Research Policy 52 (2023) 104885

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

The impacts of lockdown on open source software contributions during the COVID-19 pandemic

Jin Hu [a,b], Daning Hu [b,*], Xuan Yang [c], Michael Chau [a]

[a] Faculty of Business and Economics, The University of Hong Kong, Hong Kong
[b] Business School, Southern University of Science and Technology, Shenzhen, Guangdong 518055, China
[c] Department of Informatics, University of Zurich, 8006 Zurich, Switzerland

ARTICLE INFO

Keywords:
COVID-19
Lockdown
Work productivity
Open source software
Face-to-face interactions

ABSTRACT

The COVID-19 pandemic instigated widespread lockdowns, compelling millions to transition to work-from-home (WFH) arrangements and rely heavily on computer-mediated communications (CMC) for collaboration. This study examines the impacts of lockdown on innovation-driven work productivity, focusing on contributions to open source software (OSS) projects on GitHub, the world's largest OSS platform. By leveraging two lockdowns in China as natural experiments, we discover that developers in the 2021 Xi'an lockdown increased OSS contributions by 9.0 %, while those in the 2020 Wuhan lockdown reduced their contributions by 10.5 %. A subsequent survey study elucidates this divergence, uncovering an adaptation effect wherein Xi'an developers became more accustomed to the new norm of WFH over time, capitalizing on the flexibility and opportunities of remote work. Moreover, our findings across both lockdowns reveal that the lack of face-to-face (F2F) interactions significantly impeded OSS contributions, whereas the increased available time at home positively influenced them. This finding is especially noteworthy as it challenges the assumption that CMC can effortlessly substitute for F2F interactions without negatively affecting productivity. We further examine the impacts of stay-at-home orders in the United States (US) on OSS contributions and find no significant effects. Collectively, our research offers valuable insights into the multifaceted impacts of lockdown on productivity, shedding light on how individuals adapt to remote work norms during protracted disruptions like a pandemic. These insights provide various stakeholders, including individuals, organizations, and policymakers, with vital knowledge to prepare for future disruptions, foster sustainable resilience, and adeptly navigate the evolving landscape of remote work in a post-pandemic world.

1. Introduction

The COVID-19 pandemic has catalyzed a global transition to work-from-home (WFH) arrangements, as nations implemented lockdown measures to limit human mobility and curb the spread of the virus (Fang et al., 2020; Sheridan et al., 2020; Wang, 2022). This unprecedented shift to remote work, facilitated by a myriad of computer-mediated communications (CMC) technologies, has instigated profound and lasting impacts on work productivity, an area that has garnered significant attention in recent scholarly investigations (Barber et al., 2021; Cui et al., 2022). Understanding such impacts on work productivity is crucial for guiding policy and decision-making at multiple levels. It can help reshape individual approaches to work-life balance, redefine organizational strategies on WFH arrangements, and inform governmental policies or legislation aimed at supporting remote work. Moreover, the significant disruptions brought by the pandemic highlight the imperative for adaptability and resilience at all these levels. Studying the effects of lockdown on work productivity can provide valuable insights, enabling stakeholders to better navigate future upheavals and cultivate enduring resilience. However, the impact of lockdown on work productivity, especially within innovation-driven domains such as open source software (OSS) development, remains largely unexplored.

To address this research gap, our study leverages the lockdowns implemented in two of the world's largest economies – the United States (US) and China – during various stages of the pandemic. These lockdowns serve as natural experiments, enabling us to study their impacts on OSS developers' contributions to GitHub, the world's largest OSS platform (GitHub, 2022b). China's Zero-COVID strategy, marked by its

* Corresponding author.
E-mail address: hdaning@gmail.com (D. Hu).

https://doi.org/10.1016/j.respol.2023.104885
Received 18 October 2021; Received in revised form 29 August 2023; Accepted 29 August 2023
Available online 16 September 2023

uniform and strict lockdown measures across various cities at different times, provides an ideal setting to study OSS contributors' responses to lockdowns. More importantly, it allows us to understand their adaptation to the new normal of WFH throughout various pandemic stages. Meanwhile, the US, with its prominent role in the OSS community and extensive data availability, serves as an optimal environment to extend and validate our findings derived from the Chinese lockdowns, thereby enhancing the generalizability of our insights beyond the specific context of China. Taken together, these natural experiments enable us to delve deeper into how different approaches to managing the pandemic influence OSS contributors' productivity.

Our main difference-in-differences (DID) analysis focused on two lockdowns in China: the initial lockdown in Wuhan in 2020 and another one occurred in Xi'an in 2021. Interestingly, the results revealed a significant positive impact of the 2021 lockdown on the OSS contributions of Xi'an developers, in contrast to the negative impact observed among Wuhan developers during the 2020 lockdown. Moreover, in both lockdowns, the results indicated that developers who made more online comments to their local peers experienced a more pronounced decline in their contributions. To delve deeper into the underlying mechanisms driving these outcomes, we conducted a targeted survey among the developers affected by these two lockdowns.

The survey findings reveal that Xi'an developers reported significantly fewer interruptions and a marked increase in flexibility in making OSS contributions during the later lockdown in 2021. Factors such as fear related to COVID-19 and increased housework responsibilities, which had significantly reduced Wuhan developers' contributions during the initial 2020 lockdown, became insignificant for developers during the 2021 Xi'an lockdown. These findings point to a notable adaptation effect, as developers became more accustomed to the new norms of WFH imposed by the COVID-19 pandemic over time. The survey also found that, for both Wuhan and Xi'an developers, the increase in available time positively influenced OSS contributions.

Moreover, our survey study unveiled that, for both Wuhan and Xi'an developers, the lack of face-to-face (F2F) interactions significantly was found to significantly reduce their contribution levels. This finding is further corroborated by another survey discovery that identified a strong positive correlation between developers' tendency to comment on GitHub and their propensity for F2F interactions prior to the lockdown. Coupled with the aforementioned DID analysis, which demonstrated a more pronounced negative impact on contributions from Wuhan and Xi'an developers who engaged in more online commenting activities with their local collaborators, this evidence leads to the inference that developers who frequently engaged in F2F interactions were more adversely affected by the lockdowns in terms of their contributions. This finding underscores the importance of F2F interactions in collaborative work environments and challenges the assumption that CMC can seamlessly replace F2F interactions without any adverse impact on productivity.

Furthermore, we use the DID analysis to examine the impact of stay-at-home lockdown orders in the US on developers' OSS contributions. This empirical approach is guided by three key considerations. First, assessing the generalizability of the findings from Chinese lockdowns to other contexts is vital, as the impacts of strict lockdown measures like those in China may differ from the effects of milder restrictions adopted elsewhere. Second, the prominence of OSS development in the US, coupled with the extensive data available on GitHub, makes it an apt context for this analysis. Third, the variation in policies regarding lockdowns across different US states offers a unique opportunity for comparative analysis. This allows for a nuanced understanding of how diverse approaches to pandemic management can influence OSS contributions.

In addition, by comparing the effects observed in China and the US, we aim to provide valuable insights into the broader implications of lockdown measures on OSS contributions on a global scale. Interestingly, our analysis revealed no significant impact of US lockdowns on developers' OSS contributions. We posit that this may be attributable to the less strict nature of stay-at-home orders in the US compared to the lockdown measures enforced in China. The relatively lenient restrictions in the US, which permitted essential activities and work, may not have led to significant disruptions in potential F2F interactions or provided additional available time for developers. Consequently, these factors may have exerted minimal effects on their OSS contributions.

Our contributions are threefold. First, by examining the impact of lockdowns on OSS contributions, our study provides novel insights into the effects of remote work on productivity. The nuanced findings on how individuals adapt to new norms of WFH during prolonged periods of disruption can equip various stakeholders – including individuals, organizations, and governments – with essential knowledge. This knowledge can guide preparations for similar future disruptions and build sustainable resilience. Second, our research reveals the detrimental effects of reduced F2F interactions, challenging the assumption that CMC can effortlessly replace F2F interactions without compromising productivity. This is especially salient in innovation-driven domains like OSS development. This insight enriches the discussion on the comparative impacts of CMC and F2F on the efficacy of virtual teams, a discussion that has become increasingly pertinent in an era where reliance on CMC for remote work is likely to persist even beyond the pandemic (Airbnb, 2022; Warren, 2020). Third, our study stands out through the adoption of systematic causal analysis methods. While previous research on the impact of lockdown has mainly relied on survey methods, our use of DID analysis on empirical data from GitHub enables a more robust examination of the causal effects of lockdowns. This methodological approach, reinforced with various robustness tests, not only strengthens the findings of our study but also offers a valuable framework that can be leveraged in future research. This includes exploring the impact of policy interventions or organization strategies in response to similar disruptions.

2. Literature review

2.1. COVID-19 and work productivity

The COVID-19 pandemic has led to an unprecedented shift to remote work, with millions mandated to work from home due to government-imposed lockdowns. The impact of WFH arrangements, brought about by those lockdowns, on work productivity has been the subject of intensive study, yielding mixed findings. Several studies found that lockdown-induced WFH is associated with declines in productivity, especially in innovation-oriented work such as software development (Ralph et al., 2020) and scholarly research (Barber et al., 2021; Walters et al., 2022). Ralph et al. (2020) surveyed 2225 software developers across 53 countries and found that both their productivity and well-being were diminished due to COVID-19. The primary influencing factors were fear related to the pandemic, disaster preparedness, and home office ergonomics. Barber et al. (2021) surveyed 1008 members of the American Finance Association, with 78.1 % of the respondents suggesting that their research productivity is negatively affected by COVID-19. This was due to the lack of traditional F2F communications to disseminate research and obtain feedback, as well as overwhelming health concerns. Another survey study by Walters et al. (2022) investigated the reasons behind the reported decline in research activity among female academics during lockdowns. The primary reason was that while working from home, female academics were burdened with traditional family roles typically assumed by women, as well as increasing teaching and administrative workloads.

On the other hand, some studies found that productivity in lockdown-induced WFH scenarios has actually increased during this pandemic. Asay (2020) reports that OSS developers consistently increased their work volume in 2020, as they never truly left their work. Cui et al. (2022) found an overall 35 % increase in productivity and a 13 % increase in the gender gap among social science scholars in the US since the lockdown began. They suggest that while the lockdown could result in substantial time savings for work-related tasks such as commuting, female researchers may find themselves allocating more time for home-related tasks such as childcare.

Another line of research suggests that lockdowns in general have little effect on software developers. Forsgren (2020) reports that the activity of GitHub developers in the early days of COVID-19 was similar to or slightly increased compared to the previous year. Neto et al. (2021) surveyed 279 developers of GitHub projects developed using Java and found that WFH during the pandemic did not affect task completion time, code contribution, or quality. Similar studies were conducted to survey developers at major IT companies like Microsoft (Ford et al., 2021) and Baidu (Bao et al., 2022). They found that lockdown generally had little impact on developers' productivity. However, these developers had differing opinions about the effects of lockdown. Some suggest their productivity benefited from WFH because of fewer disturbances, saved commuting time, and improved work-life balance. Others suggested their productivity suffered from WFH due to increased home-related tasks, decreased collaboration with others, and interruptions from family members.

