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

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#### The transformative power of AI

April 2<sup>nd</sup>, 2025 - European Central Bank, Frankfurt am Main

... we provide new empirical and theoretical insights on **the impact of GenAl** on firm-level productivity, in terms of *startup funding* and *employment dynamics*.

... we address the following research questions:

- $\rightarrow$  Does GenAl increase startup productivity and, if so, under which circumstances?
- $\rightarrow$  What **complementary assets** are needed in order for firms to create and capture value from GenAl?
- $\rightarrow$  How can firms exploit valuable but non-exclusive technological innovation as a source of competitive advantage?



ARTIFICIAL INTELLIGENCE

# Generative AI could raise global GDP by 7%

April 5, 2023 Share <

 Goldman Sachs
 Across 6

 Artificial intelligence
 Generative Al could GDP by 7%

 April 5, 2023
 Share <</td>

McKinsey & Company

Across 63 use cases, generative AI has the potential to generate \$2.6 trillion to \$4.4 trillion in value across industries.

#### FINANCIAL TIMES

Artificial intelligence (+ Add to myFT

# Generative AI set to affect 300mn jobs across major economies

Technology could boost global GDP by 7% but also risks creating 'significant disruption'

#### A new productivity revolution

The economic benefits of generative AI have only just begun to be felt, say experts. Almost every sector could see gains from using this transformative technology Kinsey & Company

ross 63 use cases, pegagge AI has the tential to generate .6 trillion to \$4.4 trillion value across industries.



## Forbes

Unleashing Economic Growth: How Generative AI Is Shaping The Future Of Prosperity

### Artificial intelligence (+ Add to myFT) Generative AI set t major economies

Bloomberg

Technology could boost global GDF

# Generative AI Could Solve the Productivity Paradox

A new pi

The economic benefits of genera every sector could see gains fror

What the new technology tells us about human work performance

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### GenAI and productivity - what do we know?

- GenAl is found to boost the productivity of *individuals* by complementing human labor, e.g., in programing, writing, or consulting tasks, ... (e.g. Brynjolfsson *et al.*, 2023; Dell'Acqua *et al.* 2023; Noy & Zhang, 2023)
- ... but little is known about its impact in more complex, *organizational* settings. (Eisfeldt *et al.*, 2023; Demirci *et al.*, 2025)

- $\rightarrow$  The effect of GenAl on individual startups is unclear from the *resource-based view*:
  - GenAl's task-specific productivity gains may help startups overcome resource constraints, enabling the exploration of business ideas
  - GenAl solutions are neither unique, imperfectly imitable, nor controlled by a specific firm, limiting their potential as source of competitive advantage

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# Empirical approach

#### Quasi-natural experiment:

- Identifying event: The release of GitHub Copilot in 2021 as a positive shock to the productivity of software developers.
  - $\rightarrow$  GitHub Copilot is a GenAl-powered coding assistant
- Cross-sectional variation: The propensity to respond to the shock depends on how central software development is for a startups' main product or service
  - ightarrow Essentially, comparing software-developing and other (software-) startups

#### Measurement:

- We measure productivity via funding dynamics, primarily time-to-funding as an early efficiency indicator, and employee counts at funding (Hsu *et al.*, 2007)
- Differences in founding team characteristics (technological and entrepreneurial experience) to assess the role of human resources as complementary assets to GenAl (Colombo & Grilli, 2005; Dencker & Gruber, 2015)

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- 1. Software-developing startups secure initial funding **20% faster**, while deal sizes remain stable
- 2. Software-developing startups achieve these funding outcomes with **22% fewer software developers**
- 3. Effects are driven by startups whose founders have **technological** (e.g. computer science degrees) and **entrepreneurial experience** (e.g. serial founders)
- ⇒ Bundling GenAl with complementary human capital can give startups a competitive advantage

- 1. Data & the empirical setting
- 2. Estimation strategy, baseline results, and extensions
- 3. Employment effects and mechanism
- 4. Implications and conclusion

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#### Data sources and sample construction

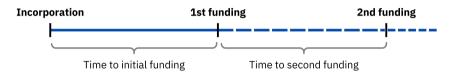
- 1. Repeated cross-sectional data from Crunchbase
  - $\rightarrow\,$  Data on startup, investor, and funding characteristics, incl. deal sizes and timing
  - $\rightarrow$  Exhaustive sensitivity tests on potential truncation issues (*show*)
- 2. Snapshot of Revelio Labs employee level data
  - $\rightarrow$  Highly granular employee-level data on individual characteristics and employment histories, extracted from publicly available professional profiles (mostly LinkedIn)

