

The Impact of AI on Developer Productivity: Evidence from GitHub Copilot

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Abstract

Generative AI tools hold promise to increase human productivity. This paper presents results from a controlled experiment with GitHub Copilot, an AI pair programmer. Recruited software developers were asked to implement an HTTP server in JavaScript as quickly as possible. The treatment group, with access to the AI pair programmer, completed the task 55.8% faster than the control group. Observed heterogeneous effects show promise for AI pair programmers to help people transition into software development careers.

Introduction

Artificial intelligence (AI) applications hold promise to increase human productivity. A variety of AI models have demonstrated human-level capabilities in fields ranging from natural language understanding to image recognition [Zhang et al., 2022]. As these systems are deployed in the real-world, how do they change labor productivity? While there is a growing literature studying perceptions of AI tools, how people use them, and their implications for security and education [Nguyen and Nadi, 2022, Barke et al., 2022, Finnie-Ansley et al., 2022, Sandoval et al., 2022] there has been little research on productivity impacts of AI-powered tools

in professional contexts, cf. [Mozannar et al., 2022, Vaithilingam et al., 2022, Ziegler et al., 2022]. The potential productivity impacts of AI have major implications for the labor market and firms, including changes in employment, skills, and firm organization [Raj and Seamans, 2018, Agrawal et al., 2019].

This paper studies the productivity effects of AI tools on software development. We present a controlled trial of GitHub Copilot, an AI pair programmer that suggests code and entire functions in real time based on context. GitHub Copilot is powered by OpenAI’s generative AI model, Codex [Chen et al., 2021]. In the trial, programmers were tasked and incentivized to implement an HTTP server in JavaScript as quickly as possible. The treated group had access to GitHub Copilot and watched a brief video explaining how to use the tool. The control group did not have access to GitHub Copilot but was otherwise unconstrained, i.e., they were free to use internet search and Stack Overflow to complete the task.

The performance difference between treated and control groups are statistically and practically significant: the treated group completed the task 55.8% faster (95% confidence interval: 21-89%). Developers with less programming experience, older programmers, and those who program more hours per day benefited the most. These heterogeneous effects point towards promise for AI-pair programmers in support of expanding access to careers in software development.

The paper proceeds as follows. We first describe the design of the controlled trial and provide summary statistics. We then present the results. We conclude by a discussion on implications of the study for productivity research on AI-powered tools, its limitations, and future research directions on the broader economic impacts of AI-driven productivity.

Study Design

We conducted a controlled experiment to measure the productivity impact of using GitHub Copilot in programming tasks. The experiment began on May 15, 2022 and ended on June 20, 2022, right before GitHub Copilot became generally available. We recruited 95 professional programmers through Upwork, a freelancing platform. Participation in the experiment was advertised on Upwork as a job posting, looking to recruit freelancer developers. Figures 1 and 2 show (respectively) the job posting and the contract that was sent to participants to sign, in accordance with Upwork’s policies. Once participants signed the contract, they were randomly split into control and treatment groups.

Figure 3 shows the instructions sent to each group through email. The treated group was instructed to watch a 1-minute video introducing them to GitHub Copilot. In addition to the instructions, they also received an automated email with installation instructions for GitHub Copilot once granted access to the tool. We verify from telemetry after the experiment that all participants from the treated group have configured GitHub Copilot and accepted recommendations other than five who did not finish the sign up and thus started the experiment without the GitHub Copilot. Both treated and control groups were instructed to complete an entry survey to provide demographic information such as age, gender, location, and educational background. Before we began recruitment, we received approval for the study from the Microsoft Research Ethics Review Board.

Participants were instructed to write an HTTP server in JavaScript—the treatment group would use GitHub Copilot to complete the task, while the control group would not. Besides the use of GitHub Copilot in the treated group, participants were unconstrained in their software development—they could use any sources of information as they normally do, such as internet search and Stack Overflow.

We calculated two metrics as a measure of performance for each group: **task success** and **task completion time**. Task success was measured as the percentage of participants in a group that adequately completed the task. Task completion time was measured as the time from start to end of the task. Using a standardized task provides us with precise measures of performance as it is difficult to measure productivity of software developers.

