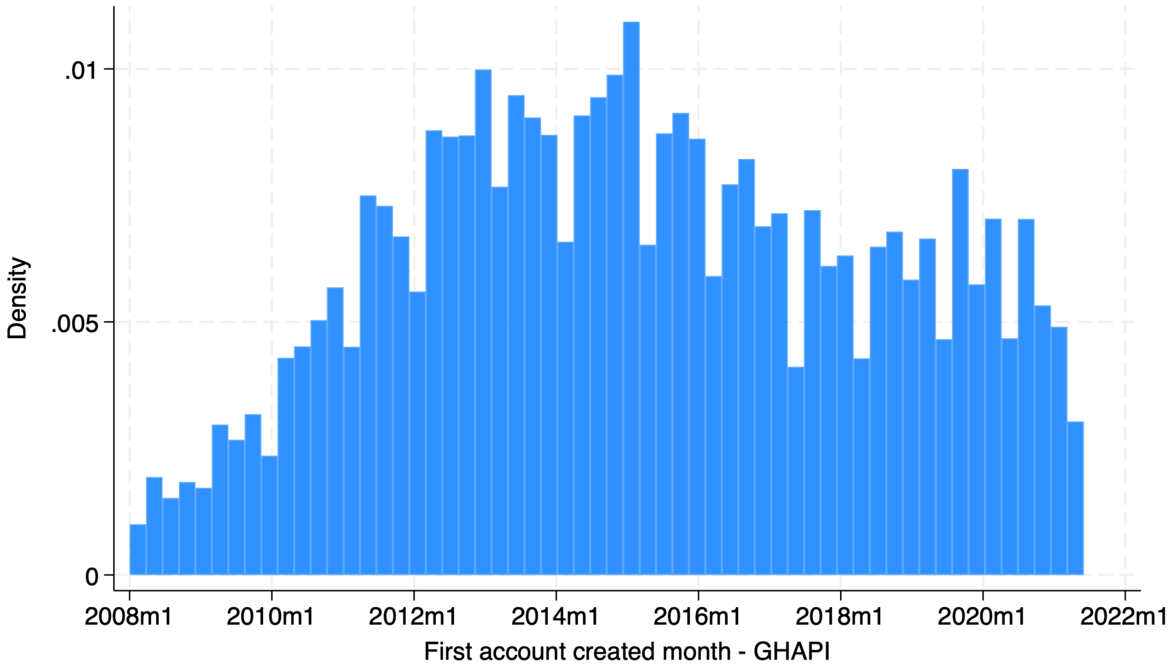

Figure 2. Density of Account Created Month

This figure plots the density of account create months of firms's developers, which is obtained via GitHub API.

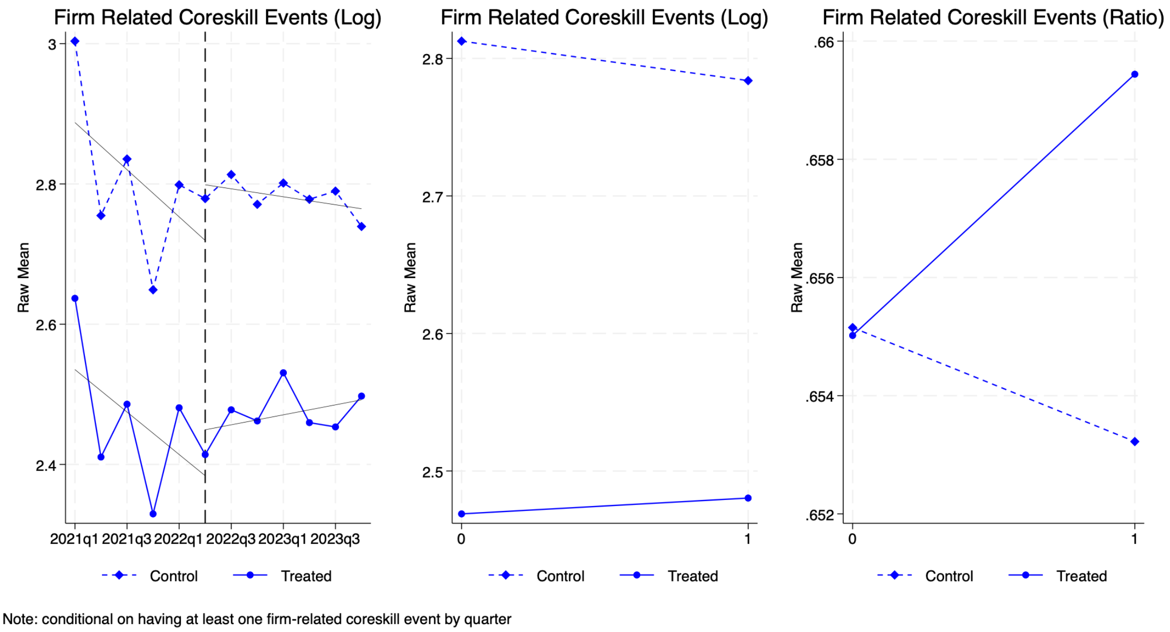

Figure 3. Raw Changes in Coding Productivity of Developers

This figure plots the raw mean of firms' developers coding related events in firm-owned repositories. The first graph shows the natural logarithm of activity count per quarter of developers with high (treated) and low (control) AI exposure. The second graph shows the average of the natural logarithm of quarterly activity count before and after the introduction of GitHub Copilot. The third graph shows the share of contributions made to firm-owned repositories before and after the introduction of GitHub Copilot.