To summarize, existing studies on the impact of pandemic-induced lockdowns on work productivity have yielded mixed findings and are heavily reliant on survey methods. Moreover, these studies have not sufficiently explored how knowledge workers, such as developers, adapt to remote work settings and how this adaptation influences their productivity during prolonged periods of lockdown. There is a clear need for systematic causal analyses on large empirical datasets to study the impacts and underlying mechanisms of pandemic-induced lockdowns on innovation-related work considering the effects of adaptation.

2.2. Face-to-face communications and computer-mediated communications

Previous research (NicCanna et al., 2021; Smite et al., 2023) has highlighted that one of the direct implications of pandemic-induced lockdowns is the diminished opportunity for traditional F2F interactions and an increased reliance on CMC, both of which have been considered crucial in the realm of OSS development (Crowston et al., 2007; O'Mahony and Ferraro, 2007). Crowston et al. (2007) identify several settings in which OSS developers engage in F2F meetings and the benefits they derive from such interactions. For instance, F2F meetings provide OSS developers with great opportunities to socialize, build teams, and verify each other's identity. They also find that certain OSS development activities are best suited for F2F interactions, such as conveying important news (Boden and Molotch, 1994). Kock (2004) suggests that it is because human beings evolved over many years to excel at F2F interactions. Moreover, O'Mahony and Ferraro (2007) discovered that F2F interactions with OSS community members could increase one's likelihood of ascending to a community leadership role. This is achieved through 1) building more trusting and reciprocal relationships and 2) creating potential coalitions. Butler and Jaffe (2021) also suggested that F2F interactions can significantly influence one's efforts in community building.

These OSS studies are typically conducted in empirical contexts where F2F interactions and CMC co-exist among OSS community members, making it difficult to disentangle their effects. However, the strict lockdown measures in China have presented a unique opportunity to examine developers' OSS contributions in a setting where F2F interactions are entirely absent. An important conjecture is that OSS developers, who have been accustomed to working productively using CMC in a remote and asynchronous manner for decades (Columbro, 2020; Wellman et al., 1996), are less likely to be affected by the absence of F2F interactions during the COVID-19 pandemic. Our study puts this conjecture to the test by examining the scenario where F2F interactions are largely absent due to the lockdowns in China.

Moving from the specific context of OSS to a more general comparison of F2F interactions and CMC in virtual teams, the findings remain inconclusive. Townsend et al. (1998) find that CMC can facilitate efficient connections between individuals regardless of their geographical locations, thereby significantly improving the performance of virtual teams. Moreover, team members distributed across different time zones can leverage CMC to coordinate more effectively and operate within a more flexible and efficient 24-hour cycle (Lipnack and Stamps, 1999). Therefore, Bergiel et al. (2006) suggest that virtual collaboration via CMC can overcome the constraints of time, distance, and organizational boundaries, leading to improvements in productivity and efficiency among team members.

On the other hand, another stream of the literature suggests that compared with F2F interactions, CMC carries fewer physical and emotional cues, thereby limiting the extent and synchronicity of information exchange (Cramton and Webber, 2005; Daft and Lengel, 1986; Dennis et al., 2008). This can negatively affect team members' capabilities to establish mutual understanding (Kraut et al., 1982; Sproull and Kiesler, 1986; Straus and McGrath, 1994), their sense of belonging, and awareness of group activities (Cramton, 2001). Moreover, in the absence of F2F interactions, individuals are more likely to experience heightened conflicts (Wakefield et al., 2008), leading to decreased team productivity and satisfaction (Hambrick et al., 1998; Lau and Murnighan, 1998). Furthermore, despite recent advances in communication technologies, such as videoconferencing, which allow users to convey more non-verbal information cues than before, the lack of F2F interactions can still negatively affect innovation that relies on collaborative idea generation. A recent study (Brucks and Levav, 2022) discovered that, despite technological advancement, the absence of F2F interactions during the COVID-19 pandemic still negatively affected innovation. The authors attribute this finding to the differences between the physical nature of videoconferencing and F2F interactions, as the former focuses individuals on a display with a narrower cognitive focus.

To summarize, the existing literature has yet to conclusively establish whether, despite technological advancement, CMC can effectively replace the role of F2F interactions without impacting the productivity of collaborative work. Some studies (Crowston et al., 2007; Ocker et al., 1998) suggest that a mix of both CMC and F2F interactions is most beneficial for teamwork. However, as the preference for remote work and reliance on CMC continue to rise at an unprecedented scale even in the post-pandemic era, our research aims to fill this gap by studying whether CMC can fully replace F2F interactions without negatively affecting teamwork productivity.

2.3. Motivations for open source software contributions

Another stream of research that is very relevant to our study is the literature on motivations for contributing to OSS development. The prevailing framework in this field typically categorizes OSS developers' motivations into intrinsic and extrinsic factors. Intrinsic motivations often stem from developers' personal needs such as altruism and joy derived from contributing (Davidson et al., 2014; Hertel et al., 2003), whereas extrinsic motivations are usually related to utility-based external rewards, such as opportunities for career advancement (Fang and Neufeld, 2009; Yang et al., 2021). Studies by Hertel et al. (2003) and Shah (2006) have found that intrinsic motivations, such as enjoyment and fun, significantly influence OSS developers' contributions. However, during the COVID-19-induced lockdowns, developers may experience fear and stress related to the health of their family and friends, which could negatively affect these intrinsic motivations, especially in the early stages of the pandemic.

However, there is a dearth of OSS motivation research that focuses on the social effects through which developers' contribution motivations are influenced by their interactions with their peers. For instance, individuals' OSS contributions are encouraged by the attention they received from their peers (Moqri et al., 2018) and collaboration with other team members (Crowston et al., 2007; Daniel and Stewart, 2016;

Xu et al., 2009). von Krogh et al. (2012) suggest that aspects of social practice like ethics and virtues are largely overlooked as a context for contribution motivations. These aspects are typically cultivated through social interactions among OSS community members, including both F2F interactions and CMC. Our study aims to enrich the understanding of the research community and policymakers on how major disruptions like lockdowns may limit such social effects, particularly through the reduced F2F interactions, and thereby influence OSS developers' contribution motivations.

3. Methods

In this section, we first adopt a mixed-method approach to study the impacts of two lockdowns in China on OSS developers' contributions. We treat the lockdowns in Wuhan and Xi'an as natural experiments, and for each GitHub developer in Wuhan or Xi'an, we match her with a developer in comparable regions that did not experience lockdown measures. We then utilize DID and difference-in-difference-in-differences (DDD) analyses, combined with propensity score matching (PSM), to discern the impacts. To delve deeper into the mechanisms that underpin the changes in developers' OSS contributions during the lockdowns, we also administer a survey to GitHub developers in both lockdowns. In Section 4, we report the main results of this analysis and perform a series of robustness tests to validate our findings.

Moreover, in Section 5, we extend our empirical approaches, such as the DID analysis, to data collected from a distinct context – the US. This supplementary analysis is designed to investigate whether the patterns observed in our findings on Chinese lockdowns are also present in other regions. By comparing the effects in China and the US, we aim to provide valuable insights into the wider implications of lockdown measures on OSS contributions on a global scale.

3.1. Experimental settings

COVID-19 has become one of the most severe global pandemics in recent decades (Fang et al., 2020). Our first natural experiment leverages the lockdown imposed in Wuhan, China from January 23 to April 8, 2020, in response to the initial major outbreak of COVID-19. The authorities enforced a citywide lockdown in Wuhan, leading to the closure of all public transport and non-essential businesses. The residents of all the 7148 residential communities in Wuhan were mandated to stay at home, with leaving only permitted in emergencies. The abrupt imposition of the Wuhan lockdown, which was implemented without prior warning, serves as an exogenous shock. This natural experimental setting provides us with an opportunity to examine the impact of the Wuhan lockdown on OSS contributions.

We designate Wuhan developers as the treatment group and choose developers in Hong Kong, Macau, and Taiwan (HMT) regions as the control group for several reasons. Firstly, most major cities in mainland China swiftly followed Wuhan's lead in implementing strict lockdown or social distancing measures, while the HMT regions did not implement such measures until March 2020. Hong Kong authorities prohibited indoor and outdoor public gatherings of more than four people in March 2020. Meanwhile, although Macau authorities took some ad-hoc measures such as closing casinos and public parks, they did not implement any citywide lockdown measures. Therefore, while developers in Wuhan were strictly required to stay at home in the early stage of this COVID-19 outbreak, those in HMT regions could go out and engage in F2F interactions. Secondly, compared with developers in other parts of the world, HMT developers are much more similar to Wuhan developers as they belong to the same ethnic group – Han Chinese (Wikipedia, 2022) and share similar cultural backgrounds.

We have chosen a ten-week period surrounding the day of the Wuhan lockdown (i.e., between December 19, 2019, and February 27, 2020) as the time frame for the DID analysis mainly for two reasons. Firstly, this timeframe is too short, allowing us to observe potential changes in developers' contributions. Secondly, as COVID-19 began to spread to other parts of the world, including the HMT regions, their developers might have started to consciously avoid F2F meetings with others to prevent potential COVID-19 infections, even before any lockdown or social distancing measures were implemented. This would make HMT developers less ideal control subjects in the natural experiment. Therefore, we set the end of the time window as February 27, 2020, as COVID-19 cases in HMT regions only started to increase significantly in March.

We also leverage the lockdown of Xi'an in China as a second natural experiment. The strictness of a city's lockdown measures often corresponds to the severity of the local outbreak, leading to endogeneity when attempting to causally identify the impacts of the lockdown measures. During the pandemic, China's Zero-COVID policy provides an ideal opportunity to address this endogeneity issue. This policy, which is centered around lockdowns, aims to halt the transmission of COVID-19 as soon as they are detected through mass testing (Chen et al., 2022a). Even a few COVID-19 cases can trigger a full-scale citywide lockdown in a very short period (Chen et al., 2022a). Such swift lockdowns in response to even the smallest number of new COVID-19 cases minimize the endogeneity of policy responses.

The Xi'an lockdown, which lasted from December 23, 2021, to January 23, 2022, was as strict as the Wuhan lockdown, even with far fewer initial infection cases, thus minimizing the endogeneity of policy responses. During the Xi'an lockdown, all public transport and non-essential businesses were suspended, and all Xi'an residents were strictly required to stay at home except for emergencies. Thus, we use Xi'an developers as the treatment group. To construct the control group, we follow existing studies (Muralidharan and Prakash, 2017; Wang, 2022) by choosing developers in the seven capitals of provinces (or municipalities) neighboring Xi'an that did not implement any lockdown measures during the Xi'an lockdown. This is because developers in these neighboring capitals are more similar to Xi'an developers in many aspects. The timeframe of the DID analysis covers the eight weeks surrounding the day of Xi'an lockdown (i.e., between November 25, 2021, and January 20, 2022).