To administer the task, we used GitHub Classroom, a platform for teachers to issue and grade coding assignments. In this way, we accurately measured the timing and completion for each participant. The instructions gave participants a link to a particular GitHub Classroom instance with a single assignment referencing a template repository. When joining the assignment, participants received a personal copy of the template repository, with the task description (shown in Figure 4) and a skeleton codebase for participants to build upon. The creation date and time of that personal copy created a timestamp. Each participant’s repository was private to them and visible to the researchers conducting the experiment—but not to other participants.

We included a test suite in the repository, comprising twelve checks for submission correctness. If a submission passes, all twelve tests we counted are successfully completed. Participants could see the tests but were unable to alter them.

When participants committed and pushed their changes to GitHub, GitHub Classroom ran the test suite on their submission and reported the number of passing tests. Participants could push as often as they pleased, automatically logging a timestamp each time. The time elapsed between the timestamp of repository creation and the timestamp of the first commit to successfully pass all 12 tests was counted as the participant’s task completion time.

The full history of test suite runs is visible on each repository, enabling researchers to observe partial results for participants that did not fully complete the task. The participants’ final compensation is calculated based on their time to completion and the scale we had previously shared with them (shown in Figure 1).

After participants had completed the task, we sent them the link to an exit survey. We asked the treatment group how helpful they found GitHub Copilot as they worked on the task, as well as asked them to estimate how much faster they completed the task compared to how long this task would have taken them without using GitHub Copilot. We also asked the control group to estimate the size of the speed gain they would *have experienced if they used GitHub Copilot*, after showing them a 1-minute demo video.

Results

A total of 166 offers were sent during the experiment, and 95 were accepted. The 95 developers were randomly assigned into control and treated groups, with 45 in the treated group and 50 in control. Thirty-five developers from both the treated and control groups completed the task and survey. Figure 5 presents the summary statistics of these participants.

Most of the participants are in the age group of 25-34 and come from India and Pakistan. This group of participants is also characterized by relatively lower income (median yearly income between \$10,000-\$19,000) compared to US standards but high education level (the majority have a 4-year degree and above). The group has an average coding experience of 6 years and, on average, reported spending 9 hours on coding in a working day.

Figure 6 plots the distribution between time to completion between treated and control groups. Conditioning on completing the task, the average completion time from the treated group is 71.17 minutes and 160.89 minutes for the control group. This represents a 55.8% reduction in completion time. The p-value for the t-test is 0.0017, and a 95% confidence interval for the improvement is between [21%, 89%]. There are four outliers with time to completion above 300 min. All outliers are in the control group, however our results remain robust if these outliers are dropped. This result suggests that Copilot increases average productivity significantly in our experiment population. We also find that the treated group’s success rate is 7

Table 1: Heterogeneous Treatment Effects

	Estimates	SE	t-Stat	p-Value
(Intercept)	78.01	67.84	1.15	0.2552
Programming experience (years)	8.23	4.36	1.90	0.0629
Hours of programming per day	-11.70	4.74	-2.47	0.0168
Age: 25-44	-74.55	33.52	-2.22	0.0303
Unemployed	-35.98	36.33	-0.99	0.3263
Income less than \$20,000	0.64	27.47	0.02	0.9814
No college	-36.57	32.89	-1.11	0.2711
Language Preference: Java	-11.77	33.16	-0.35	0.7240
Language Preference: Python	22.90	42.19	0.54	0.5895

Note: This table presents the heterogeneous treatment effects. The results suggest developer with less programming experience are more likely to benefit from Copilot, similarly for developers with more daily programming hours and in the age group above 25.

percentage points higher than the control group, but the estimate is not statistically significant, with a 95% confidence interval of [-0.11, 0.25].

We then investigate whether this effect is heterogeneous across different dimensions including experience, employment status, income, education and software language preference. We assume the treatment effect is a linear function of the covariates of interest. We apply Horvitz-Thomson transformation in [Athey and Imbens, 2015] (see also [Banerjee and Duflo, 2003] and [Carneiro et al., 2011])) and then regress the transformed outcome of interest on observables. The estimates in Table 1 report coefficients from this regression. The results show that less experienced developers (years of professional coding), developers with heavy coding load (hours of coding per day), and older developers (developers aged between 25 and 44) benefit more from Copilot.