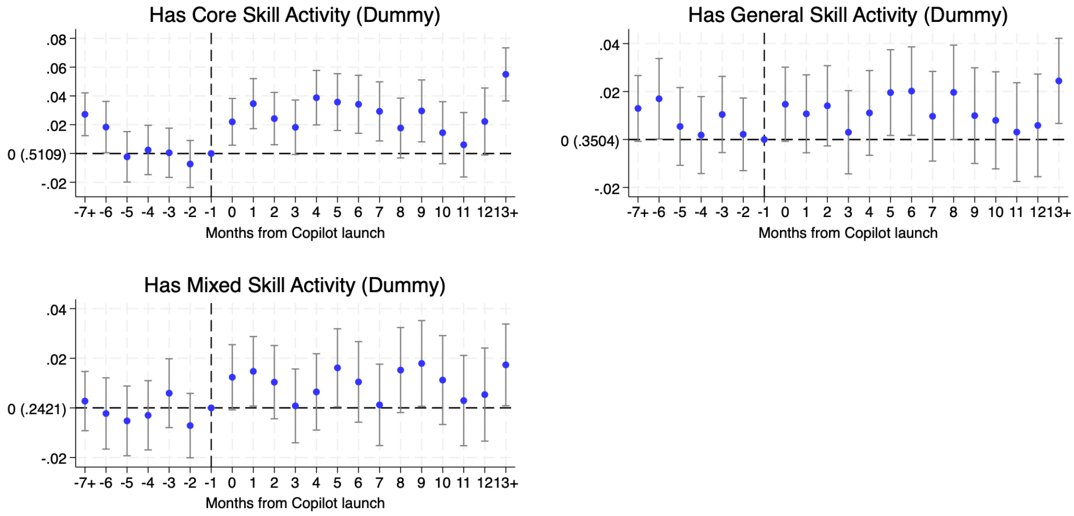

Figure 4. Monthly Firm Related Github Activity After Copilot Launch

This figure plots coefficients of the event study specification described in equation 3 with 95% confidence intervals. The outcome variables are dummy variables that equals one if a developer has any public activity in firm-owned repositories in a given month. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. Standard errors are clustered at developer level.

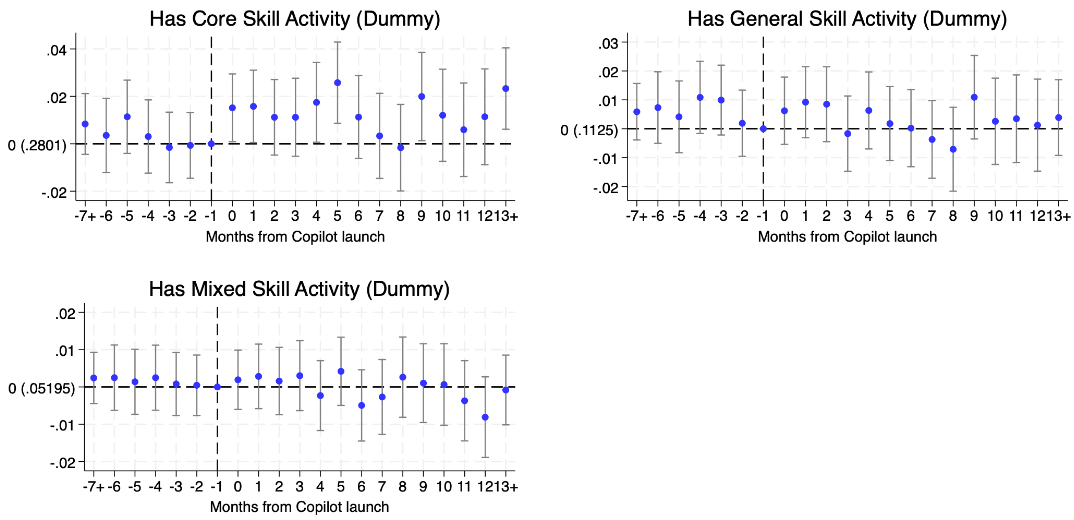

Figure 5. Monthly Non-Firm-Related Github Activity After Copilot Launch

This figure plots coefficients of the event study specification described in equation 3 with 95% confidence intervals. The outcome variables are dummy variables that equals one if a developer has any public activity in non-firm-related repositories in a given month. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. Standard errors are clustered at developer level.

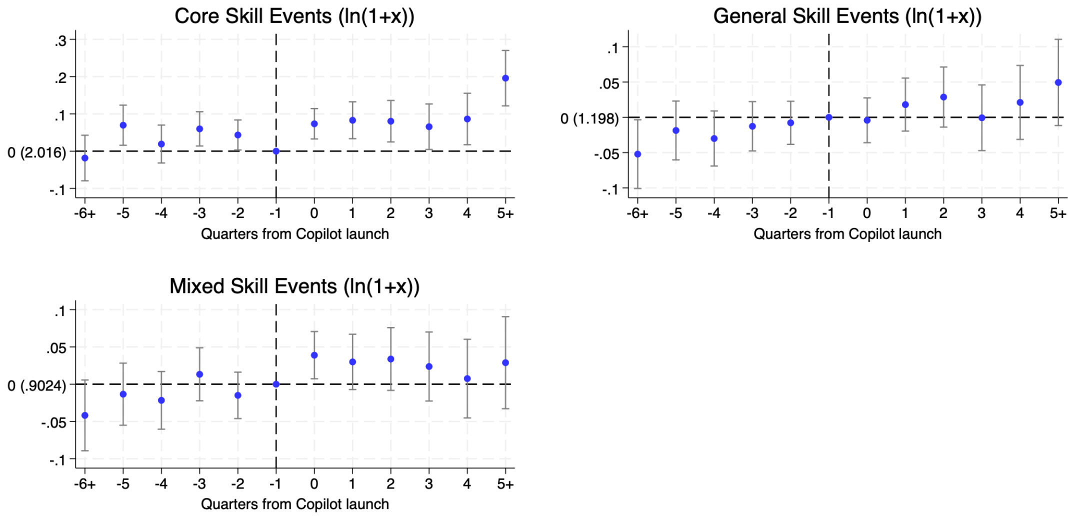

Figure 6. Quarterly Firm Related Github Activity After Copilot Launch

This figure plots coefficients of the event study specification described in equation 3 with 95% confidence intervals. The outcome variables are natural logarithms of one plus the number of quarterly public activities in firm-owned repositories. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. Standard errors are clustered at developer level.