Sampling: Startups that have raised an initial funding round between Q1 2020 and Q3 2023, from all sectors, headquartered in the US, Canada, or Europe

- $\rightarrow$  Remove startups whose initial round are not early-stage grant or equity investments; cleaning implausible observations following Townsend (2015).
- $\Rightarrow$  Final sample: **21 834 startups**, 39 769 investment rounds, 225 508 employees



# Measuring startup productivity via time-to-funding



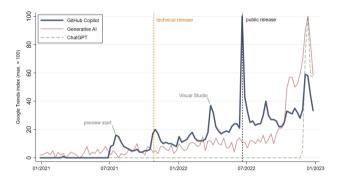
Measuring productivity via time-to-funding:

- Funding rounds provide some of the first observable data points for evaluating startup performance
- Time-to-funding measures how quickly a startup achieves key milestones required to secure funding (e.g. prototype, customer acquisition) (e.g. Hsu, 2007)

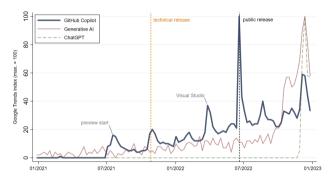
 $\rightarrow$  An acceleration in time-to-funding can reflect a productivity increase



- Copilot is a GenAl-powered coding assistant developed by GitHub and OpenAl that completes lines of code and generates whole algorithmic solutions
- In February 2023, the share of code generated by Copilot ranged between 46 and 61% for popular coding languages (GitHub, 2023)
- Experimental evidence reports that Copilot leads to an average reduction of 56% in time-to-completion for development tasks (Peng *et al.*, 2023)



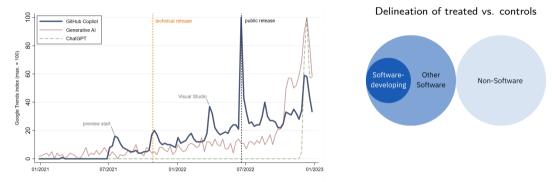
The timeline: Google Search Trends



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Its properties qualify the GitHub Copilot launch as a quasi-natural experimental setting:

1. The launch is largely unaffected from general trends in GenAl technologies.



The timeline: Google Search Trends

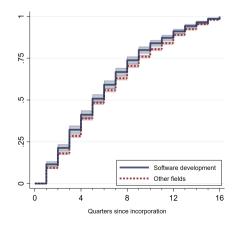
Its properties qualify the GitHub Copilot launch as a quasi-natural experimental setting:

- 1. The launch is largely unaffected from general trends in GenAl technologies.
- 2. Unlike other GenAl-related technology shocks, GitHub Copilot has varying effects on startups' productivity, depending on the relevance of software development (*details*).

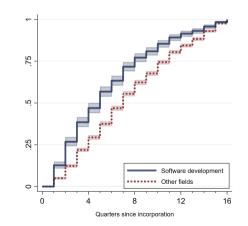
#### Descriptive evidence

Cumulative hazard rates: Time-to-funding of software-developing and other startups

Panel A: Before the GitHub Copilot preview phase

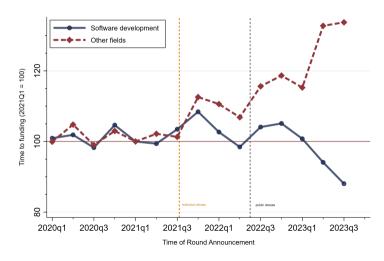






#### Descriptive evidence

#### Average time-to-funding, by quarter (indexed)



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### Defining the baseline model

The impact of GitHub Copilot on startup productivity as the differential effect on the time-to-funding, comparing software-developing startups with other startups:

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

with

- $Y_{ijct}$ : DV, time-to-funding for startup *i*, in industry *j*, in country *c*, and at time *t*
- Developer<sub>i</sub>: Dummy equals one for software- developing startups
- Post<sub>t</sub>: Dummy equals one for startups that raised initial funding after the Copilot release
- $\beta_1$ : Average treatment effect
- $X_i$ : Vector of control variables for firm-specific investor characteristics and base variables
- Fixed effects to control for time  $(\gamma_t)$ , country  $(\delta_c)$ , and industry  $(\mu_j)$  specific factors
- $\epsilon_{ijct}$ : Error term, standard errors clustered at the startup level