We conducted an exit survey with two questions to learn about the experience of subjects. First, we asked them to estimate how much productivity gain or loss (in percentage term) Copilot provided to them for completing the task. While the control group was not exposed to Copi-

lot during the task, they were given the tutorial video before answering this question so that they are aware of the features of Copilot. Figure 7 presents the distribution of the self-reported productivity gain estimates from the control and treated groups. On average, participants in both treated and control groups estimated a 35% increase in productivity, which is an underestimation compared with the 55.8% increase in their revealed productivity.

In the second question, participants were asked the highest monthly price at which they would be interested in getting notified about the release of GitHub Copilot. The intention is to learn about developers' willingness to pay for Copilot as the answer to this question provides an upper bound for the developers' willingness to pay. Figure 8 presents the distribution of the irrelevant price separated for the control and treated groups. The average irrelevant price for the treated group is \$27.25, and the average irrelevant price for the control group is \$16.91, both per month. The difference is statistically significant at the 95% level. This result provides indirect evidence that treated group benefited from Copilot during their task as their willingness to pay is significantly higher than the control group.

Discussion

This paper presents evidence on the productivity effects of generative AI tools in software development. To the best of our knowledge, it is the first controlled experiment to measure the productivity of AI tools in professional software development. Our results suggest that Copilot has statistically and practically significant impact on productivity: the treated group that has access to GitHub Copilot was able to complete the task 55.8% faster than the control group.

Further investigations into the productivity impacts of AI-powered tools in software development are warranted. This study examines a standardized programming task in an experiment to obtain a precise measure of productivity, instead of a task where developers collaborate on large projects in professional proprietary and/or open-source settings. Productivity benefits may

vary across specific tasks and programming languages, so more research is needed to understand how our results generalize to other tasks. Finally, this study does not examine the effects of AI on code quality. AI assistance can increase code quality if it suggests code better than the programmer writes, or it can reduce quality if the programmer pays less attention to code. The code quality can have performance and security considerations that can change the real-world impact of AI.

The heterogeneous effects identified in this study warrant close attention. Our results suggest that less experienced programmers benefit more from Copilot. If this result persists in further studies, the productivity benefits for novice programmers and programmers of older age point to important possibilities for skill initiatives that support job transitions into software development.

The economic impacts of these models also warrant further research [Manning et al., 2022], with particular attention on their implications for labor market. In 2021, over 4.6 million people in the United States worked in computer and mathematical occupations,¹ a Bureau of Labor Statistics category that includes computer programmers, data scientists, and statisticians. These workers earned \$464.8 billion or roughly 2% of US GDP. If the results of this study were to be extrapolated to the population level, a 55.8% increase in productivity would imply a significant amount of cost savings in the economy and have a notable impact on GDP growth. It is, as of yet, unclear how such gains would be distributed and how job tasks would change to incorporate AI-powered developer tools. It is important to consider such impacts and to begin research on these implications at the outset [Klinova and Korinek, 2021].

¹<https://www.bls.gov/oes/current/oes150000.htm>

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Needs to hire 50 Freelancers

Background:

We are looking for experienced JavaScript engineers to participate in a study on coding efficiency.

Tasks Include:

- onboarding an AI driven productivity tool called Copilot
<https://copilot.github.com/>
- completing a routine engineering task similar to writing a simple HTTP server with or without the AI help
- completing a survey questionnaire about your user experience and demographic information

Candidates Will Need to Have:

- experience developing in JavaScript
- a GitHub account (you can create a new one if you don't have one already)
- Microsoft VisualStudio Code installed
<https://code.visualstudio.com/>

Timeline:

- the max time expected is around 1 hour
- the goal is to complete the task as quickly as possible

Budget:

- the compensation will be between \$20 and \$160, depending on the speed of completing the task
- faster results will earn higher compensation via bonus payment
- ** Note: compensation is based on successfully completing the task and your code compiling

Payment Scale:

- completed within 30 min = \$160
- completed in 31-60 \$120
- completed in 61-90 \$80
- completed in 91-120 \$50
- completed in 121-150 \$30
- completed in 150+ minutes \$20

- ** NOTE: the contract will be for the lowest amount and a bonus will be paid for faster performance
- Candidates who do not complete the task will be paid less

Project Scope:

1. An Upwork contract will be created, you may not begin until the contract is active
2. A survey link will be provided to collect basic information including your GitHub username
3. You will be sent an email with instructions on accessing the GitHub code repo and the coding task to be done, you may also receive instructions for enabling CoPilot
4. You will complete the task as quickly as possible and submit your code
5. You will be asked to complete an exit survey
6. Based on the time taken to complete the task, your payment will be issued according to the payment scale above

Figure 1: Upwork job posting

Note: Job posting on Upwork starting May 25th 2022. The posting includes the task description, skill requirements and budget information.

upwork

Search

Hiring

Jobs

Talent

Reports

Messages

100%

?