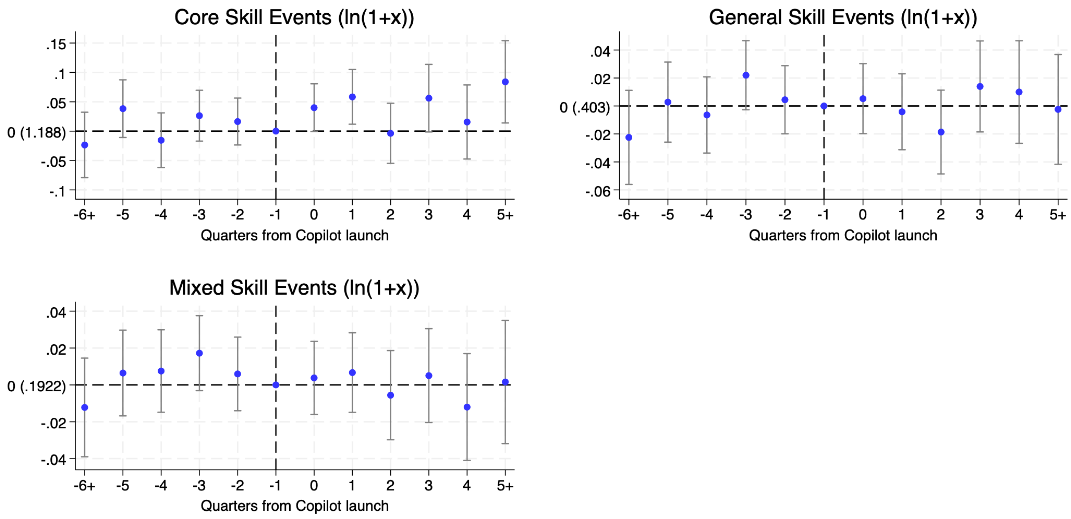

Figure 7. Quarterly Non-Firm-Related Github Activity After Copilot Launch

This figure plots coefficients of the event study specification described in equation 3 with 95% confidence intervals. The outcome variables are natural logarithms of one plus the number of quarterly public activities in non-firm-related repositories. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. Standard errors are clustered at developer level.

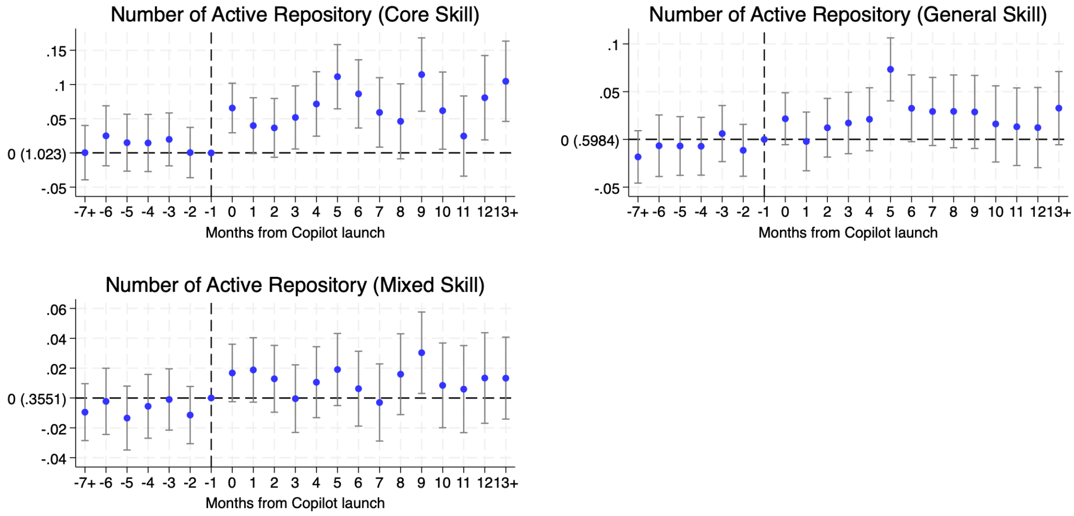

Figure 8. Monthly Number of Active Firm-Owned Repository After Copilot Launch

This figure plots coefficients of the event study specification described in equation 3 with 95% confidence intervals. The outcome variables are number of firm-owned repositories in which a developer is actively engaged per month. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. Standard errors are clustered at developer level.