#### Baseline results

#### The effect of GitHub Copilot on startups' time-to-funding

Dependent variable:	Time-to-funding							
	(I)	(11)	(111)	(IV)	(V)	(VI)		
$Developer\timesPost$	-4.793*** (0.669)	-3.815*** (0.629)	-3.843*** (0.690)	-3.073*** (0.648)	-6.189*** (0.836)	-5.360*** (0.791)		
OtherSoftware  imes Post					-2.107*** (0.626)	-2.178*** (0.627)		
Sample:	F	ull	Software startups		Full			
Post definition (release):	Public	Technical	Public	Technical	Public	Technical		
Additional controls:								
Time FE	Yes	Yes	Yes	Yes	Yes	Yes		
Country FE	Yes	Yes	Yes	Yes	Yes	Yes		
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes		
N R <sup>2</sup>	21,834 0.19	21,834 0.19	16,754 0.18	16,754 0.18	21,834 0.19	21,834 0.19		

#### Baseline results: extensions and robustness tests

#### Several tests underpin the validity of our main findings:

- Choosing alternative treatment group definitions (*show*)
- Distinguishing between investment types (*show*)
- Placebo tests on regulated industries (*show*)

We also assess several alternative factors that may affect funding:

- Remote labor and Covid-19 (show)
- VC market sentiment (*show*)
- ChatGPT release (*show*)

### The effect of GitHub Copilot on deal sizes

Dependent variable:	log( <i>DealSize</i> )						
	(I)	(11)	(111)	(IV)	(V)	(VI)	
$Developer\timesPost$	0.097 (0.085)	0.015 (0.080)	0.273** (0.114)	0.124 (0.108)	-0.046 (0.088)	-0.077 (0.082)	
Sample:	Full		Excluding other software		Software startups		
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	
Additional controls: Time FE Country FE Industry FE Firm-level controls	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	
N R <sup>2</sup>	14,175 0.33	14,175 0.33	5,457 0.36	5,457 0.36	10,936 0.34	10,936 0.34	

 $\rightarrow$  Startups raise funding more quickly, but deal-sizes remain stable

# The effect of GitHub Copilot in subsequent funding rounds

Dependent variable:	Time-to-funding								
	2 <sup>nd</sup> round			3 <sup>rd</sup> round					
	(I)	(11)	(111)	(IV)	(V)	(VI)	(VII	(VIII)	
$Developer \times Post$	-2.354*** (0.877)	-1.200 (0.799)	-2.312** (0.910)	-1.276 (0.828)	0.753 (1.222)	1.029 (1.124)	0.453 (1.269)	1.054 (1.167)	
Sample:	Full		Software startups			Full		Software startups	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical	
Additional controls:									
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Ν	12,234	12,234	10,003	10,003	5,701	5,701	4,732	4,732	
R <sup>2</sup>	0.18	0.18	0.19	0.19	0.21	0.21	0.23	0.23	

 $\rightarrow$  Effects are strongest for earliest stages and vanish at later funding rounds

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Chang Kim • 3.+ + Folgen Currently building something new. Serial entrepreneur (2x ... 3 Monate • (5)

I've recently heard two different stories that illustrate the stark differences in how AI is affecting the job market:

 One startup founder said heliaid off two junior engineers. Now, he's involved in[<u>coding himself]</u>(he has a background in software engineering) and uses GPT/Copilot. He mentioned that[<u>product development is much faster now</u>] compared to when he had the two junior engineers.

 Out of this year's graduates from a top 50 computer science master's program, <u>[only one person received a job offer upon graduation.]</u>One student applied to 60 companies and received zero interview requests—not zero job offers, but zero interviews.

It seems like AI is making experienced, senior professionals more effective at their jobs, reducing the need for junior employees. But if no one hires juniors, how can anyone become senior?

#### THE WALL STREET JOURNAL.

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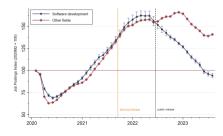
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#### **Computer-Science Majors Graduate Into a World of Fewer Öpportunities** Those from top schools can still get jobs. They are just not all going to Facebook or Google.