100%

100%

MSFT264 - GitHub CoPilot User Study (A)

Add Milestones

Give Bonus

End Contract

Milestones & Payments

Messages & Files

Terms & Settings

Feedback

...

Contract info

Start Date

June 15, 2022

End Date

June 19, 2022

View history of contract changes

Purchase Order

US-006159

Talent Cloud

Microsoft UTC: Github - CoPilot

Your Microsoft Alias

ekali

Ensuring Accessibility

Yes

Will the Freelancer have access, view or process Personal Data?

No

Will the work be performed in Australia?

No

On Behalf Of (email)

ikalism@github.com

Enterprise Service Fees

Yes

Will the Freelancer have access, view or process Microsoft Confidential Data classified as Highly Confidential (HB) or Confidential (MB) data?

No

IO Number

N/A

Hired By

Rowena Castro

Contact Person

Rowena Castro

Contract ID

30684638

Description of Work

Freelancer will complete a JavaScript development task as quickly as possible, we estimate the task should not take more than 1 hour. Once the task is completed and the code has been submitted you will need to take an exit survey.

NOTE: You may not begin until the Upwork contract is active

1. Complete the survey linked below which will collect basic information including your GitHub username https://microsoft.qualtrics.com/jfe/form/SV_5ng3N1FEWY0IFqu
2. Register for the CoPilot technical preview at the link below <https://github.com/features/copilot/signup>
3. You will be sent an email (from copilot-research@github.com) with instructions on accessing the GitHub code repo and the coding task to be done. **you will also receive a tutorial and instructions on how to enable Copilot

NOTE: the timer will begin once you click a link we will provide to join a GitHub classroom, and will complete when you submit your code via push to GitHub. The "total time" will be the number of minutes between joining the classroom and pushing your code.

- Your code will need to compile and pass validation or it will be rejected and the timer will continue

4. Once your code has been submitted, you must complete the exit survey linked below https://microsoft.qualtrics.com/jfe/form/SV_0pwtzC0mMy8Uv5IO
5. Based on the time taken to complete the task (number of minutes between joining the GitHub classroom and pushing your code), your payment will be issued

View original job posting

View original proposals

Microsoft: Upwork Talent Group Upwork Talent Group Contract Terms

To provide services as an independent contractor for this project, you will need to enter into a contract with Upwork Talent Group ("UTG"). The independent contractor must agree to the terms of the contract. [View more](#)

Document	Uploaded	Uploaded By
UTG_IndependentContractorAgreement_Microsoft_Oct2017.pdf	Nov 3, 2017	Upwork Administrator

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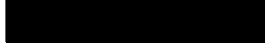
Mobile app

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Figure 2: Upwork contract

Note: The contract sent to participants through Upwork. Upon accepting the contract, participants were randomized into control and treatment groups and given instructions for the task.

Welcome to the GitHub Copilot experiment. Read on for instructions!



Reply Reply All Forward Mon 6/20/2022 1:42 PM

Hi there!

Thank you for participating in our study! The task you will perform will be timed so preparation is key. In this email you will find instructions and guidelines. **Make sure you read everything before you start!**

Before you start your task, do these two things:

- By now you should have received access to GitHub Copilot. Please find installation instructions [here](#) and watch [this video](#) to get acquainted with Copilot. This is not counted towards the experiment time.

Before you start your task, read this overview of what will happen for the rest of the study:

- We will give you a link to join a GitHub Classroom
- **This will start the timer** → When you join, it will create a private-to-you repo for the experiment. You can see the test suite runs at <https://github.com/CopilotResearch/copilot-timed-experiment-YOURGITHUBUSERNAME/actions> to know if you've passed.
- The README.md at the root of the repo will contain basic instructions
- index.js will contain the task
- At that point you start coding!
- Create as few or as many commits as you like, it doesn't matter
- Push your work up to your repo as often as you like, this does not affect scoring
- Every push to GitHub will run the test suite for you.
- **This will stop the timer** → When your latest push makes the CI test suite pass, the clock stops.