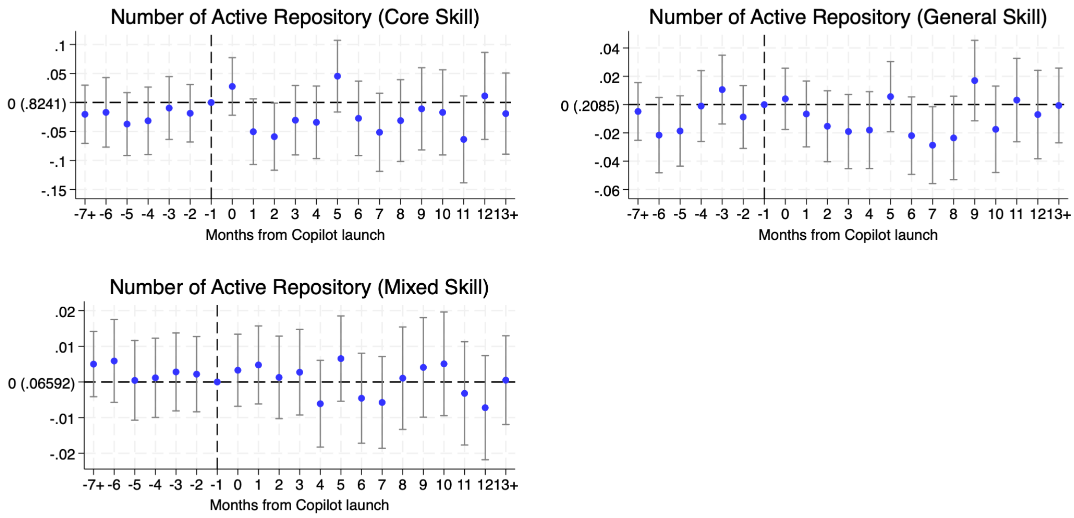

Figure 9. Monthly Number of Active Non-Firm-Related Repository After Copilot Launch

This figure plots coefficients of the event study specification described in equation 3 with 95% confidence intervals. The outcome variables are number of non-firm-related repositories in which a developer is actively engaged per month. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. Standard errors are clustered at developer level.

Table 1. GPT Generated AI Exposure Score of Selected Languages

This table lists the LLM-based Generative AI exposure scores of selected languages, which is later used to calculate developer-level exposure to Generative AI. The score ranges from 0 to 1. See Section B.3 for the prompt used to obtain AI exposure scores for programming languages.

High AI Exposure Languages		Low AI Exposure Languages		Random without AI Exposure
language	score	language	score	language
Python	1.0	BASIC	0.4	BrighterScript
C#	0.9	LiveScript	0.4	CSV
Java	0.9	Visual Basic 6.0	0.4	Cadence
JavaScript	0.9	ASP	0.5	DTrace
Jupyter Notebook	0.9	Cython	0.5	Futhark
TypeScript	0.9	Markdown	0.5	Inno Setup
CSS	0.8	SAS	0.5	Lex
Go	0.8	Stata	0.5	Oxygene
HTML	0.8	TeX	0.5	Self
PHP	0.8	VBA	0.5	TOML

Table 2. User-Month Github Activity Summary Statistics (Jan2021-Jun2022)

This table presents summary statistics of user-month GitHub activity before the official launch of GitHub Copilot, i.e., from January 2021 to June 2022. Panel (a) summarizes key outcome variables used in the regression analysis by gender and seniority. Panel (b) summarizes key outcome variables and developer characteristics by AI exposure level. Gender is inferred based on developer name and LLM-based gender likelihood score. A developer is considered to be male/female when the likelihood score is above 0.5. See B.2 for the methodology. A developer is considered as senior if the tenure of the developer on the GitHub platform, approximated based on the account's create date, is in the fourth quartile. *High AI Exposure* is a dummy that equals one if the developer's AI exposure score is in the fourth quartile. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. Repository ownership can be firm or non-firm. The latter includes repositories owned by organization accounts (org) or individuals (ind). Count variables are winsorized at 95% level.

(a) By Developer Characteristics

	All		Female		Male		Senior		Junior	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Core skill events	29.59	58.56	28.63	54.20	30.32	58.69	32.65	61.64	25.45	53.81
General skill events	8.88	22.62	7.86	19.45	9.52	23.35	10.93	25.16	6.14	18.32
Mixed skill events	5.44	14.42	5.73	14.45	5.85	14.98	6.25	15.53	4.36	12.70
Has core	0.69	0.46	0.69	0.46	0.69	0.46	0.71	0.45	0.65	0.48
Has general	0.48	0.50	0.48	0.50	0.51	0.50	0.54	0.50	0.41	0.49
Has mixed	0.33	0.47	0.36	0.48	0.35	0.48	0.37	0.48	0.29	0.45
AI exposure from push events	0.81	0.13	0.82	0.13	0.81	0.13	0.82	0.13	0.81	0.14
Active repositories (total)	3.79	5.55	3.18	4.62	4.00	5.67	4.47	6.08	2.86	4.58
Active repositories (core events)	2.57	3.75	2.33	3.33	2.69	3.82	2.92	4.03	2.09	3.28
Active repositories (general events)	1.19	2.00	1.05	1.73	1.29	2.09	1.46	2.24	0.83	1.55
Active repositories (mixed events)	0.57	1.03	0.59	0.99	0.61	1.07	0.66	1.12	0.45	0.88
Active repositories (total) (firm)	1.60	2.17	1.57	2.05	1.62	2.17	1.69	2.24	1.48	2.05
Active repositories (total) (org)	0.71	1.86	0.46	1.42	0.78	1.93	0.94	2.13	0.39	1.35
Active repositories (total) (ind)	1.32	2.48	1.03	2.04	1.46	2.58	1.67	2.77	0.86	1.93

(b) By Generative AI Exposure

	All		High AI Exposure		Low AI Exposure	
	Mean	SD	Mean	SD	Mean	SD
Female (inferred)	0.13	0.34	0.13	0.34	0.13	0.34
Senior developers (GHAPI)	0.57	0.49	0.55	0.50	0.58	0.49
Core skill events	29.59	58.56	22.38	50.48	31.79	60.65
General skill events	8.88	22.62	5.99	17.57	9.77	23.88
Mixed skill events	5.44	14.42	4.18	12.72	5.83	14.89
Has core	0.69	0.46	0.63	0.48	0.70	0.46
Has general	0.48	0.50	0.42	0.49	0.50	0.50
Has mixed	0.33	0.47	0.27	0.45	0.35	0.48
Active repositories (total) (firm)	1.60	2.17	1.29	1.82	1.69	2.25
Active repositories (total) (org)	0.71	1.86	0.57	1.61	0.75	1.93
Active repositories (total) (ind)	1.32	2.48	1.14	2.27	1.38	2.54