#### Job postings on Indeed, 2020-2023



...

+ Folgen



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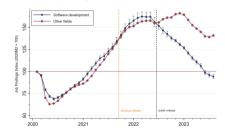
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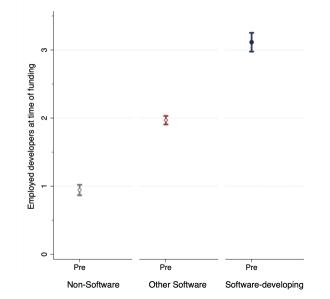
#### Job postings on Indeed, 2020-2023



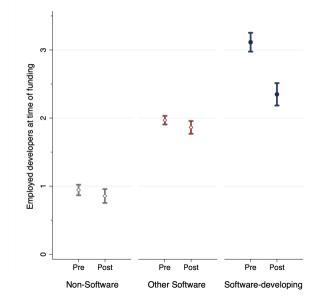
 $\rightarrow$  Does the release of GitHub Copilot reduce the demand for software developers?

 $\rightarrow$  Does GenAI make more experienced professionals more effective at their jobs?

#### Descriptive statistics: Employed software developers at time of funding



#### Descriptive statistics: Employed software developers at time of funding



#### The effect on employed software developers

Dependent variable:	Number of Software Developers						
	(I)	(11)	(111)	(IV)	(V)	(VI)	
$Developer\timesPost$	-0.568*** (0.139)	-0.427*** (0.136)			-0.630*** (0.142)	-0.436*** (0.141)	
OtherSoftware  imes Post			-0.050 (0.090)	0.001 (0.086)	-0.052 (0.090)	-0.008 (0.086)	
Sample:		Software startups		Excluding software- developing startups		Full	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	
Additional controls: Time FE Country FE Industry FE Firm-level controls	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	
N R <sup>2</sup>	14,139 0.24	14,139 0.24	15,137 0.24	15,137 0.24	18,295 0.25	18,295 0.25	



## Founder experience and the productivity effects of GitHub Copilot

Dependent variable:				Time-to	-funding			
	(I)	(11)	(111)	(IV)	(V)	(VI)	(VII)	(VIII)
$Developer \times Post$	-6.796*** (2.624)	-2.040 (1.878)	-6.057** (2.459)	-1.828 (2.598)	-2.763** (1.319)	0.605 (2.567)	-4.711** (2.033)	-2.367 (1.497)
Experience measure:	Compute	r degree	Found	er age	Crunchb	ase rank	Serial f	ounder
Experience $(1/0)$	=1	= 0	=1	= 0	=1	= 0	=1	= 0
Additional controls: Time FE Country FE Industry FE Firm-level controls	Yes Yes Yes Yes							
Mean dep. variable:	19.495	22.879	22.643	22.164	19.617	25.496	20.171	23.443
N R <sup>2</sup>	958 0.34	4,073 0.25	1,922 0.28	1,699 0.33	4,829 0.23	4,773 0.22	2,855 0.25	6,775 0.22

- $\rightarrow$  Effects are driven by startups whose founders have more technological and entrepreneurial experience
- $\rightarrow$  Successful integration of GenAl depends on the capabilities of the founding team

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#### Theoretical implications

Can new, generally available technologies - despite being non-rare and imitable still provide a source of competitive advantage?

- Our results show that, despite lacking some classical properties of valuable assets, GenAl can significantly impact funding dynamics across startups
- Complementarities between founders' human capital (educational & practical experience) and the nature of the new technology determines its firm-specific value
- ⇒ Valuable but non-exclusive technological innovations *can* provide a source of competitive advantage if firms leverage them as complementary assets to their existing skill set

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#### Summary and conclusion

We examine the effects of GenAl technologies on startup productivity by exploring the release of GitHub Copilot as a quasi-natural experiment that exogenously affected startups' funding dynamics.