3.2. Data collection for the Chinese lockdowns

Our empirical study collects and uses two types of data: GitHub data and COVID-19 case data. We obtain historical GitHub data through its API and GH Archive database. The latter archives public OSS development activities on GitHub since February 2011 and has been widely used in recent OSS research (Moqri et al., 2018; Negoita et al., 2019). We first use the "search-by-location" function of the GitHub API to extract developers who had at least one public repository and were located in the regions chosen for the natural experiments. For each experiment, we further select developers who joined GitHub before the chosen time window and exclude developers who did not push any commit within that time window. This procedure yields 1695 Wuhan developers and 5282 HMT developers for the Wuhan case. The selected sample of the Xi'an case includes 919 Xi'an developers and 4274 developers in the seven neighboring provincial capitals (or municipalities). Moreover, we obtain data about COVID-19 cases from relevant health authorities such as the National Health Commission of China as well as mainstream media. This comprehensive data collection allows us to conduct a robust analysis of the impact of Chinese lockdowns on OSS contributions.

3.3. Propensity score matching

To address potential endogeneity issues, we employ the DID technique in conjunction with PSM, following the methodology of previous studies (Chen et al., 2019; Foerderer, 2020). PSM selects control subjects by measuring their distance from the treated subjects based on pre-treatment covariates. This method is particularly effective in overcoming the curse of dimensionality (i.e., too many covariates) by transforming covariate vectors into a single propensity score and then selecting control subjects closest to the treated ones (Chen et al., 2022b). It allows us to create a more balanced and comparable control group, thereby enhancing the robustness of our findings.

More specifically, we apply a one-on-one nearest neighbor matching without replacement to select a control developer for each treated developer based on a set of observable characteristics before the lockdown (Fang and Neufeld, 2009; Foss et al., 2021; Moqri et al., 2018; Zhang and Zhu, 2011). These characteristics include the number of *weeks* since the developer joined GitHub, whether the developer is a *student* or an *employee* based on her profile, whether the developer reports her *contact* information in her profile, the *number of* OSS *projects* that the developer created, the number of *commits* that the developer contributed on GitHub, the number of *stars/issues/comments* that the developer *received* for her repositories, the number of *stars/issues/comments* that the developer *sent out*, whether the developer used the following core language on GitHub – *C/C++/C#/Go/Java/JavaScript/PHP/Python/Ruby /Scala/TypeScript* (GitHub, 2022a) as her primary programming language, the number of the developer's *collaborators* that contributed to the same projects with her, the number of the developer's *local collaborators* who contributed to the same projects and lived in the same region with her, the *average age of* the developer's OSS *projects*, and the *number of projects with* the General Public License (*GPL*) created by the developer. GPL, being the most restrictive license, could serve as a proxy for the developer's ideological level (Foss et al., 2021). This PSM procedure yields 1608 matched pairs of Wuhan (treatment) and HMT (control) developers for the Wuhan lockdown and 919 matched pairs of Xi'an (treatment) and neighboring-city (control) developers for the Xi'an lockdown case.

Table 1 summarizes the mean values of the pre-treatment characteristics for all developers in the selected regions before matching. The results of the *t*-test indicate significant differences across many observable characteristics between the developers in lockdown areas and those in non-lockdown areas for both lockdowns. These differences suggest that a direct comparison between the treatment and control groups in the two natural experiments may not be appropriate. Therefore, we apply the aforementioned matching procedure. Table 2 reports the mean values of the same characteristics for the matched sample. The *t*-test results in Table 2 show that there are no significant differences across these observable characteristics between the treatment and matched control groups for both lockdowns. This suggests that the matching procedure has effectively balanced the observable characteristics between the treatment and matched control groups.

3.4. Empirical models

3.4.1. Difference-in-differences model

For each natural experiment, we now examine the change in OSS contributions of every developer selected in the matched sample using the following DID regression framework:

$$CONTRIBUTION_{it} = \alpha + \beta AFTER_t \times LOCKDOWN_i + \gamma CV_{it} + \mu_i + \theta_t + \epsilon_{it} \quad (1)$$

where *i* indexes the developer and *t* indexes the week. The dependent variable, $CONTRIBUTION_{it}$, is the weekly OSS contributions of each developer. We add one to the weekly number of commits a developer contributed to GitHub and then take a logarithm to measure her weekly OSS contributions following previous literature (Hu et al., 2023; Moqri et al., 2018; Zhang and Zhu, 2011). A commit is a change made to an OSS project, such as adding, modifying, and deleting codes. $AFTER_t$ is a dummy variable that equals one if the time period is after the day of lockdown and zero otherwise. $LOCKDOWN_i$ is a dummy variable that equals one if the developer is in the treatment group (i.e., in the city

Table 1
T-tests in the overall sample for Chinese lockdowns.

	Lockdown of Wuhan			Lockdown of Xi'an		
	Mean		*T*-test	Mean		*T*-test
	All the Wuhan developers	All the HMT developers	Difference	All the Xi'an developers	All the neighboring-city developers	Difference
Weeks	174.761	224.249	−49.488***	258.309	259.105	−0.796
Student	0.305	0.162	0.143***	0.279	0.224	0.054***
Employee	0.232	0.290	−0.058***	0.288	0.277	0.011
Contact	0.721	0.690	0.031**	0.703	0.730	−0.027*
Number of projects	21.780	26.074	−4.294***	27.349	30.320	−2.970
Commits	709.337	1489.132	−779.795**	1869.550	1725.299	144.251
Stars received	126.292	77.595	48.697	139.702	260.150	−120.448
Issues received	6.959	9.129	−2.169	11.473	15.097	−3.624
Comments received	12.684	24.629	−11.945**	29.706	39.904	−10.198
Stars sent out	104.883	107.217	−2.334	118.405	153.768	−35.364***
Issues sent out	8.740	12.421	−3.681*	13.799	14.680	−0.881
Comments sent out	23.530	47.056	−23.526**	61.226	49.162	12.064
C	0.041	0.041	0.000	0.039	0.036	0.003
C++	0.086	0.061	0.025***	0.073	0.064	0.009
C#	0.019	0.041	−0.022***	0.027	0.031	−0.003
Go	0.026	0.024	0.002	0.065	0.070	−0.005
Java	0.198	0.075	0.123***	0.177	0.180	−0.003
JavaScript	0.202	0.225	−0.023**	0.182	0.199	−0.018
PHP	0.021	0.032	−0.012**	0.021	0.026	−0.005
Python	0.170	0.196	−0.026**	0.186	0.148	0.038***
Ruby	0.004	0.021	−0.017***	0.007	0.004	0.002
Scala	0.002	0.002	−0.000	0.003	0.001	0.002
TypeScript	0.007	0.010	−0.003	0.016	0.025	−0.008
Collaborators	367.333	899.337	−532.003***	632.457	683.823	−51.366
Local collaborators	0.835	10.044	−9.208***	1.342	2.193	−0.851***
Average age of projects	64.415	88.233	−23.819***	100.200	102.360	−2.160
Number of projects with GPL	1.045	1.187	−0.142	1.256	1.681	−0.425**

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 2
T-tests in the matched sample for Chinese lockdowns.

	Lockdown of Wuhan			Lockdown of Xi'an		
	Mean		*T*-test	Mean		*T*-test
	Treatment group	Control group	Difference	Treatment group	Control group	Difference
Weeks	176.027	176.157	−0.130	258.309	259.829	−1.520
Student	0.294	0.300	−0.006	0.279	0.284	−0.005
Employee	0.236	0.243	−0.006	0.288	0.282	0.007
Contact	0.711	0.716	−0.005	0.703	0.717	−0.014
Number of projects	21.062	21.553	−0.491	27.349	26.248	1.101
Commits	649.231	488.878	160.353	1869.550	1552.262	317.287
Stars received	56.409	87.703	−31.294	139.702	129.087	10.615
Issues received	5.354	5.461	−0.106	11.473	9.350	2.123
Comments received	9.868	10.910	−1.042	29.706	28.098	1.608
Stars sent out	92.615	95.453	−2.838	118.405	111.262	7.143
Issues sent out	7.420	7.304	0.116	13.799	11.668	2.131
Comments sent out	20.850	19.223	1.627	61.226	52.357	8.869
C	0.042	0.042	−0.001	0.039	0.044	−0.004
C++	0.086	0.086	−0.001	0.073	0.086	−0.013
C#	0.021	0.021	−0.001	0.027	0.032	−0.004
Go	0.027	0.027	−0.001	0.065	0.071	−0.005
Java	0.172	0.170	0.002	0.177	0.173	0.004
JavaScript	0.205	0.216	−0.012	0.182	0.177	0.004
PHP	0.021	0.021	0.001	0.201	0.020	0.001
Python	0.177	0.168	0.009	0.186	0.182	0.004
Ruby	0.004	0.004	0.000	0.007	0.004	0.002
Scala	0.002	0.001	0.001	0.003	0.002	0.001
TypeScript	0.007	0.006	0.002	0.016	0.020	−0.003
Collaborators	186.058	162.380	23.678	632.457	576.312	56.145
Local collaborators	0.782	0.816	−0.034	1.342	1.124	0.218
Average age of projects	64.507	64.700	−0.193	100.200	98.979	1.221
Number of projects with GPL	0.984	1.124	−0.140	1.256	1.350	−0.095

*p < 0.1.
**p < 0.05.
***p < 0.01.

where lockdown is implemented) and zero otherwise. CV_{it} contains a set of control variables that might influence a developer's OSS contributions according to previous research (Fang and Neufeld, 2009; Moqri et al., 2018; Zhang and Zhu, 2011): the number of OSS projects created by the developer ($REPO_{it}$), the number of weeks since the developer joined GitHub ($TENURE_{it}$), the number of stars the developer received for her repositories ($STARR_{it}$), the number of stars the developer sent out ($STARS_{it}$), the number of issues the developer received for her repositories ($ISSUER_{it}$), the number of issues the developer sent out ($ISSUES_{it}$), the number of comments the developer received for her repositories ($COMMENTR_{it}$), the number of comments the developer sent out ($COMMENTS_{it}$), and the number of new COVID-19 cases in the developer's region ($CASE_{it}$).

To control for the effects of time-invariant individual characteristics of developer i, especially those that are unobservable, we incorporate the individual fixed effect μ_i in our DID model. Moreover, as opposed to the standard two-period DID model, our DID model spans ten periods for the Wuhan lockdown case and eight periods for the Xi'an lockdown case. Consequently, we need to control for variables that remain constant across subjects but vary over different periods. Therefore, we include the time fixed effect θ_t, which comprises weekly time dummies that control for time trends. The $LOCKDOWN_i$ and $AFTER_t$ in the standard two-period DID model are then absorbed by the individual and time fixed effects, respectively. ϵ_{it} is the error term. The coefficient β indicates the impact of lockdown on developers' OSS contributions. A negative coefficient would suggest the lockdown reduces developers' OSS contributions, whereas a positive coefficient would indicate otherwise.