Table 3. Github Activity After Copilot Launch (Monthly)

This table reports regression results of equation 1 and equation 2. The outcome variables are dummy variables that equals one if a developer has any public activity in firm-owned repositories (Panel (a)) or non-firm-related repositories (Panel (b)) in a given month. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. *Post* is a dummy that equals one if the time period is after July 2022. *AI Exposure* or *AI* are dummy variables that equals one if the developer's AI exposure score is in the fourth quartile. *Female* is a dummy that equals one if the developer is inferred to be female based on the self-reported name. *Senior* is a dummy that equals one if the developer's tenure is in the fourth quartile. Standard errors are clustered at developer level. Significance: *, p < 0.1; **, p < 0.05; ***, p < 0.01.

(a) Activity of Firm-Owned Projects

	Has Core Event			Has General Event			Has Mixed Event		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×AI Exposure	0.0122***	0.0152***	0.0075	0.0033	0.0057	0.0008	0.0099**	0.0110**	0.0041
	(2.72)	(2.92)	(0.90)	(0.75)	(1.12)	(0.11)	(2.50)	(2.37)	(0.55)
Post×Female		0.0157**	0.0125*		0.0174**	0.0144**		0.0116*	0.0092
		(2.24)	(1.75)		(2.54)	(2.08)		(1.70)	(1.33)
Post×AI×Female		-0.0287*	-0.0259*		-0.0156	-0.0136		-0.0111	-0.0087
		(-1.96)	(-1.75)		(-1.08)	(-0.94)		(-0.79)	(-0.62)
Post×Senior			-0.0142***			-0.0130***			-0.0106**
			(-3.01)			(-2.89)			(-2.42)
Post×AI×Senior			0.0115			0.0071			0.0103
			(1.14)			(0.72)			(1.14)
N	663,868	563,877	563,803	663,868	563,877	563,803	663,868	563,877	563,803
Adj. R2	0.4033	0.4040	0.4040	0.4977	0.4911	0.4911	0.5231	0.5187	0.5187
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

(b) Activity of Non-Firm-Related Projects

	Has Core Event			Has General Event			Has Mixed Event		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×AI Exposure	0.0080**	0.0113**	0.0083	-0.0024	-0.0020	0.0014	-0.0021	-0.0022	-0.0029
	(1.98)	(2.37)	(1.12)	(-0.86)	(-0.59)	(0.30)	(-1.01)	(-0.88)	(-0.86)
Post×Female		-0.0060	-0.0084		0.0037	0.0028		0.0017	0.0010
		(-0.92)	(-1.28)		(0.82)	(0.62)		(0.48)	(0.27)
Post×AI×Female		-0.0287**	-0.0273**		0.0064	0.0057		-0.0004	0.0000
		(-2.08)	(-1.96)		(0.75)	(0.66)		(-0.06)	(0.00)
Post×Senior			-0.0106**			-0.0038			-0.0031
			(-2.45)			(-1.19)			(-1.29)
Post×AI×Senior			0.0042			-0.0055			0.0010
			(0.46)			(-0.89)			(0.22)
N	663,868	563,877	563,803	663,868	563,877	563,803	663,868	563,877	563,803
Adj. R2	0.4943	0.4844	0.4844	0.4372	0.4327	0.4327	0.4088	0.4085	0.4085
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 4. Github Activity After Copilot Launch (Quarterly)

This table reports regression results of equation 1 and equation 2. The outcome variables are natural logarithms of one plus the number of quarterly public activities in firm-owned repositories (Panel (a)) or non-firm-related repositories (Panel (b)). Activities are grouped based on their related skill requirements. See Section B.1 for classification details. *Post* is a dummy that equals one if the time period is after the third quarter of 2022. *AI Exposure* or *AI* are dummy variables that equals one if the developer's AI exposure score is in the fourth quartile. *Female* is a dummy that equals one if the developer is inferred to be female based on the self-reported name. *Senior* is a dummy that equals one if the developer's tenure is in the fourth quartile. Standard errors are clustered at developer level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(a) Activity of Firm-Owned Related Projects

	Ln (1 + Core Event)			Ln (1 + General Event)			Ln (1 + Mixed Event)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×AI Exposure	0.0589***	0.0725***	0.0158	0.0346**	0.0484***	0.0141	0.0413***	0.0531***	0.0104
	(2.99)	(3.15)	(0.43)	(2.23)	(2.66)	(0.50)	(2.73)	(2.99)	(0.37)
Post×Female		0.0486	0.0331		0.0448*	0.0285		0.0430	0.0321
		(1.50)	(1.01)		(1.74)	(1.10)		(1.63)	(1.21)
Post×AI×Female		-0.1031	-0.0844		-0.0578	-0.0448		-0.0628	-0.0488
		(-1.53)	(-1.25)		(-1.09)	(-0.84)		(-1.17)	(-0.91)
Post×Senior			-0.0674***			-0.0706***			-0.0472***
			(-3.12)			(-4.24)			(-2.78)
Post×AI×Senior			0.0863*			0.0508			0.0652*
			(1.93)			(1.46)			(1.88)
N	229,946	195,049	195,024	229,946	195,049	195,024	229,946	195,049	195,024
Adj. R2	0.6861	0.6835	0.6836	0.7528	0.7500	0.7501	0.7149	0.7125	0.7125
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