Before you start your task, remember these guidelines:

- The task will be timed, and there's no pause button.
- Do you have a recent NodeJS installation? Your favorite editor warmed up and ready to go? You don't want setup time to be counted, so make sure you have everything you need to do the task in one go
- You can run the test suite locally for convenience but only pushing code up to GitHub will count for the study. The test suite passing on your local machine *DOES NOT COUNT*
- Number of commits has no impact. Solve it in one commit or one hundred! Only thing that matters is making the test suite pass on GitHub.

Ready to start? [Click here to start the timer!](#)

Have fun, and thank you!
The GitHub Copilot team

Welcome to the GitHub Copilot experiment. Read on for instructions!



Reply Reply All Forward Tue 6/14/2022 3:20 PM

Hi there!

Thank you for participating in our study! The task you will perform will be timed so preparation is key. In this email you will find instructions and guidelines. **Make sure you read everything before you start!**

Before you start your task, read this overview of what will happen for the rest of the study:

- We will give you a link to join a GitHub Classroom
- **This will start the timer** → When you join, it will create a private-to-you repo for the experiment. You can see the test suite runs at <https://github.com/CopilotResearch/copilot-timed-experiment-YOURGITHUBUSERNAME/actions> to know if you've passed.
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- Number of commits has no impact. Solve it in one commit or one hundred! Only thing that matters is making the test suite pass on GitHub.

Ready to start? [Click here to start the timer!](#)

Have fun, and thank you!
The GitHub Copilot team

Figure 3: Instruction email to participants

Note: Email instructions sent to participants in the treatment (top) and control (bottom) groups.

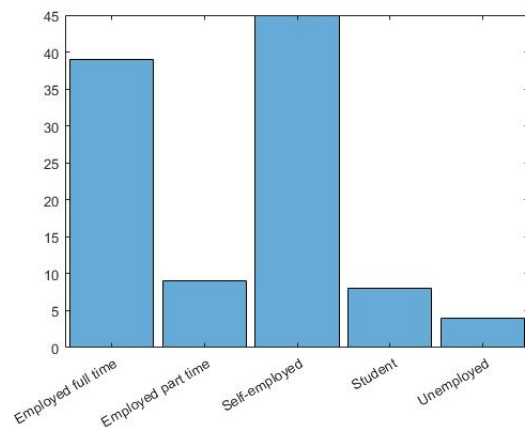
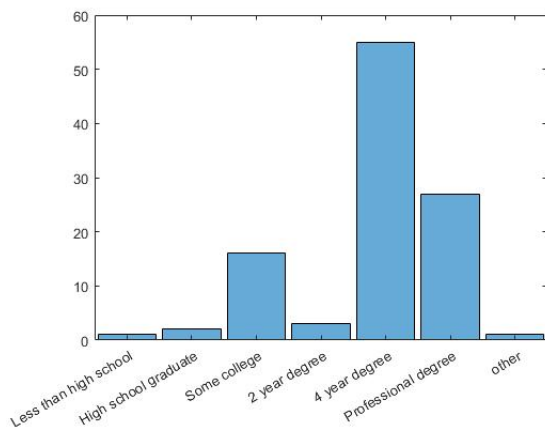
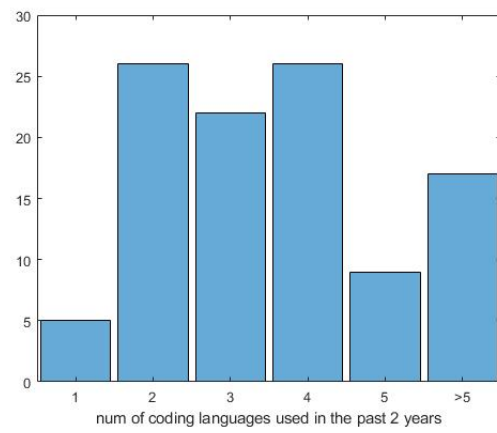
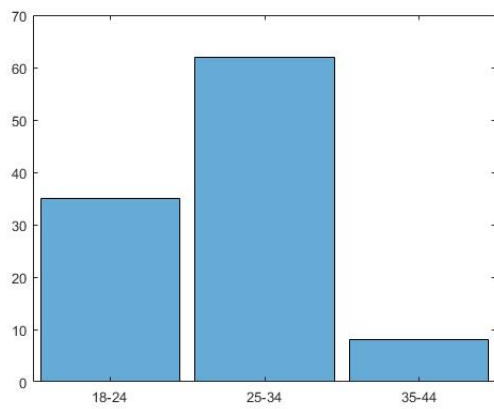
```

1  /*
2
3  Welcome to the GitHub Copilot study!
4  Your mission, should you choose to accept it:
5
6  Write a toy HTTP server engine.
7  You do not need to actually handle network requests.
8  Just parse a request string and return a response string.
9
10 This is a good reference for the structure of HTTP requests and responses:
11 https://developer.mozilla.org/en-US/docs/Web/HTTP/Messages
12
13 You must parse the request headers, but you do not need to validate them.
14 You must return a valid HTTP response with a correct content length.
15 You must serve files from the content/ directory as the root.
16   Meaning, `GET /index.html HTTP/1.1` should return content/index.html.
17   You do not need to handle `GET /`
18
19 Return HTTP status 404 if the file is not found.
20 Return HTTP status 400 if the request is invalid.
21 Return HTTP status 405 for any HTTP method other than GET.
22 Return HTTP status 200 with the contents of the file if the request is valid.
23
24 A proper HTTP response with no body has two trailing newlines:
25   `HTTP/1.1 404 Not Found\n\n`
26
27 A proper HTTP response with a body has a Content-Length header and a body:
28   `HTTP/1.1 200 OK\nContent-Length: ${THELENGTH}\n\n${THEFILEBODY}`
29 */