3.4.2. Difference-in-difference-in-differences models

We now examine the impact of the absence of F2F interactions caused by the lockdowns. If F2F interactions serve as important motivations for OSS contributions, as previous research has suggested (Crowston et al., 2007; Stam, 2009), we expect that developers who regularly engaged in F2F meetings with their collaborators would be more profoundly affected by the lockdown. To this end, we use a GitHub developer's engagement with online comments (i.e., GitHub-supported CMC) as a proxy for her tendency to meet OSS collaborators F2F before the lockdown. This approach is grounded by previous studies that have observed that people who engage more in CMC are also more likely to meet F2F. Such a correlation is understood to reflect underlying social needs and preferences (Huang et al., 2022; Khalis and Mikami, 2018; Suphan and Mierzejewska, 2016). Furthermore, CMC has been found to cultivate social relationships and facilitate the coordination of F2F meetings (DiMaggio et al., 2001; Howard et al., 2001; Kraut et al., 2002; Suphan et al., 2012). This relationship between online and offline interaction is further supported by Brandtzæg and Nov (2011), who discovered that Facebook users who prioritize CMC with close friends also interact more frequently in F2F settings. In addition, our survey study in Section 4.3.4 finds that developers in lockdowns who made more online comments to their local GitHub collaborators before the lockdown were also more likely to meet with each other F2F, which is consistent with the findings of previous studies (Huang et al., 2022; Khalis and Mikami, 2018; Suphan and Mierzejewska, 2016).

This intricate relationship between CMC and F2F interactions lays the groundwork for our DDD analysis. To operationalize a GitHub developer's tendency to meet her local collaborators F2F, we compute the number of online comments she made to them on the GitHub platform before the lockdown. This metric serves as a proxy for her social engagement and preference for F2F interactions. Building on the baseline DID specification, we develop a more nuanced DDD specification:

$$\begin{aligned} CONTRIBUTION_{it} = & \alpha + \beta_1 AFTER_t \times LOCKDOWN_i + \beta_2 AFTER_t \\ & \times LOCCOMS_i + \beta_3 AFTER_t \times LOCKDOWN_i \\ & \times LOCCOMS_i + \gamma CV_{it} + \mu_i + \theta_t + \epsilon_{it} \end{aligned} \tag{2}$$

where $LOCCOMS_i$ is the number of online comments that developer i

made to her GitHub collaborators in the same region before the lockdown. It is important to note that the individual fixed effect μ_i absorbs the $LOCKDOWN_i \times LOCCOMS_i$ term (Foerderer, 2020). We anticipate the coefficient β_3 to be significant and negative, indicating that developers who engaged more in online interactions with their local collaborators were adversely affected by the lockdown, leading to reduced contributions to OSS projects.

Moreover, there is an alternative explanation for the anticipated finding that developers with larger values of $LOCCOMS_i$ are more affected by the lockdown. These developers, being more socially engaged, might be more sensitive to the general well-being of others. Thus they may become more worried about the negative impacts of the pandemic and less likely to contribute to OSS projects (Miller et al., 2019). To ensure that our results are robust to this alternative explanation, we consider the following DDD specification:

$$\begin{aligned} CONTRIBUTION_{it} = & \alpha + \beta_1 AFTER_t \times LOCKDOWN_i + \beta_2 AFTER_t \times COMS_i \\ & + \beta_3 AFTER_t \times LOCKDOWN_i \times COMS_i + \gamma CV_{it} + \mu_i \\ & + \theta_t + \epsilon_{it} \end{aligned} \tag{3}$$

where $COMS_i$ is the number of online comments that developer i made to all her GitHub collaborators (including non-local ones) before the lockdown. If the alternative explanation is true, then the coefficient β_3 should be significant like the one in Eq. (2), as the general social effects should apply to all the GitHub collaborators, regardless of their location. On the other hand, if the coefficient β_3 is insignificant in Eq. (3) but significant in Eq. (2), this alternative explanation can be dismissed.

4. Results and robustness checks for Chinese lockdowns

4.1. Results from the difference-in-differences model

Table 3 reports the results of Eqs. (1)–(3). Columns (1) and (4) show the results of Eq. (1) for the Wuhan and Xi'an lockdowns, respectively. The coefficient of $AFTER_t \times LOCKDOWN_i$ in Column (1) is negative and statistically significant at the 1 % significance level, suggesting that the Wuhan lockdown led to a reduction in developers' OSS contributions. Specifically, a coefficient of -0.111 suggests that Wuhan developers' contributions decreased by 10.5 % ($= e^{-0.111} - 1$) over the five weeks following the lockdown. In contrast, the coefficient of $AFTER_t \times LOCKDOWN_i$ in Column (4) is positive and significant at the 5 % level, suggesting the Xi'an lockdown resulted in an increase in developers' OSS contributions. A coefficient of 0.086 suggests that the Xi'an developers' contributions increased by roughly 9.0 % ($= e^{0.086} - 1$) over the four weeks after the lockdown.

According to the findings of our survey study presented in Section 4.3.4, these contrasting results between the Wuhan and Xi'an lockdowns can be mainly attributed to an adaption effect. When COVID-19 initially emerged in Wuhan, the unprecedented nature of the virus, coupled with its rapid spread, and severity likely instilled a high level of fear and uncertainty among the population. Therefore, Wuhan developers may

Table 3
Regression results for Chinese lockdowns.

	Dependent variable: $CONTRIBUTION_{it}$					
	Wuhan Lockdown (2020)			Xi'an Lockdown (2021)		
	(1)	(2)	(3)	(4)	(5)	(6)
$AFTER_t \times LOCKDOWN_i$	−0.111***	−0.108***	−0.110***	0.086**	0.089**	0.085**
	(0.029)	(0.030)	(0.030)	(0.043)	(0.043)	(0.043)
$AFTER_t \times LOCCOMS_i$		0.003***			0.001**	
		(0.001)			(0.000)	
$AFTER_t \times LOCKDOWN_i \times LOCCOMS_i$		−0.007***			−0.003***	
		(0.003)			(0.001)	
$AFTER_t \times COMS_i$			0.000			−0.000
			(0.000)			(0.000)
$AFTER_t \times LOCKDOWN_i \times COMS_i$			−0.000			0.000
			(0.000)			(0.000)
$REPO_{it}$	0.024	0.024	0.024	0.372***	0.372***	0.372***
	(0.022)	(0.022)	(0.022)	(0.028)	(0.028)	(0.028)
$TENURE_{it}$	−0.030	−0.030	−0.029	0.044	0.047	0.044
	(0.039)	(0.039)	(0.039)	(0.051)	(0.051)	(0.051)
$STARR_{it}$	0.016**	0.016**	0.016**	0.003	0.003	0.003
	(0.008)	(0.008)	(0.008)	(0.002)	(0.002)	(0.002)
$STARS_{it}$	0.015**	0.015**	0.015**	0.027***	0.027***	0.027***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
$ISSUER_{it}$	−0.021	−0.020	−0.022	0.014	0.014	0.014
	(0.025)	(0.025)	(0.025)	(0.038)	(0.038)	(0.038)
$ISSUES_{it}$	0.076***	0.076***	0.077***	0.058*	0.058*	0.057*
	(0.028)	(0.028)	(0.028)	(0.033)	(0.033)	(0.033)
$COMMENTR_{it}$	0.022	0.022	0.022	0.011	0.011	0.011
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.011)
$COMMENTS_{it}$	0.047***	0.047***	0.047***	0.053***	0.053***	0.053***
	(0.014)	(0.014)	(0.014)	(0.007)	(0.007)	(0.008)
$CASE_{it}$	0.000	0.000	0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	5.769	5.727	5.585	−10.529	−11.429	−10.494
	(6.688)	(6.690)	(6.685)	(13.023)	(13.052)	(13.041)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,160	32,160	32,160	14,704	14,704	14,704
R-squared	0.048	0.048	0.048	0.083	0.083	0.083

Robust standard errors in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

have found it challenging to focus on and contribute to OSS projects during this turbulent period (Neto et al., 2021; Ralph et al., 2020). On the other hand, the Xi'an lockdown occurred nearly two years after Wuhan's, following more than a dozen city-level lockdowns. By that time, the residents in Xi'an were much more familiar with the virus and the associated lockdown measures, and they did not experience the same level of fear as those in Wuhan. They have adapted more readily to the new lifestyles induced by lockdown measures, including the new norm of WFH. This adaptation, coupled with the opportunities offered by WFH, such as increased available time and flexibility, may have enabled Xi'an developers to increase their OSS contributions (Ford et al., 2021; Neto et al., 2021).

4.2. Results from the difference-in-difference-in-differences models

Columns (2) and (5) of Table 3 present the results of Eq. (2) for the Wuhan and Xi'an lockdowns, respectively. The significant and negative coefficient of $AFTER_t \times LOCKDOWN_i \times LOCCOMS_i$ in Column (2) suggests that Wuhan developers who engaged more in online comments with their local GitHub collaborators were more negatively affected by the Wuhan lockdown. As indicated by our survey results in Section 3.4.2, developers who made more online comments to their local collaborators were more likely to meet with each other F2F before the lockdown. Therefore, the above result indicates that Wuhan developers who were more likely to have F2F interactions before the lockdown experienced a more pronounced reduction in their OSS contributions. On the other hand, the significant and negative coefficient of $AFTER_t \times LOCKDOWN_i \times LOCCOMS_i$ in Column (5) suggests that the positive effect on OSS contributions was weaker for the Xi'an developers who engaged more in online comments with local collaborators before. These Xi'an developers were also more likely to have F2F interactions, reflecting a similar pattern to that observed in the Wuhan lockdown. These findings highlight the importance of F2F interactions in affecting OSS contributions, and the loss of these interactions during lockdowns has a significant impact on such contributions.

Columns (3) and (6) of Table 3 report the results of Eq. (3) for the Wuhan and Xi'an lockdowns, respectively. The coefficients of $AFTER_t \times LOCKDOWN_i \times COMS_i$ are insignificant at the 10 % level in both columns. As elaborated in Section 3.4.2, these results demonstrate that developers who were more socially engaged (i.e., those who made more online comments to all their GitHub collaborators) were not disproportionately affected by the lockdowns. This evidence refutes the alternative explanation that more socially active developers (such as those who made more online comments to their local collaborators) might become more concerned about the pandemic's negative impacts on others, leading to a decrease in their OSS contributions. Instead, these results of Eqs. (2) and (3) highlight that it is not the social nature of the developers but specifically the loss of F2F interactions during lockdowns that influences developers' OSS contributions.