(b) Activity of Non-Firm-Related Projects

	Ln (1 + Core Event)			Ln (1 + General Event)			Ln (1 + Mixed Event)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×AI Exposure	0.0319*	0.0457**	0.0350	-0.0003	-0.0000	0.0167	-0.0038	-0.0044	-0.0018
	(1.85)	(2.23)	(1.11)	(-0.03)	(-0.00)	(1.04)	(-0.49)	(-0.47)	(-0.14)
Post×Female		-0.0369	-0.0447		0.0279*	0.0208		0.0038	-0.0001
		(-1.32)	(-1.58)		(1.86)	(1.37)		(0.29)	(-0.01)
Post×AI×Female		-0.1273**	-0.1227**		-0.0012	-0.0041		0.0025	0.0027
		(-2.25)	(-2.14)		(-0.04)	(-0.15)		(0.11)	(0.11)
Post×Senior			-0.0338*			-0.0311***			-0.0168*
			(-1.81)			(-2.89)			(-1.89)
Post×AI×Senior			0.0153			-0.0276			-0.0048
			(0.39)			(-1.32)			(-0.28)
N	229,946	195,049	195,024	229,946	195,049	195,024	229,946	195,049	195,024
Adj. R2	0.7010	0.6942	0.6942	0.6891	0.6866	0.6866	0.5967	0.5975	0.5975
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 5. Number of Active Projects After Copilot Launch (Monthly)

This table reports regression results of equation 1 and equation 2. The outcome variables are number of firm-owned repositories (Panel (a)) or non-firm-related repositories (Panel (b)) in which a developer is actively engaged in a given month. Activities are grouped based on their related skill requirements. See Section B.1 for classification details. *Post* is a dummy that equals one if the time period is after July 2022. *AI Exposure* or *AI* are dummy variables that equals one if the developer's AI exposure score is in the fourth quartile. *Female* is a dummy that equals one if the developer is inferred to be female based on the self-reported name. *Senior* is a dummy that equals one if the developer's tenure is in the fourth quartile. Standard errors are clustered at developer level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(a) Activity of Firm-Owned Projects

	Repos With Core Event			Repos With General Event			Repos With Mixed Event		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×AI Exposure	0.0665***	0.0643***	0.0140	0.0382***	0.0487***	0.0063	0.0204***	0.0228***	0.0051
	(4.20)	(3.64)	(0.45)	(3.63)	(3.99)	(0.32)	(2.99)	(2.88)	(0.38)
Post×Female		0.0242	0.0027		0.0292	0.0098		0.0058	-0.0006
		(0.86)	(0.09)		(1.51)	(0.50)		(0.45)	(-0.05)
Post×AI×Female		-0.0307	-0.0122		-0.0241	-0.0083		-0.0027	0.0035
		(-0.48)	(-0.19)		(-0.61)	(-0.21)		(-0.11)	(0.14)
Post×Senior			-0.0937***			-0.0837***			-0.0277***
			(-5.08)			(-6.91)			(-3.44)
Post×AI×Senior			0.0751**			0.0630***			0.0267*
			(2.05)			(2.60)			(1.68)
N	663,868	563,877	563,803	663,868	563,877	563,803	663,868	563,877	563,803
Adj. R2	0.6525	0.6420	0.6422	0.6618	0.6570	0.6572	0.5919	0.5904	0.5904
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

(b) Activity of Non-Firm-Related Projects

	Repos With Core Event			Repos With General Event			Repos With Mixed Event		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×AI Exposure	-0.0018	0.0103	-0.0066	-0.0030	-0.0033	0.0069	-0.0035	-0.0043	-0.0039
	(-0.10)	(0.46)	(-0.22)	(-0.42)	(-0.38)	(0.72)	(-1.18)	(-1.18)	(-0.85)
Post×Female		-0.0056	-0.0206		0.0158	0.0083		-0.0010	-0.0016
		(-0.18)	(-0.67)		(1.43)	(0.75)		(-0.19)	(-0.32)
Post×AI×Female		-0.0939	-0.0858		0.0138	0.0129		0.0028	0.0029
		(-1.64)	(-1.49)		(0.73)	(0.68)		(0.31)	(0.31)
Post×Senior			-0.0650***			-0.0324***			-0.0027
			(-3.14)			(-4.10)			(-0.78)
Post×AI×Senior			0.0237			-0.0174			-0.0006
			(0.59)			(-1.21)			(-0.09)
N	663,868	563,877	563,803	663,868	563,877	563,803	663,868	563,877	563,803
Adj. R2	0.6376	0.6293	0.6293	0.6059	0.6020	0.6021	0.4828	0.4844	0.4844
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 6. Firm-Owned Open-Source Innovation Activity After Copilot Launch

This table reports regression results of equation 1 and equation 2. In Columns (1)-(3), the outcome variables are a dummy that equals one if a developer initiated at least one new firm-owned repository (project) in a given quarter. In Column (4)-(6), the outcome variables are number of newly initiated projects of a developer in a given quarter. *Post* is a dummy that equals one if the time period is after the third quarter of 2022. *AI Exposure* or *AI* are dummy variables that equals one if the developer's AI exposure score is in the fourth quartile. *Female* is a dummy that equals one if the developer is inferred to be female based on the self-reported name. *Senior* is a dummy that equals one if the developer's tenure is in the fourth quartile. Standard errors are clustered at developer level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	Initiated Project			# of Initiated Project		
	(1)	(2)	(3)	(4)	(5)	(6)
Post×AI Exposure	-0.0013	-0.0016	-0.0060**	-0.0011	-0.0016	-0.0002
	(-0.90)	(-1.04)	(-2.35)	(-0.28)	(-0.61)	(-0.04)
Post×Female		0.0010	0.0008		-0.0035	-0.0022
		(0.54)	(0.42)		(-0.50)	(-0.32)
Post×AI×Female		-0.0039	-0.0027		0.0029	0.0022
		(-0.76)	(-0.52)		(0.17)	(0.13)
Post×Senior			-0.0009			0.0056
			(-0.69)			(1.26)
Post×AI×Senior			0.0069**			-0.0019
			(2.20)			(-0.27)
N	229,946	195,049	195,024	229,946	195,049	195,024
Adj. R2	0.0889	0.0594	0.0594	0.3652	0.1430	0.1430
Individual FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y