#### Key takeaways:

- 1. GenAl has the capabilities to increase productivity at the firm-level
- 2. Productivity effects are strongest in the earliest stages of startups, when the liabilities of newness and smallnes are strongest
- 3. Productivity effects are ultimately determined by founders' technological and entrepreneurial experience
- 4. New non-rival technologies can provide a source of competitive advantage, once combined with human capabilities to form complementary resource bundles

# Looking forward to your feedback - Thank you! dominik.asam@ip.mpg.de

# Appendix

#### Related literature

#### 1. Strategic Management and Entrepreneurship:

- Technology-based resources as a central driver of firms' competitive advantage (e.g. Mata *et al.*, 1995; Arora and Nandkumar, 2012; Giustiziero *et al.*, 2023)
   → GenAl represents a newly available technological resource, but does it yield a source of competitive advantage?
- The role of founders' human capital in new venture development and growth
   (e.g. Colombo and Grilli, 2005; Unger *et al.*, 2011; Dencker and Gruber, 2015)
   → We identify founder's technological and entrepreneurial experience as drivers
   behind GenAl-enabled productivity gains
- The strategic management of AI in learning, decision-making, and as substitute to human capital

(e.g. Choudhury et al., 2020; Gaessler and Piezunka, 2023; Krakowski et al., 2023)

ightarrow We extend the literature from isolated settings (e.g. chess) to the real world

#### 2. The Economics of AI:

- First evidence on the implications of GenAl focuses on the productivity gains of individuals (e.g. Brynjolfsson *et al.*, 2023; Dell'Acqua *et al.*, 2023; Noy and Zhang, 2023)
  - ightarrow We analyse firm-level productivity effects

#### 3. Entrepreneurial Finance:

The effect of technology shocks (e.g. cloud computing and low-code tools) on startup financing (e.g. Ewens *et al.* 2018; Dushnitsky and Stroube 2021)
 → We extend prior contributions by exploring a different, though crucially important technology shock

#### Summary statistics

	Obs.	Mean	SD	p10	p25	Median	p75	p90
Time-to-funding	21,834	24.468	17.452	5.033	10.833	20.267	35.533	51.700
log(DealSize)	14,699	13.586	2.030	10.898	12.206	13.816	15.060	16.002
DealSize (in TUSD)	14,699	3,412	6,307	54	200	1,000	3,470	8,900
Follow-on investment	21,834	0.317	0.466	0	0	0	1	1
Total DealSize (in TUSD)	16,402	12,732	87,260	100	300	2,000	6,583	22,401
Developers	21,834	0.165	0.371	0	0	0	0	1
OtherSoftware	21,834	0.776	0.417	0	1	1	1	1
# investors	21,834	2.423	2.932	1	1	1	3	6
Syndicate	18,826	0.305	0.460	0	0	0	1	1
US investors	21,834	0.644	0.479	0	0	1	1	1
European investors	21,834	0.380	0.485	0	0	0	1	1
Remote	21,834	0.615	0.487	0	0	1	1	1
LowPropensity	21,834	0.300	0.458	0	0	0	1	1
Computer Science degree	6,143	0.222	0.415	0	0	0	0	1
Founder rank	10,970	435,486	478,176	49,992	132,923	321,120	648,826	1,008,53
Founder age (since grad.)	4,750	14.760	9.076	4.332	8.006	13.011	20.014	28.019
Founder with exit	10,970	0.084	0.278	0	0	0	0	0
Serial founder	10,970	0.319	0.466	0	0	0	1	1
Founding team size	10,970	1.801	0.909	1	1	2	2	3
Time-to-funding; 2nd round	12,234	32.085	16.755	11.800	18.700	29.667	43.600	56.933
log(DealSize); 2 <sup>nd</sup> round	8,519	14.473	2.021	11.562	13.182	14.734	15.847	16.907
Time-to-funding; 3 <sup>rd</sup> round	5,701	38.629	15.749	18.233	26.433	37.700	50.467	61.300
log( <i>DealSize</i> ); 3 <sup>rd</sup> round	4,126	13.922	2.089	11.842	13.764	15.187	16.497	17.453

#### Summary statistics – country distribution

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



#### Summary statistics - firm size distribution

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



#### Summary statistics - investment types of first deal

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



## Classifying treatment and control groups

Category	Keywords	Example
Software- developing startups	software-as-a-service, software development kit, machine learning	"world's fastest and most optimal route optimization engine"
Other software startups	e-commerce, webapp, customer relationship management	"an on-demand mobile application that allows consumers to book event vendors in minutes"
Non-software startups	all other	"selling of human-grade dog food that is rich in vitamins and miner- als"