In summary, the DID regression results suggest that the Wuhan lockdown led to a significant reduction in developers' OSS contributions, while the Xi'an lockdown resulted in an increase. Further analysis through the DDD regressions highlights the importance of F2F interactions in driving developers' OSS contributions on GitHub. The absence of these F2F interactions, brought about by lockdown measures, appears to negatively influence such contributions.

4.3. Robustness checks

4.3.1. Parallel trends

The key identification assumption for the DID estimation is the parallel trends assumption. This assumption posits that, before the lockdown, the OSS contributions of both the treatment group and the control group would follow the same temporal trend. If this assumption was not satisfied, the estimated effects could be biased, as the results could be driven by systematic differences between the treatment and control groups rather than the lockdown itself.

To ascertain the validity of our analysis, we conduct two sets of tests to examine whether our analysis satisfies this assumption. First, we plot the weekly average contributions (per developer) made by the treatment group (blue) and the control group (red) during the time window surrounding the Wuhan lockdown in Fig. 1(a) and the Xi'an lockdown in Fig. 1(b). To measure a developer's weekly contributions, we add one to the weekly number of commits she contributed to GitHub and then take the logarithm, consistent with the measure in our DID and DDD models. The green vertical line in each figure demarcates the day of lockdown. As Fig. 1(a) shows, the treatment and control groups exhibit almost identical contribution trends before the Wuhan lockdown, thereby fulfilling the parallel trends assumption. On the other hand, in the five weeks following the day of Wuhan lockdown, the contributions of the treatment group consistently fall below those of the control group, as evidenced by the substantial and persistent gap between the red and blue lines. Fig. 1(b) shows a similar pattern for the Xi'an lockdown, where both the treatment and control groups tend to contribute less over time before the lockdown, thus satisfying the parallel trends assumption. However, after the day of Xi'an lockdown, the control group continues the decreasing trend, while the treatment group exhibits a tendency to increase contributions.

Second, to further validate our findings, we adopt an event-study approach, a method commonly used in previous literature (Leslie and Wilson, 2020; Tanaka and Okamoto, 2021). This approach involves fitting the following equation:

$$CONTRIBUTION_{it} = \alpha + \sum_{k=-n, k\neq -1, k\neq 0}^{n} \beta_k (WEEK_{tk} \times LOCKDOWN_i) + \gamma CV_{it} + \mu_i + \theta_t + \epsilon_{it} \quad (4)$$

where n equals 5 for the Wuhan lockdown and equals 4 for the Xi'an lockdown. $WEEK_{tk}$ is a dummy variable that equals one if week t corresponds to k, and zero otherwise. We do not construct the week $k = 0$ in our sample but use the day of lockdown to separate the pre-treatment and post-treatment periods. $k = -1$ indicates the week just before the day of lockdown, so it is dropped from the equation as the reference week. Intuitively, β_k captures the difference in contributions between the treatment and control groups in each week relative to $k = -1$. We expect the two groups to make similar contributions before the day of lockdown ($k < 0$) and to diverge after the day of lockdown ($k > 0$).

Fig. 2(a) and Fig. 2(b) show the estimated β_k in Eq. (4) for the Wuhan and Xi'an lockdowns, separately. The green vertical line in each figure represents the day of lockdown, while the gray dotted lines surrounding each coefficient depict 95 % confidence intervals. In both figures, the estimated β_k ($k < 0$) are all nearly zero, indicating no pre-treatment difference in the contribution trends between the treatment and control groups. Such a pattern confirms that the parallel trends assumption is satisfied in our analysis.

4.3.2. A falsification test

To ensure that our estimated effects are not artifacts of seasonality, we conduct a falsification test to demonstrate that the effects are not replicated in a period without the lockdowns. This involves repeating the DID analysis for the same time window in previous years when COVID-19 had not yet emerged (Cui et al., 2022; Zhang and Zhu, 2011). For the Wuhan lockdown, we repeat the DID analysis using data a lunar year ago, as the time window encompasses the Chinese New Year holiday. For the Xi'an lockdown, we use data from two years earlier, considering that some developers might have experienced lockdowns a year ago, during a period when lockdowns had become more common in China. The control variable $CASE_{it}$ is excluded from this analysis since COVID-19 had not yet broken out during these earlier periods. This falsification test serves as a robustness check. If our original DID analysis was merely capturing seasonal effects, we would expect to find significant effects in these previous years as well. However, the absence of such effects would strengthen the validity of our main findings, confirming

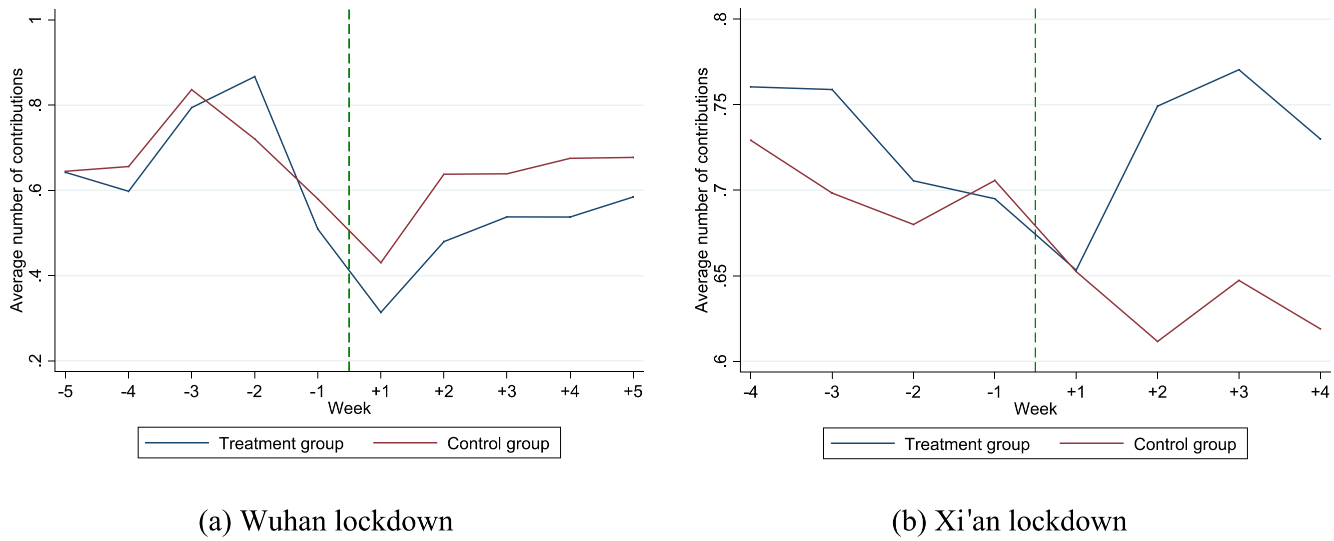

Fig. 1. Time trends of weekly average contributions on GitHub for Chinese lockdowns.

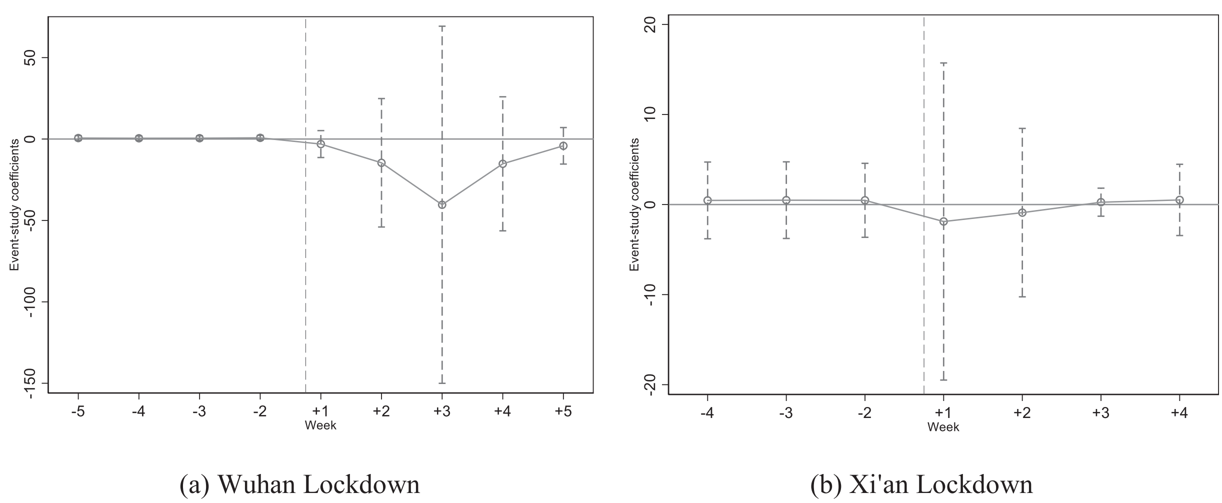

Fig. 2. Event-study estimation results for Chinese lockdowns.

that the observed changes in OSS contributions are indeed attributable to the lockdowns and not to underlying seasonal patterns.

Table 4 reports the results of the falsification test. The placebo-treated treatment effects are found to be insignificant for both Wuhan and Xi'an lockdowns. This implies that the developers in the treated groups did not significantly change their contributions during the same time window in previous years, thus ruling out the seasonal effects as a driving factor behind the observed changes in OSS contributions.

4.3.3. *Alternative samples*

We also replicate the DID and DDD analyses using two alternative matched samples to ensure that our results are not driven by the specific choice of the caliper in propensity score matching. In the main analysis, we used a caliper of 0.3 for the Wuhan lockdown to ensure no statistical difference in developer characteristics between the treatment and control groups (Chen et al., 2019; Wang, 2022). The caliper defines the range within which the (logit of) propensity scores must fall to be considered a valid match (Cochran and Rubin, 1973). While a narrower caliper can result in the inclusion of fewer subjects, it can also enhance the balance between the treatment and control groups, thereby reducing bias in estimating treatment effects (Wang, 2022; Wang et al., 2013). To further validate our findings, following Wang (2022), we employed alternative calipers of 0.1 for the Wuhan lockdown and 0.001 for the Xi'an lockdown. The new PSM with these calipers yielded a matched sample of 1557 developers for the Wuhan lockdown and a matched sample of 906 developers for the Xi'an lockdown, in both the treatment and control groups. Table 5 presents the *t*-test results after matching with the new calipers. Importantly, for both lockdowns, none of the differences between the treatment and control groups were found to be significant at the 10 % level, indicating the two groups remained comparable for the DID analysis after matching, even with the alternative calipers.

Table 6 shows the regression results of Eqs. (1)–(3) based on the alternative matched samples. The coefficients of $AFTER_t \times LOCKDOWN_i$, $AFTER_t \times LOCKDOWN_i \times LOCCOMS_i$, and $AFTER_t \times LOCKDOWN_i \times COMS_i$ are found to be consistent with those in the main analyses for both Wuhan and Xi'an lockdowns, suggesting that our results are not driven by the choice of the caliper in the PSM process.