Table 7. Value of Firm's Open-Source Innovation After Copilot Launch

This table reports regression results of equation 4. In Panel (a), the outcome variables are the natural logarithm of one plus the number of stars received as of February 2024. In Panel (b), the outcome variables are the natural logarithm of repository value estimated based on stock-market reaction within three days of the project's public release. See Emery et al. (2024) for methodology details. *Post* is a dummy that equals one if the time period is after July 2022. *Innovator AI Expo* or *AI* are dummy variables that equals one if the AI exposure score of at least one member of the innovator team is in the fourth quartile. *Repo AI Expo* is a dummy that equals one of the repository's AI exposure score, based on repository's language composition, is in the fourth quartile. *Female* is a dummy that equals one if the developer is inferred to be female based on the self-reported name. *Senior* is a dummy that equals one if the developer's tenure is in the fourth quartile. Control variables include the natural logarithms of one plus cumulative number of firm-owned repository, market capitalization, volatility, number of employees, and one plus value of patent portfolio. I also control for return on assets, R&D expenditure as a share of assets, whether R&D expenditure is missing, and innovator team size. All firm-year control variables are one-year lagged and winsorized at 1% and 99% levels. See Table IA1 for variable descriptions and sources. Standard errors are clustered at industry level (defined based on 3-digit SIC code). Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(a) Dependent Variable: Ln(1+Stars)

	(1)	(2)	(3)	(4)	(5)
Innovator AI Expo	0.1102		-0.0616	0.1888	-0.4544*
	(0.75)		(-0.54)	(1.60)	(-1.83)
Post×Innovator AI Expo	0.5600*		0.6655**	0.4353	0.6444**
	(2.01)		(2.81)	(1.55)	(2.47)
Repo AI Expo		0.5272***	0.5427***	0.3589***	0.5477***
		(3.24)	(4.04)	(3.16)	(4.25)
Post×Repo AI Expo		0.0604	0.0173	0.1536	-0.0124
		(0.29)	(0.10)	(1.02)	(-0.07)
Female				0.2068	
				(1.03)	
Post×Female				-0.4046**	
				(-2.54)	
Innovator AI×Female				-1.3647***	
				(-7.11)	
Post×AI×Female				1.7139***	
				(4.95)	
Senior					0.5510***
					(6.01)
Post×Senior					-0.0344
					(-0.20)
Innovator AI×Senior					0.6555*
					(1.95)
Post×AI×Senior					0.0011
					(0.01)
N	2,077	2,077	2,077	1,714	2,075
Adj. R2	0.1967	0.2114	0.2167	0.2159	0.2447
Industry FE	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y

(b) Dependent Variable: Ln(Repo Value)

	(1)	(2)	(3)	(4)	(5)
Innovator AI Expo	0.1453***		0.1606***	0.2040***	0.0957***
	(5.75)		(8.54)	(9.12)	(7.24)
Post×Innovator AI Expo	0.0817*		0.0619*	-0.0208	0.1876**
	(2.05)		(1.93)	(-0.64)	(2.28)
Repo AI Expo		-0.0104	-0.0491*	-0.1021***	-0.0473*
		(-0.36)	(-1.87)	(-3.10)	(-2.01)
Post×Repo AI Expo		0.0711	0.0990**	0.1171*	0.0921**
		(1.42)	(2.17)	(1.96)	(2.39)
Female				0.0547**	
				(2.78)	
Post×Female				-0.1073	
				(-0.91)	
Innovator AI×Female				-0.2116***	
				(-5.42)	
Post×AI×Female				0.6377***	
				(4.42)	
Senior					0.1130***
					(3.24)
Post×Senior					0.0302
					(0.33)
Innovator AI×Senior					0.1073***
					(3.48)
Post×AI×Senior					-0.2638*
					(-1.96)
N	2,077	2,077	2,077	1,714	2,075
Adj. R2	0.8193	0.8176	0.8193	0.8170	0.8203
Industry FE	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y

B Internet Appendix

B.1 Skill-Based GitHub Activity Classification

B.1.1 Prompt Used With GPT-4 Model in April 2024

Suppose you are a programmer who is active on Github platform. Define what may be job-specific core skills and what may be transferable general skills.

For the following Github events, classify them into three categories: job-specific core skills, transferable general skills, mixture of core and general skills, and others. Each event should be uniquely assigned to only one category that is the most relevant.

List of GitHub events: CommitCommentEvent, CreateEvent, DeleteEvent, ForkEvent, GollumEvent, IssueCommentEvent, IssuesEvent, MemberEvent, PublicEvent, PullRequestEvent, PullRequestReviewEvent, PullRequestReviewCommentEvent, PullRequestReviewThreadEvent, PushEvent, ReleaseEvent, SponsorshipEvent, WatchEvent

B.1.2 Classification Details

Job-specific core skills

- PushEvent: Relates to pushing code to a repository, a basic GitHub operation.
- PullRequestEvent: Central to managing code contributions and integrations.
- PullRequestReviewEvent: Linked to the code review process within pull requests.

General skills

- IssueCommentEvent: Involves communication and discussion over issues.
- IssuesEvent: Engages problem-solving, managing bug reports, and feature requests

Mixture of core and general skills

- CommitCommentEvent: Tied to code reviews, requiring technical insights as well as communication skills.
- PullRequestReviewCommentEvent: Specific to commenting on code reviews in pull requests, requiring technical understanding and collaborative feedback.
- PullRequestReviewThreadEvent: Involves discussions around specific parts of a pull request, blending code-specific knowledge with teamwork and communication.