### Crunchbase business fields classifying startups

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

## Summary statistics, by industry groups

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

#### Baseline results - full coefficient table

Dependent variable:	Time-to-funding							
	(I)	(11)	(111)	(IV)	(V)	(VI)		
$Developer \times Post$	-4.793***	-3.815***	-5.754***	-5.099***	-3.843***	-3.073***		
	(0.669)	(0.629)	(0.849)	(0.803)	(0.690)	(0.648)		
Developer	1.835***	2.317***	-0.014	0.660	1.565**	1.960***		
	(0.692)	(0.734)	(1.774)	(1.802)	(0.698)	(0.743)		
# investors	-0.401***	-0.402***	-0.383***	-0.380***	-0.325***	-0.325***		
	(0.039)	(0.039)	(0.079)	(0.079)	(0.040)	(0.041)		
US-based investors	3.550***	3.562***	4.029***	4.006***	3.482***	3.505***		
	(0.542)	(0.542)	(0.910)	(0.908)	(0.595)	(0.595)		
European-based investors	3.384***	3.365***	4.130***	4.044***	2.680***	2.665***		
	(0.483)	(0.483)	(0.820)	(0.818)	(0.524)	(0.523)		
Constant	22.338***	22.334***	23.841***	23.926***	21.007***	20.995***		
	(0.454)	(0.454)	(1.039)	(1.039)	(0.498)	(0.498)		
Sample:	F	ull		Excluding other software		Excluding non-software		
Treatment definition (release):	Public	Technical	Public	Technical	Public	Technical		
Additional controls: Time FE Country FE Industry groups	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes		
N	21,834	21,834	8,521	8,521	16,754	16,754		
R <sup>2</sup>	0.19	0.19	0.23	0.23	0.18	0.18		

#### Robustness Test: Remote work and COVID-19

Dependent variable:	Time-to-funding					
	(I)	(11)	(111)	(IV)	(V)	(VI)
$Remote\timesPost$	-1.012 (0.684)	-0.859 (0.624)		0.603 (1.388)	-0.863 (1.328)	
Remote $\times$ Covid			0.694 (1.197)			0.250 (2.392)
Sample:		Software startups		I	Non-softwar startups	e
Post definition:	Public	Technical	-	Public	Technical	-
Additional controls: Time FE Country FE	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Industry FE Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes Yes
N R <sup>2</sup>	16,754 0.18	16,754 0.18	16,754 0.18	4,662 0.20	4,662 0.20	4,662 0.20

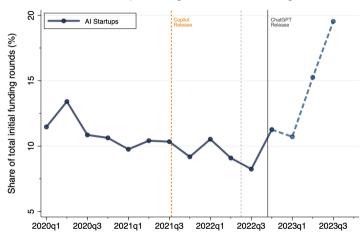


### Robustness Test: VC market sentiment

Dependent variable:	Time-to-funding							
	(I)	(11)	(111)	(IV)	(V)	(VI)		
$Developer \times VC \text{ sentiment}$	0.200*** (0.039)	2.373** (1.206)	-0.133 (1.005)	0.168*** (0.041)	2.380* (1.247)	-0.801 (1.045)		
Sample:		Full		Software startups				
VC sentiment definition:	Continuous	Hot market	Cold market	Continuous	Hot market	Cold market		
Additional controls:								
Time FE	Yes	Yes	Yes	Yes	Yes	Yes		
Country FE	Yes	Yes	Yes	Yes	Yes	Yes		
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes		
Ν	18,295	18,295	18,295	13,986	13,986	13,986		
R <sup>2</sup>	0.19	0.19	0.19	0.19	0.19	0.19		



#### Robustness test: VC Hype for AI startups



Share of AI startups among total initial funding rounds

### Robustness test: Release of ChatGPT

Dependent variable:			Tim	e-to-funding		
	(I)	(11)	(111)	(IV)	(V)	(VI)
Developer $ imes$ Post	-2.169***	-2.093***	-2.094**	-1.869**	-2.023***	-1.785**
	(0.836)	(0.661)	(0.865)	(0.712)	(0.743)	(0.767)
Sample (timeframe):		Pre Chat	GPT 4.0		Pre initial C	hatGPT release
Sample (firms):	F	Full		tware rtups	Full	Software startups
Post definition (release):	Public	Technical	Public	Technical	Technical	Technical
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Ν	18,768	18,768	14,511	14,511	17,092	13,235
R <sup>2</sup>	0.18	0.18	0.18	0.18	0.18	0.18