4.3.4. *A survey study*

We further complement our empirical analyses with a survey study, conducted to delve into the underlying mechanisms and influencing factors behind the changes in developers' OSS contributions before and after the lockdowns. This survey targeted the treated developers in our

Table 4
Falsification test results for Chinese lockdowns.

	Dependent variable: $CONTRIBUTION_{it}$	
	Wuhan lockdown (1)	Xi'an lockdown (2)
$AFTER_t \times LOCKDOWN_i$	0.018	−0.024
	(0.019)	(0.024)
$REPO_{it}$	0.128***	0.296***
	(0.028)	(0.031)
$TENURE_{it}$	0.010	0.030
	(0.026)	(0.036)
$STARR_{it}$	0.001	−0.000
	(0.001)	(0.000)
$STARS_{it}$	0.045***	0.030***
	(0.007)	(0.005)
$ISSUER_{it}$	−0.002	0.045
	(0.038)	(0.050)
$ISSUES_{it}$	0.078**	0.095**
	(0.040)	(0.045)
$COMMENTR_{it}$	0.006	−0.010
	(0.013)	(0.014)
$COMMENTS_{it}$	0.079***	0.078***
	(0.016)	(0.015)
Constant	−0.928	−4.253
	(3.143)	(5.374)
Individual FE	Yes	Yes
Time FE	Yes	Yes
Observations	32,160	14,704
R-squared	0.151	0.083

Robust standard errors in brackets.
*$p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

matched sample who had provided their email addresses on GitHub, encompassing 879 Wuhan developers and 463 Xi'an developers. To encourage participation, we offered an incentive of 20 Chinese Yuan to each respondent who successfully completed the questionnaire. The questionnaire, detailed in Appendix A, was designed with questions answered on a five-point Likert scale. Eventually, we received 109 responses from the Wuhan developers and 71 responses from the Xi'an developers.

Another objective of our survey study was to justify an important assumption underlying our DDD analysis: developers who engaged in more online comments with their local collaborators on GitHub were also more likely to meet F2F. To examine this relationship, we surveyed the treated developers about their tendencies in both online commenting and F2F interactions with their local collaborators. We then conduct a correlation test on these tendencies for both the Wuhan and Xi'an developers, the results of which are detailed in Table A1 in Appendix A. The findings reveal significant and positive correlation coefficients between the tendencies for online commenting and F2F interactions. This supports the assumption of our DDD analysis, reinforcing the validity of our empirical approach and the conclusions drawn from it.

Table 7 shows the results of a linear regression analysis that explores various surveyed factors to explain the changes in OSS contributions during the two Chinese lockdowns. The dependent variable represents the change in contributions, calculated as the difference between a respondent's total contributions on GitHub during the post-treatment period and her total contributions during the pre-treatment period. The independent variables consist of the respondents' ratings for each of the surveyed factors, as detailed in Questions 2–6 in the questionnaire provided in Appendix A. These factors were carefully selected for inclusion in the questionnaire based on previous research findings related to work productivity during COVID-19-induced WFH scenarios (Bao et al., 2022; Ford et al., 2021; Miller et al., 2021; Neto et al., 2021; Walters et al., 2022).

Table 5
T-tests in the alternative matched sample for Chinese lockdowns.

	Wuhan lockdown			Xi'an lockdown		
	Mean		*T*-test	Mean		*T*-test
	Treatment group	Control group	Difference	Treatment group	Control group	Difference
Weeks	177.281	177.547	−0.266	257.616	258.481	−0.865
Student	0.277	0.290	−0.013	0.277	0.281	−0.004
Employee	0.244	0.247	−0.003	0.286	0.278	0.008
Contact	0.705	0.713	−0.008	0.702	0.721	−0.019
Number of projects	21.423	21.780	−0.357	27.156	25.883	1.273
Commits	663.480	499.008	164.473	1710.940	1299.883	411.057
Stars received	64.570	90.427	−25.857	140.910	126.865	14.044
Issues received	5.550	5.620	−0.071	11.545	9.189	2.357
Comments received	10.196	11.230	−1.034	29.975	27.722	2.253
Stars sent out	94.332	94.636	−0.304	119.413	110.372	9.041
Issues sent out	6.821	7.455	−0.634	12.710	10.969	1.741
Comments sent out	16.331	19.586	−3.255	46.818	40.392	6.426
C	0.043	0.041	0.002	0.040	0.044	−0.004
C++	0.086	0.083	0.003	0.073	0.086	−0.013
C#	0.021	0.022	−0.001	0.028	0.032	−0.004
Go	0.027	0.028	−0.001	0.064	0.070	−0.006
Java	0.153	0.170	−0.017	0.180	0.174	0.006
JavaScript	0.209	0.215	−0.006	0.184	0.180	0.004
PHP	0.021	0.021	0.001	0.021	0.020	0.001
Python	0.182	0.168	0.014	0.183	0.179	0.004
Ruby	0.004	0.004	0.000	0.004	0.003	0.001
Scala	0.002	0.001	0.001	0.001	0.000	0.001
TypeScript	0.008	0.006	0.002	0.017	0.020	−0.003
Collaborators	184.192	167.135	17.057	561.135	527.577	33.557
Local collaborators	0.789	0.830	−0.041	1.254	1.092	0.162
Average age of projects	65.386	65.249	0.137	100.184	98.570	1.615
Number of projects with GPL	1.002	1.140	−0.138	1.267	1.329	−0.062

*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

Table 6
Regression results for the alternative sample for Chinese lockdowns.

	Dependent variable: $CONTRIBUTION_{it}$					
	Wuhan lockdown			Xi'an lockdown		
	(1)	(2)	(3)	(4)	(5)	(6)
$AFTER_t \times LOCKDOWN_i$	−0.106***	−0.103***	−0.101***	0.089**	0.092**	0.090**
	(0.030)	(0.030)	(0.030)	(0.043)	(0.044)	(0.043)
$AFTER_t \times LOCCOMS_i$		0.003***			0.001**	
		(0.001)			(0.000)	
$AFTER_t \times LOCKDOWN_i \times LOCCOMS_i$		−0.007***			−0.003***	
		(0.003)			(0.001)	
$AFTER_t \times COMS_i$			0.000			−0.000**
			(0.000)			(0.000)
$AFTER_t \times LOCKDOWN_i \times COMS_i$			−0.000			0.000
			(0.000)			(0.000)
$REPO_{it}$	0.024	0.024	0.024	0.371***	0.371***	0.371***
	(0.021)	(0.021)	(0.021)	(0.028)	(0.028)	(0.028)
$TENURE_{it}$	−0.038	−0.038	−0.038	0.046	0.050	0.047
	(0.040)	(0.040)	(0.040)	(0.051)	(0.051)	(0.051)
$STARR_{it}$	0.014**	0.014**	0.014**	0.003	0.003	0.003
	(0.007)	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)
$STARS_{it}$	0.015**	0.015**	0.015**	0.027***	0.027***	0.027***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
$ISSUER_{it}$	−0.036	−0.036	−0.037	0.010	0.010	0.012
	(0.027)	(0.027)	(0.027)	(0.039)	(0.039)	(0.039)
$ISSUES_{it}$	0.088***	0.087***	0.089***	0.065*	0.064*	0.063*
	(0.031)	(0.031)	(0.031)	(0.036)	(0.035)	(0.036)
$COMMENTR_{it}$	0.023	0.023	0.023	0.012	0.012	0.012
	(0.015)	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)
$COMMENTS_{it}$	0.047***	0.047***	0.047***	0.052***	0.052***	0.050***
	(0.016)	(0.016)	(0.016)	(0.008)	(0.008)	(0.009)
$CASE_{it}$	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	7.166	7.125	7.101	−11.153	−12.068	−11.456
	(6.877)	(6.879)	(6.874)	(13.010)	(13.038)	(13.058)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,140	31,140	31,140	14,496	14,496	14,496
R-squared	0.048	0.048	0.048	0.082	0.082	0.084

Robust standard errors in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Columns (1) and (2) of Table 7 present the regression results based on the responses from the Wuhan and Xi'an developers, respectively. These results reveal that fear related to the COVID-19 pandemic and housework burden, which significantly curtailed OSS contributions during Wuhan's initial lockdown, no longer impacted Xi'an developers in 2021. On the other hand, the availability of uninterrupted time and increased flexibility positively influenced Xi'an developers' OSS contributions, a pattern not observed among their Wuhan counterparts in 2020. These findings, taken together with our DID and DDD regression results, highlight an adaptation effect of Xi'an developers.

More specifically, we posit that the Xi'an lockdown, occurring nearly two years after the Wuhan's and following numerous city-level lockdowns, allowed developers to adapt to the new norm of remote work. This adaptation allowed Xi'an developers to leverage the flexibility and opportunities provided by WFH, resulting in increased OSS contributions. In contrast, Wuhan developers, facing the novel threat of COVID-19, were impeded by fear and possibly lacked the capacity to engage in voluntary activities like OSS contributions. Moreover, the results show consistent patterns for both Wuhan and Xi'an developers, where the lack of F2F interactions significantly reduced their OSS contributions, while increased available time at home positively influenced them. These findings offer valuable insights into our understanding of how individuals adapt to unprecedented disruptions, providing valuable guidance for stakeholders in preparing for future challenges and fostering resilience.

5. Results for the US lockdowns

In the preceding sections, we have conducted a comprehensive examination of the impacts of lockdowns on OSS contributions within the context of China. To broaden our understanding and assess the applicability of our findings beyond China, this section introduces the results of an additional empirical analysis, focusing on the lockdowns in the US. As explained in Section 1, the rationale for focusing on the US stems from its prominent role in the global OSS development community, as well as its unique circumstances surrounding the implementation of lockdown measures (i.e., stay-at-home orders) during the COVID-19 pandemic. By comparing the observed effects in China with those in the US, we seek to determine whether similar patterns emerge across different regions. This comparative analysis not only enhances the robustness of our findings but also contributes valuable insights into the broader implications of lockdown measures on the OSS development community worldwide.

During the early stages of the virus' spread, between March and April of 2020, a total of 45 states and the District of Columbia in the US implemented either statewide or partial-state stay-at-home orders. These orders restricted residents from leaving their homes except for essential activities, such as obtaining food and performing essential work functions. In contrast, the remaining 5 states in the US questioned the necessity of such strict lockdown measures and refrained from issuing stay-at-home orders (Wu et al., 2020). One primary rationale behind this resistance was the belief that the residents would continue to

Table 7
What explains the changes in OSS contributions during Chinese lockdowns?