```

Figure 4: Participants' view of the task description

Note: The task description participants saw in the index.js file in the repository that was automatically created for them by GitHub Classroom.



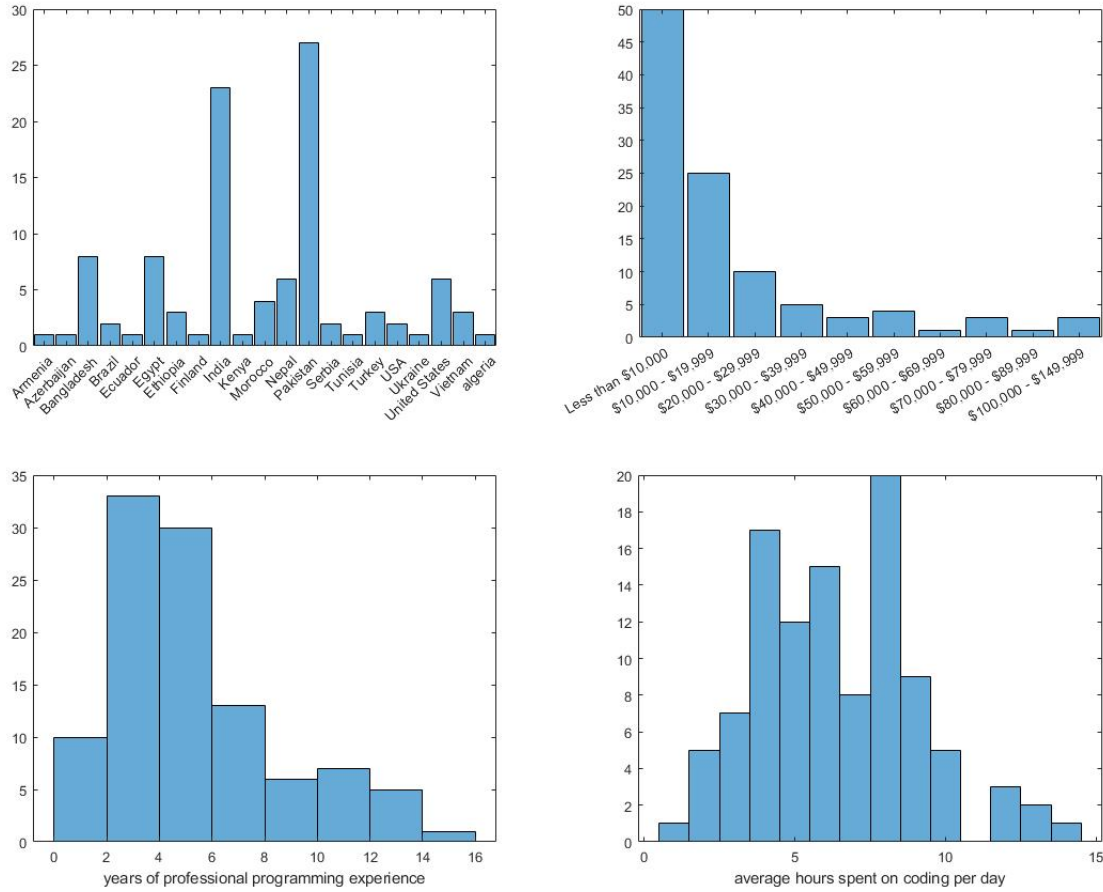


Figure 5: Summary statistics of the experiment participants

From left to right on each row see the following distributions: Participant age; Number of different languages used in the last 2 years; Level of education; Employment status; Geographical location; Yearly income; Programming experience; Time spent coding daily.

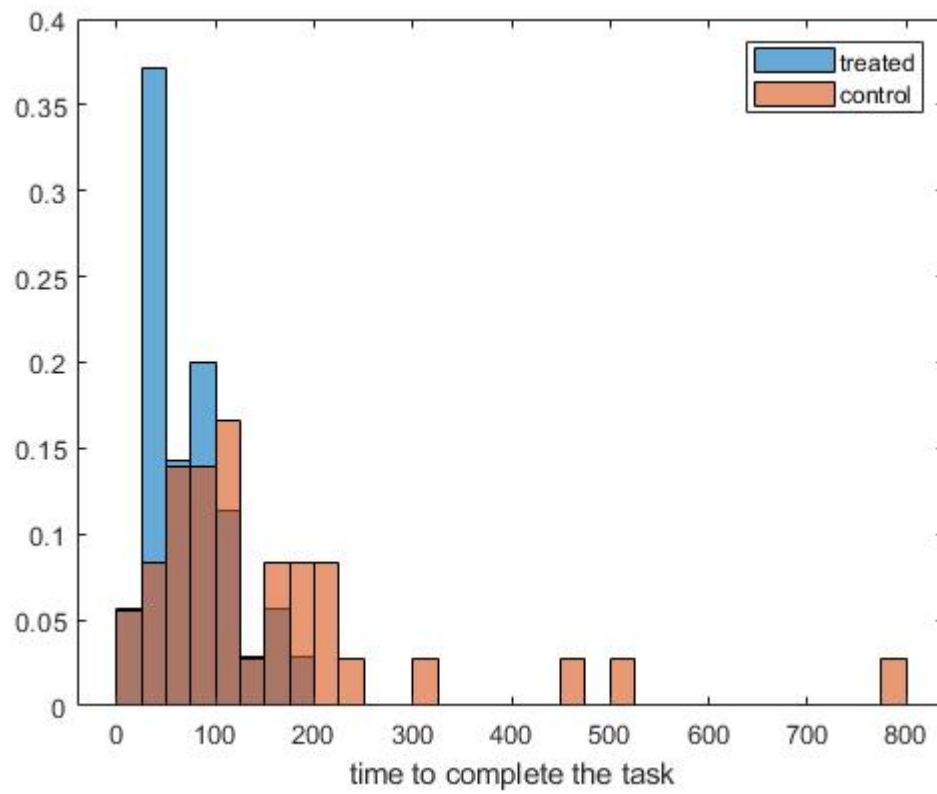


Figure 6: Time to task completion

Note: Distribution of time to task completion between treated (blue) and control (orange) groups