#### Robustness Test: Alternative treated group

Dependent variable:	Time-to-funding								
	(I)	(11)	(111)	(IV)	(V)	(VI)	(VII	(VIII)	
$Developer^{profile} \times Post$	-4.219*** (0.642)	-3.086*** (0.605)	-5.230*** (0.846)	-4.471*** (0.802)					
$Software^{broad} \times Post$					-2.434*** (0.543)	-1.573*** (0.507)	-5.747*** (0.849)	-5.135*** (0.802)	
Sample:	F	Full Excluding other software		Full		Excluding other software			
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical	
Additional controls:									
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Ν	21,834	21,834	8,521	8,521	21,834	21,834	8,521	8,521	
R <sup>2</sup>	0.19	0.19	0.24	0.23	0.19	0.19	0.23	0.23	



#### Robustness Test: Controlling for investment types

Dependent variable:				Time-to	-funding			
	(1)	(11)	(111)	(IV)	(V)	(VI)	(VII	(VIII)
$Developer^{profile} \times Post$	-3.720*** (0.644)	-2.955*** (0.599)	-3.265*** (0.664)	-2.606*** (0.617)	-3.008*** (0.674)	-2.359*** (0.575)	-3.120*** (0.697)	-2.468*** (0.643)
Investment types:	All	early-stage i	nvestment t	ypes	See	d and ventu	re capital ro	unds
Sample:	Full		Software startups		Full		Software startups	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical
Additional controls: Time FE Country FE Firm-level controls Investment type FE	Yes Yes Yes Yes							
N R <sup>2</sup>	21,834 0.25	21,834 0.25	16,754 0.24	16,754 0.24	18,238 0.26	18,238 0.26	14,661 0.25	14,661 0.25



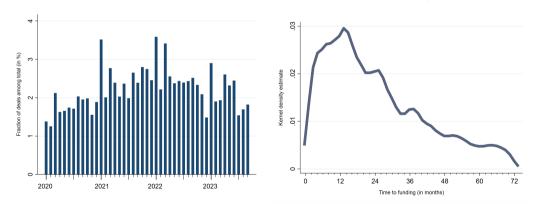
## Placebo test: Regulated industries and GitHub Copilot

Dependent variable:			Time-to	-funding		
	(I)	(11)	(111)	(IV)	(V)	(VI)
$Biotech \times Post$	-0.228 (1.057)					
$Healthcare \times Post$		0.992 (0.830)				
$Governmental\timesPost$			4.045 (6.534)			
$Energy\timesPost$				-2.569 (2.329)		
Transportation $\times$ Post					2.114 (1.560)	
$LowPropensity \times Post$						0.788 (0.710)
Additional controls:						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE Firm-level controls	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes
N R <sup>2</sup>	16,754 0.18	16,754 0.18	16,754 0.18	16,754 0.18	16,754 0.18	16,754 0.18

#### GitHub Copilot and subsequent funding sizes

Dependent variable:	log(DealSize)								
		2 <sup>nd</sup> 1	round			3 <sup>rd</sup> round			
	(I)	(11)	(111)	(IV)	(V)	(VI)	(VII	(VIII)	
$Developer\timesPost$	-0.119	-0.005	-0.091	0.018	-0.052	-0.052	-0.096	-0.085	
	(0.113)	(0.104)	(0.117)	(0.107)	(0.164)	(0.148)	(0.172)	(0.155)	
Sample:	F	Full		Software startups		Full		ftware artups	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	Public	Technical	
Additional controls: Time FE Country FE Industry FE Firm-level controls	Yes Yes Yes Yes								
N R <sup>2</sup>	8,194 0.35	8,194 0.35	6,750 0.37	6,750 0.37	3,943 0.44	3,943 0.44	3,291 0.45	3,291 0.45	

#### Summary statistics



Panel A: Distribution of initial funding rounds

Panel B: Kernel density distribution

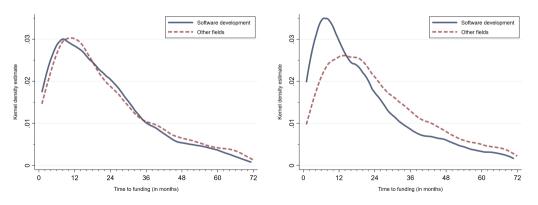


#### Descriptive statistics: Kernel density estimates

Time-to-funding of software-developing and other startups

Panel A: Before the Copilot preview phase

Panel B: After the Copilot public release



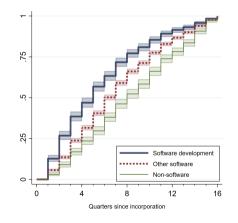
#### Descriptive statistics: Nelson-Aalen estimates, by industry