	Dependent variable: *change in contributions*	
	Wuhan developers (1)	Xi'an developers (2)
Available time	0.202**	0.725***
	(0.092)	(0.216)
Interruptions	−0.123	−0.389**
	(0.083)	(0.159)
Flexibility	0.029	0.409**
	(0.066)	(0.189)
Work environment	0.158*	0.129
	(0.094)	(0.186)
Fear	−0.987***	−0.304
	(0.072)	(0.264)
Lack of F2F interactions	−0.288***	−0.190**
	(0.068)	(0.089)
Lack of work-life boundary	−0.148	−0.172
	(0.138)	(0.190)
Lack of self-discipline	−0.013	−0.180
	(0.066)	(0.198)
Taking care of family	−0.034	−0.105
	(0.069)	(0.190)
Housework	−0.144***	−0.160
	(0.523)	(0.179)
Constant	3.921***	−0.344
	(0.523)	(1.751)
Observations	109	71
R-squared	0.850	0.614

Robust standard errors in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

leave their homes for shopping or work, rendering the stay-at-home orders ineffective (Wang, 2022).

In alignment with the methodology outlined in Wang (2022), our study design constructs a control group consisting of OSS developers in all the states that refrained from implementing any stay-at-home orders. To form a treatment group, we follow the approach employed in earlier studies (Muralidharan and Prakash, 2017; Wang, 2022), selecting developers in states that both implemented statewide stay-at-home orders and are geographically adjacent to the control states. This selection criterion is based on the assumption that neighboring states are more likely to share similarities with the control group in both observable and unobservable characteristics. To refine our selection, we first extract developers who had at least one public repository and were exclusively located in one state within the US. We then further narrow down the treatment group by including only developers in states with fewer than ten thousand GitHub developers, ensuring consistency with the control group, where all states meet this criterion. The resulting control group consists of developers in five states – Arkansas, Iowa, Nebraska, North Dakota, and South Dakota. The treatment group includes developers in six neighboring states – Louisiana, Mississippi, Missouri, Montana, Tennessee, and Wisconsin. Table 8 provides a detailed summary of the start and end dates of the stay-at-home orders in these states, as obtained from the official announcements of each respective state. This process enhances the comparability between the treatment and control groups, thereby strengthening the validity of our analysis.

Table 8
Status of stay-at-home orders by state.

State	Acronym	Order start date	Order end date
Control group			
Arkansas	AR	No statewide order	
Iowa	IA	No statewide order	
Nebraska	NE	No statewide order	
North Dakota	ND	No statewide order	
South Dakota	SD	No statewide order	
Treatment group			
Louisiana	LA	March 23, 2020	May 15, 2020
Mississippi	MS	April 3, 2020	May 11, 2020
Missouri	MO	April 6, 2020	May 3, 2020
Montana	MT	March 28, 2020	April 26, 2020
Tennessee	TN	March 31, 2020	April 30, 2020
Wisconsin	WI	March 25, 2020	May 26, 2020

Following the approach delineated by Wang (2022), we focus on the time window spanning from March 9, 2020, to April 20, 2020. This timeframe ensures that all developers in the treatment group have at least two weeks of data before and after the implementation of the stay-at-home orders. Consistent with Section 3.2, we include only those developers who joined GitHub before the chosen time window and pushed at least one commit during that period. Through this selection process, we arrive at a final data sample comprising 2583 treated developers and 4487 control developers.

Like our analysis of Chinese lockdowns, we employ DID combined with PSM on the final data sample of US lockdowns. First, we apply a one-on-one nearest neighbor matching without replacement, selecting a control developer for each treated developer. This matching is based on the same set of covariates used in the analysis of Chinese lockdowns, ensuring methodological consistency. Through this procedure, we obtain 2583 matched pairs of both the treatment and control groups. Table 9 summarizes the mean values of the pre-treatment characteristics for the treatment and control groups before and after matching. The *t*-test results confirm that there are no significant differences across these characteristics between the treatment and control groups after matching. This successful matching enhances the validity of our subsequent analysis by ensuring that the treatment and control groups are comparable in terms of observable characteristics, thereby minimizing potential biases.

We then estimate the impact of stay-at-home orders on OSS contributions using the matched sample, employing a time-varying DID model:

$$CONTRIBUTION_{it} = \alpha + \beta ORDER_{it} + \gamma CV_{it} + \mu_i + \theta_t + \epsilon_{it} \tag{5}$$

We also estimate the moderating effects of comment interactions with local collaborators and all collaborators using two separate models:

$$\begin{aligned} CONTRIBUTION_{it} = & \alpha + \beta_1 ORDER_{it} + \beta_2 ORDER_{it} \times LOCCOMS_i + \gamma CV_{it} \\ & + \mu_i + \theta_t + \epsilon_{it} \end{aligned} \tag{6}$$

$$\begin{aligned} CONTRIBUTION_{it} = & \alpha + \beta_1 ORDER_{it} + \beta_2 ORDER_{it} \times COMS_i + \gamma CV_{it} + \mu_i \\ & + \theta_t + \epsilon_{it} \end{aligned} \tag{7}$$

where *i* indexes the developer and *t* indexes the date. $ORDER_{it}$ is a binary variable that equals one if the state where developer *i* is located implemented a stay-at-home order on date *t* or earlier, and zero otherwise. The definitions of the remaining variables are consistent with those in Eqs. (1)–(3).

Table 10 reports the results from the estimation of Eqs. (5)–(7). These results adhere to the parallel trends assumption and remain robust when considering an alternative matched sample (please see the detailed robustness tests described in Appendix B). The coefficient of $ORDER_{it}$ is insignificant across all specifications, indicating that stay-at-home orders in the US did not have a significant impact on developers' OSS contributions. The insignificance of both moderating effects further corroborates this finding. These findings contrast with the impacts observed during the Wuhan and Xi'an lockdowns, suggesting that the effects identified in the Chinese context may not be generalized to the less strict lockdowns implemented in the US.

The contract between the findings in China and the US may be attributed to the underlying differences in the stringency and enforcement of lockdown measures between these two significant nations. In China, the lockdowns were characterized by strict restrictions that

Table 9
T-tests in the overall and matched samples for the US lockdowns.

	Before matching			After matching		
	Mean		*T*-test	Mean		*T*-test
	Treatment group	Control group	Difference	Treatment group	Control group	Difference
Weeks	237.195	251.904	−14.710***	237.195	232.121	5.074
Student	0.177	0.160	0.016	0.177	0.184	−0.008
Employee	0.391	0.407	−0.016	0.391	0.389	0.001
Contact	1.000	1.000	0.000	1.000	1.000	0.000
Number of projects	18.946	19.269	−0.323	18.946	18.906	0.039
Commits	2072.852	2039.565	33.286	2072.852	1813.961	258.891
Stars received	48.550	71.115	−22.565	48.550	39.534	9.016
Issues received	14.561	15.009	−0.448	14.561	11.596	2.965
Comments received	44.084	47.101	−3.017	44.084	32.748	11.336
Stars sent out	53.217	53.018	0.199	53.217	49.277	3.940
Issues sent out	25.280	26.767	−1.487	25.280	23.936	1.345
Comments sent out	138.069	163.793	−25.723	138.069	137.564	0.506
C	0.019	0.025	−0.006	0.019	0.021	−0.001
C++	0.033	0.043	−0.011**	0.033	0.034	−0.001
C#	0.055	0.047	0.008	0.055	0.055	0.000
Go	0.011	0.017	−0.006*	0.011	0.009	0.002
Java	0.101	0.115	−0.014*	0.101	0.102	−0.001
JavaScript	0.211	0.188	0.023**	0.211	0.216	−0.006
PHP	0.039	0.051	−0.012**	0.039	0.037	0.003
Python	0.123	0.133	−0.011	0.123	0.123	−0.000
Ruby	0.025	0.025	−0.000	0.025	0.027	−0.002
Scala	0.002	0.004	−0.002	0.002	0.002	0.000
TypeScript	0.018	0.020	−0.001	0.018	0.015	0.003
Collaborators	1225.186	1203.774	21.412	1225.186	1114.715	110.471
Local collaborators	1.377	2.207	−0.830***	1.377	1.377	−0.000
Average age of projects	89.021	95.269	−6.249***	89.021	87.204	1.817
Number of projects with GPL	1.081	1.181	−0.100	1.081	1.122	−0.040

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

required residents not to leave home except for emergencies. These restrictions were often rigorously enforced and severely limited developers' opportunities for F2F interactions. On the other hand, the stay-at-home orders in the US were less strict, allowing residents to leave their homes for a broader range of activities such as shopping or work. This relatively lenient approach may have allowed US developers to adapt more easily to the new circumstances, leaving an insignificant impact on their work and lifestyles. Consequently, this may mitigate the negative impacts of the lockdown measures on their OSS contributions. Moreover, the less strict nature of the US orders may not have provided more available time at home for OSS contributions, as developers could still engage in many of their usual activities outside the home.

6. Conclusion

The lockdowns induced by the COVID-19 pandemic have catalyzed a global shift towards WFH, demonstrating its feasibility on an unprecedented scale. While previous research has explored the broader implications of remote work, the nuanced dynamics between F2F and CMC in the context of work productivity remains an intricate and underexplored area. This complexity is particularly salient within technology-driven domains such as OSS development. Our study first leverages two lockdowns in China – Wuhan 2020 and Xi'an 2021 – as natural experiments to study their causal impacts on developers' OSS contributions on GitHub. To improve the generalizability and relevance of our findings from Chinese lockdowns, we also further extend our analysis to encompass the impacts of stay-at-home orders implemented across different states of the US during the early stage of the pandemic.

Our findings present a nuanced picture of the impact of lockdowns on developers' OSS contributions. We discovered that the Xi'an lockdown in 2021 corresponded to a 9.0 % increase in OSS contributions, while the Wuhan lockdown in 2020 saw a 10.5 % reduction. This apparent contradiction is illuminated by our subsequent survey study, which reveals that the differing impacts can be mainly attributed to an adaptation effect related to the COVID-19 pandemic. More specifically, as the Xi'an lockdown occurred nearly two years after Wuhan's, during which numerous city-level lockdowns had been implemented in China. This allowed developers to adapt to the new norm of WFH, optimizing the flexibility and opportunities provided by WFH to increase their OSS contributions. In stark contrast, the Wuhan lockdown, occurring at the onset of this pandemic when the virus was new, severe, and spreading rapidly, created a climate of fear and uncertainty. This atmosphere compounded by factors such as increased housework responsibilities, significantly impeded Wuhan developers' ability to focus on OSS contributions. However, these once influential factors became insignificant during the 2021 Xi'an lockdown, highlighting the adaptability and resilience of individuals in the context of remote work during large-scale disruptions. Moreover, we found consistent patterns across both Wuhan and Xi'an developers, where the lack of F2F interactions significantly reduced their OSS contributions, while increased available time at home positively influenced them. In addition to our study on China, we employed DID analysis to assess the generalizability of our findings by examining the impact of stay-at-home lockdown orders in the US on developers' OSS contributions. Interestingly, we found no significant impact of US lockdowns on these contributions. We posit that this may be due to the less strict nature of stay-at-home orders in the US, which may not have significantly disrupted developers' work and lifestyle, thereby exerting minimal effects on their OSS contributions.