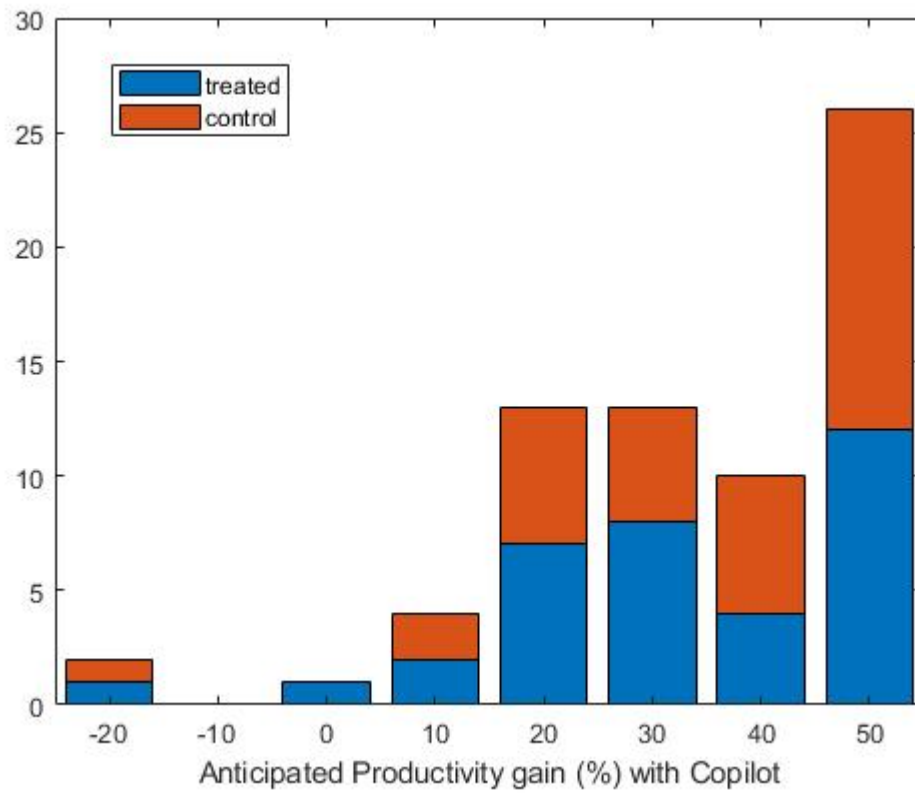


Figure 7: Self-estimated productivity gain

Note: This graph shows the distribution of the estimated productivity improvement when using Copilot. Blue represents the estimation from the treated group and orange represents the estimation from the control group.

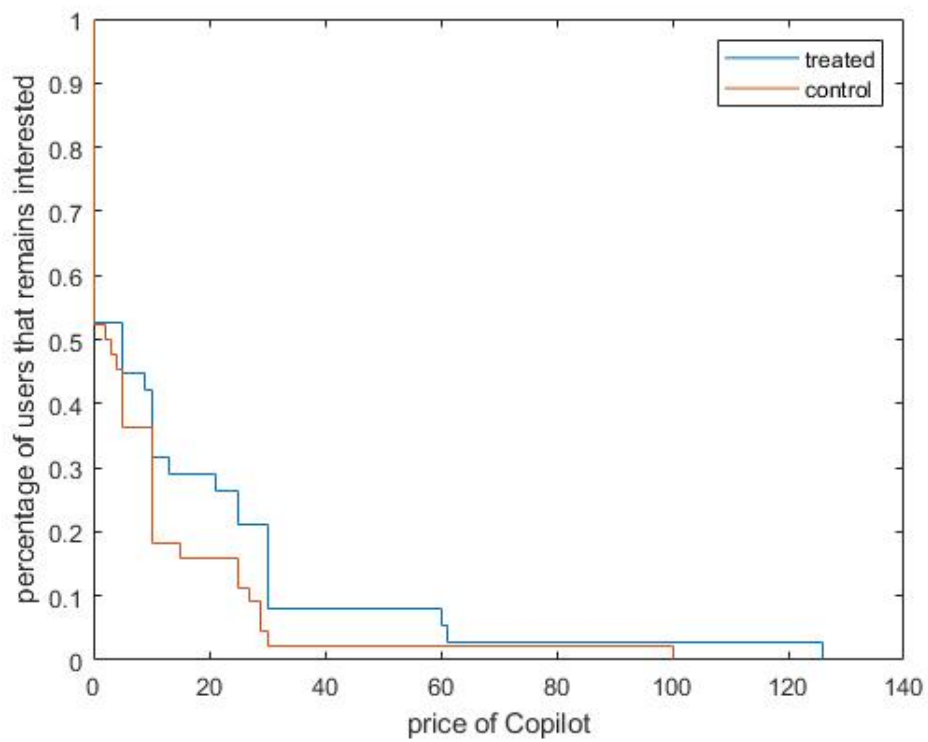


Figure 8: Distributing of irrelevant price

Note: This graph shows the distribution of the irrelevant price between the treated (blue) and control (orange) groups.