Cumulative hazard rates on the time-to-funding, by industry

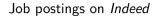
Panel A: Before the Copilot preview phase

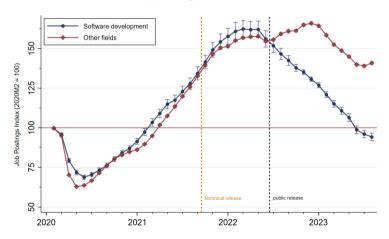
-75 S 25 Software development Other software Non-software 0 12 16 Quarters since incorporation

Panel B: After the Copilot public release



#### Descriptive insights from job postings





### Mechanism: Log number of software employees at time of funding

Dependent variable:		Log N	lumber of S	oftware Deve	lopers		
	(I)	(11)	(111)	(IV)	(V)	(VI)	
$Developer\timesPost$	-0.165***	-0.143***			-0.190***	-0.157**	
	(0.048)	(0.045)			(0.068)	(0.064)	
OtherSoftware  imes Post			-0.027	-0.026	-0.024	-0.022	
			(0.059)	(0.055)	(0.059)	(0.055)	
Sample:		ware tups		xcluding software- eveloping startups		ull	
Post definition (release):	Public	Technical	Public	Technical	Public	Technical	
Additional controls:							
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	
Ν	7,702	7,702	6,759	6,759	8,910	8,910	
R <sup>2</sup>	0.19	0.19	0.18	0.18	0.19	0.19	



#### Mechanism: Software employees X quarters after incorporation

		Numbe	r of Softw	are Developers
	Time	Pre	Post	Difference
	1 quarter	1.668 (0.107)	1.092 (0.079)	-0.577*** (0.139)
Developers	3 quarters	2.796 (0.136)	1.822 (0.124)	-0.974*** (0.199)
	б quarters	4.656 (0.103)	2.864 (0.180)	-1.792** (0.703)
	1 quarter	1.180 (0.073)	0.826 (0.073)	-0.355** (0.110)
OtherSoftware	3 quarters	2.034 (0.085)	1.348 (0.104)	-0.686*** (0.138)
	6 quarters	3.130 (0.124)	2.004 (0.124)	-1.126*** (0.124)



#### Mechanism: Software employees X quarters after incorporation

		Number of Software Developers								
	(I)	(11)	(111)	(IV)	(V)	(VI)				
Developer $ imes$ Post	-0.311**	-0.275*	-0.545***	-0.394**	-0.352*	-0.356*				
	(0.130)	(0.150)	(0.165)	(0.180)	(0.188)	(0.187)				
$\mathit{OtherSoftware}  imes$ Post	-0.132*	-0.117	-0.311***	-0.251**	-0.282***	-0.220*				
	(0.078)	(0.092)	(0.099)	(0.115)	(0.108)	(0.116)				
Time after incorporation:	1 quarter		3 qu	3 quarters		6 quarters				
Post definition (release):	Public	Technical	Public	Technical	Public	Technical				
Additional controls:										
Time FE	Yes	Yes	Yes	Yes	Yes	Yes				
Country FE	Yes	Yes	Yes	Yes	Yes	Yes				
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes				
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes				
Ν	10,617	10,617	10,648	10,648	13,250	13,250				
R <sup>2</sup>	0.22	0.22	0.25	0.25	0.28	0.28				

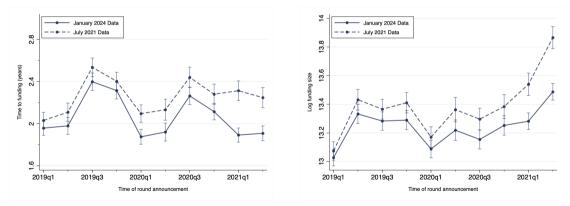


#### Truncation issues in the Crunchbase data

Comparison of January 2024 and July 2021 data

Panel A: Time to initial funding

Panel B: Log initial funding size



### Crunchbase truncation issues: Quarterly breakdown of funding data

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