Nonskill related

- ForkEvent: Represents a user's engagement with and branching off from an existing repository to potentially contribute or alter separately.
- GollumEvent: Pertains to the management of Wiki pages on a GitHub repository.
- SponsorshipEvent: Linked to the GitHub Sponsors program, reflecting community support and funding mechanisms.
- WatchEvent: Involves starring a repository, indicating interest or following updates, more about user engagement than a direct skill.

Others

There are other related events I define as core/general in a broader sense. But they are not used in the analysis.

- Broader core activities
  - CreateEvent: Involves creating branches or tags, fundamental to version control.
  - DeleteEvent: Involves deleting branches or tags, another version control aspect.
  - ReleaseEvent: Pertains to the release of new software versions, important in software lifecycle management.
- Broader general activities

- PublicEvent: While more of an administrative function, it also involves decision-making and policy setting regarding project visibility. (Initiate project)
- MemberEvent: Related to teamwork and the management of repository collaborators.

B.2 Name-Based Gender Inference

B.2.1 Parameters for GPT Model Interaction via OpenAI's API

- `model`: gpt-3.5-turbo
- `temperature`: 0
- `system_text`: Process a list of names, extracting identifiable components and infer demographic information. Return the findings in JSON format with fields for original_str, first_name, last_name, company, type (with an inf_type among "user", "organization" and "bot", and score), gender (with an inf_gender either "female" or "male", and score), race (with an inf_race and score), ethnicity (with an inf_ethnicity and score), and country_of_origin (with an inf_origin and score). Put 'NA' for string subfields with no findings, and 0 for scores with no findings. Scores are for the confidence level of the inference and range from 0 to 1 rounded to two decimals. Score closer to 1 means the inference is certain while score closer to 0 means the inference is uncertain. The output is with 'results' as the key.
- `user_text`: ['name1', 'name2', 'name3',...]

B.2.2 Example: Name-Based Inference Response

The JSON response example for a person named Bob Chen is:


```
{
  "results": [
    {
      "original_str": "Bob Chen",
      "first_name": "Bob",
      "last_name": "Chen",
      "company": "NA",
      "type": {
        "inf_type": "user",
        "score": 0.95
      },
      "gender": {
        "inf_gender": "male",
        "score": 0.85
      },
      "race": {
        "inf_race": "Asian",
        "score": 0.80
      },
      "ethnicity": {
        "inf_ethnicity": "NA",
        "score": 0
      },
      "country_of_origin": {
        "inf_origin": "United States",
        "score": 0.75
      }
    }
  ]
}
```

B.3 Prompt for Language AI Exposure Score With GPT-4 in April 2024

For the following programming languages, assign a score between 0 and 1 for its exposure to LLMs such as Github Copilot. Exposure is defined as to what extent are the Generative AI tools helpful for programmers using these languages to complete their daily tasks. If it is not a programming language, return 'NA' for the score. Return your result in JSON format (langauge:score).

Language list: ['language1', 'language2', ...]

Table IA1. Variable Description

This table provides descriptions and sources of key variables used in the empirical analysis section.

Variable	Description	Source
AI Exposure	Dummy that equals one if the AI exposure score of the developer (0-1) is in the fourth quartile	GPT-4 and author's calculation
Core Event	Number of core-skill related events in a given month/quarter	GHArchive
Cumulative Nrepo	Cumulative number of repositories released by a firm prior to month t	GHArchive
Employees	Number of employees in the firm	Compustat
Female	Dummy that equals one if the developer is inferred as female	GitHub API, GPT-3.5
General Event	Number of general-skill related events in a given month/quarter	GHArchive
Has Core Event	Dummy that equals one if a developer has at least one core-skill related event in a given month	GHArchive
Has General Event	Dummy that equals one if a developer has at least one general-skill related event in a given month	GHArchive
Has Mixed Event	Dummy that equals one if a developer has at least one mixed-skill related event in a given month	GHArchive
Initiated Project	Indicator if a developer is among the innovator team of a new project in a given quarter	GHArchive
Initiator N	Number of developers in the innovator team of a new project	GHArchive
Market Capitalization	Share price times the number of shares outstanding	CRSP
Mixed Event	Number of mixed-skill related events in a given month/quarter	GHArchive
Patent Portfolio Value	The total estimated economic value of the patents owned by the firm using stock market returns around the patent grant date	Kogan, Papanikolaou, Seru and Stoffman (2017)
Post	Dummy that equals one if the time period is or after July 2022 or the third quarter of 2022	
R&D Intensity	R&D expenses divided by lagged total assets	Compustat
R&D Missing	Dummy that equals one if R&D expense is missing	Compustat
Repo AI Exposure	Dummy that equals one if the AI exposure score of the repository (0-1) is in the fourth quartile	GPT-4 and author's calculation
Repo Value	The estimated private value of the repository in 2023 USD estimated by using stock market returns around the release date of the repository	Author's calculation based on Emery et al. (2024)
Repos With Core Event	Number of repositories with core-skill related events in a given month	GHArchive
Repos With General Event	Number of repositories with general-skill related events in a given month	GHArchive
Repos With Mixed Event	Number of repositories with mixed-skill related events in a given month	GHArchive
Return on Assets	Net income divided by lagged total assets	Compustat
Senior	Dummy that equals one if the developer's tenure is in the fourth quartile	GitHub API
Stars	Number of stars received by a repository as of Feburary 2024	GitHub API
Volatility	Standard deviation of daily returns over one month	CRSP