Our contributions are threefold. First, our findings contribute valuable insights into the effects of remote work on productivity, exploring how individuals adapt to remote work norms during prolonged disruptions such as the pandemic. These insights offer stakeholders, including individuals, organizations, and governments, the knowledge needed to prepare for future disruptions and foster sustainable resilience. Second, our findings shed light on the negative impact of reduced F2F interactions, thereby challenging the assumption that CMC can seamlessly

Table 10
Regression results for the US lockdowns.

	Dependent variable: *CONTRIBUTION$_{it}$*		
	(1)	(2)	(3)
ORDER$_{it}$	0.000	−0.000	0.000
	(0.007)	(0.007)	(0.007)
ORDER$_{it}$ × LOCCOMS$_i$		0.001	
		(0.001)	
ORDER$_{it}$ × COMS$_i$			−0.000
			(0.000)
REPO$_{it}$	0.221*	0.221*	0.221*
	(0.120)	(0.120)	(0.120)
TENURE$_{it}$	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)
STARR$_{it}$	0.012*	0.012*	0.012*
	(0.007)	(0.007)	(0.007)
STARS$_{it}$	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)
ISSUER$_{it}$	0.012	0.012	0.012
	(0.029)	(0.029)	(0.029)
ISSUES$_{it}$	0.090***	0.090***	0.090***
	(0.028)	(0.028)	(0.028)
COMMENTR$_{it}$	0.036***	0.036***	0.036***
	(0.009)	(0.009)	(0.009)
COMMENTS$_{it}$	0.076***	0.076***	0.076***
	(0.017)	(0.017)	(0.017)
CASE$_{it}$	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Constant	−0.580	−0.580	−0.580
	(0.448)	(0.448)	(0.448)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	222,138	222,138	222,138
R-squared	0.049	0.049	0.049

Robust standard errors in brackets.
** $p < 0.05$.
* $p < 0.1$.
*** $p < 0.01$.

substitute for F2F interactions without any detrimental effects on productivity. This is especially pertinent in inherently digital domains such as OSS development. Our study adds a nuanced perspective to the broader discourse on the comparative impacts of CMC vs. F2F interactions on virtual team performance. This contribution is particularly important in today's environment, where the reliance on CMC due to the shift towards WFH has not only intensified but continues to shape the way we work and collaborate, even beyond the pandemic era (Airbnb, 2022; Warren, 2020). Third, unlike previous research that mainly relied on survey methods to investigate the impacts of lockdowns, our study embraced systematic causal analysis methods such as DID analysis. Using empirical data from GitHub, this rigorous approach, reinforced with various robustness tests and complemented by a survey study, established a multifaceted research framework. It opens new avenues for exploring the impact of policy interventions or organizational strategies in response to similar disruptions, thereby extending the applicability and relevance of our findings.

Moreover, our findings may help open-innovation platforms and organizations that depend on collaborative contributions formulate WFH-related strategies or policies (Airbnb, 2022; Warren, 2020). First, these stakeholders may need to recognize that individuals' adaptation to WFH can vary significantly over time and across different contexts, and strategies must be tailored accordingly. For instance, many contextual factors analyzed in our survey should be accounted for, such as changes in work time, interruptions, flexibility, remote work technology conditions, and housework duties. Second, the absence of F2F interactions, a vital component of collaboration, requires the exploration of alternative methods to compensate for this drawback. For instance, platforms could invest in advanced collaboration tools designed to replicate or even enhance the interaction experience in a virtual environment, such as facial recognition systems that can identify and emphasize micro-expression or emotional cues. Third, the positive impact of increased home time highlights the importance of flexible work policies. These policies should enable individuals to capitalize on the benefits of remote work without sacrificing productivity. At last, the initial negative impact of fear suggests that emotional support and well-being should be essential to remote work-related policies or strategies, especially during unprecedented disruptions like the COVID-19 pandemic.

Some limitations of our study generate directions and opportunities for future research. For instance, although it is reassuring that our study leverages two citywide lockdowns in China and statewide stay-at-home orders in the US, the contrasting findings between them highlight the complexity of remote work and suggest a need for further research to further understand the generalizability of our findings across different cultures, industries, and types of work. Second, our study focuses on OSS contributions measured by the number of commits. Future research needs to consider other measures of innovation-related work productivity such as code quality or creativity.

CRediT authorship contribution statement

Jin Hu: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing - original draft, Writing - review & editing. **Daning Hu:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition, Writing - original draft, Writing - review & editing. **Xuan Yang:** Investigation, Funding acquisition, Writing - review & editing. **Michael Chau:** Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

The authors gratefully acknowledge funding from Guangdong Province Focus Research Project (Grant Number: 2019KZDZX1014), Guangdong Province Research Fund (Grant Number: 2019QN01X277), National Natural Science Foundation of China (Grant Numbers: 71971106, 72001099), and Shenzhen Humanities & Social Sciences Key Research Bases.

Appendix A. Questionnaires for the survey analysis

The questionnaire for the Wuhan developers includes the following six questions.

1. Please indicate your choice on the following statements based on your experience *before January 23, 2020* (i.e., the day of Wuhan lockdown). (1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree).

1.1 (*OnlineFrequency*) I often made online comments to GitHub developers in the same city with me (hereinafter referred to as local collaborators) on GitHub.	__
1.2 (*OnlinePreference*) I enjoyed making online comments to my local collaborators on GitHub.	__
1.3 (*OnlineNeed*) My project tasks required me to make online comments to my local collaborators on GitHub.	__
1.4 (*OfflineFrequency*) I often interacted with my local collaborators offline.	__
1.5 (*OfflinePreference*) I enjoyed interacting with my local collaborators offline.	__
1.6 (*OfflineNeed*) My project tasks required me to interact with my local collaborators offline.	__

Please answer Questions 2–5 based on your lockdown experience *during the five weeks after January 23, 2020,* compared to the five weeks before that day.

2. Did the lockdown give you more time available for making OSS contributions on GitHub?

Gave me much less time	1
Gave me less time	2
Neutral: same as before lockdown	3
Gave me more time	4
Gave me much more time	5

3. Did you have more interruptions when making OSS contributions on GitHub?

Much fewer interruptions	1
Fewer interruptions	2
Neutral: same as before lockdown	3
More interruptions	4
Much more interruptions	5

4. Did you have more flexibility for making OSS contributions on GitHub?

Much less flexible	1
Less flexible	2
Neutral: same as before lockdown	3
More flexible	4
Much more flexible	5

5. How was your work environment (e.g., internet bandwidth and hardware) at home for making OSS contributions on GitHub?

Much worse work environment	1
Worse work environment	2
Neutral: same as before lockdown	3
Better work environment	4
Much better work environment	5

6. How would you rate each of the following factors in their respective impacts on your contributions to GitHub *during the five weeks after January 23, 2020,* compared to the five weeks before that day? (1 = Very low impact, 2 = Low impact, 3 = Neutral, 4 = High impact, 5 = Very high impact).

6.1 Fear related to the COVID-19 pandemic	__
6.2 Lack of face-to-face interactions with my collaborators	__
6.3 Lack of work-life boundary	__
6.4 Lack of self-discipline	__
6.5 Taking care of my family	__
6.6 Doing housework	__

The questionnaire for the Xi'an developers is the same as that for the Wuhan developers except for the following changes:

1. … *before December 23, 2021* (i.e., the day of Xi'an lockdown). …

Please answer Questions 2–5 based on your lockdown experience *during the four weeks after December 23, 2021,* compared to the four weeks before that day. …

6. … *during the four weeks after December 23, 2021,* compared to the four weeks before that day. …

Table A1
Correlation test results for the first survey question.

Correlation between	Wuhan developers (1)	Xi'an developers (2)
OnlineFrequency & OfflineFrequency	0.305***	0.253**
OnlinePreference & OfflinePreference	0.423***	0.283**
OnlineNeed & OfflineNeed	0.442***	0.540***

*p < 0.1.
** p < 0.05.
*** p < 0.01.

Appendix B. Robustness checks for the US lockdowns

To test the parallel trends assumption for the US lockdowns, we adopt an event-study approach by fitting the following equation:

$$CONTRIBUTION_{it} = \alpha + \sum\nolimits_{k=-n,k\neq-1}^{n}\beta_k T_{itk} + \gamma CV_{it} + \mu_i + \theta_t + \epsilon_{it} \tag{B1}$$

where n equals 28. T_{itk} represents a series of dummies that indicate the chronological distance between the observation and the actual date when the state where developer i resides implemented stay-at-home orders. $k = -1$ designates the date immediately preceding the treatment, and thus it is omitted from the equation, serving as the reference date.

Fig. B1 shows the estimated coefficients β_k from Eq. (B1). The green vertical line represents the day when the stay-at-home order was enacted. The accompanying gray dotted lines delineate the 95 % confidence intervals for each coefficient. Notably, the estimated β_k values for $k < 0$ are virtually zero, indicating that there is no significant pre-treatment difference in the contribution trends between the treatment and control groups. Therefore, our DID analysis satisfies the parallel trends assumption, reinforcing the validity of our DID analysis for the US lockdowns.

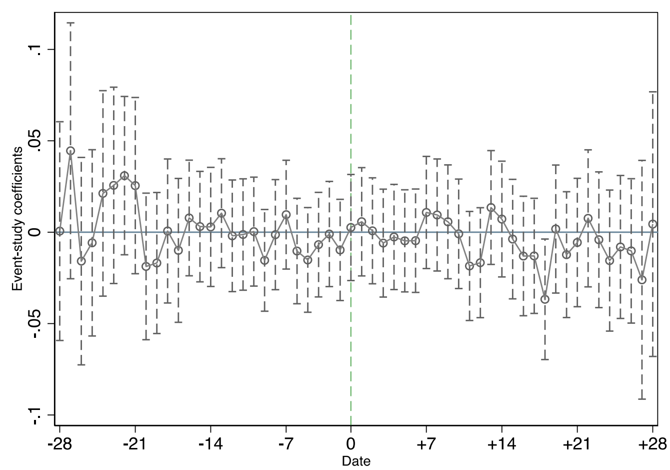

Fig. B1. Event-study estimation results for the US lockdowns.

We also perform another robustness check by re-estimating Eqs. (5)–(7) using an alternative matched sample. This is achieved by incorporating a caliper of 0.1 in the PSM procedure, resulting in a matched sample that includes 2568 pairs of developers across both the treatment and control groups. The summary of t-test results, presented in Table B1, reveals no statistically significant differences between the treatment and control groups at the 10 % significance level. This outcome substantiates the comparability of the two groups following the matching process. Table B2 summarizes the results of Eqs. (5)–(7) derived from the alternative matched sample. The coefficients of $ORDER_{it}$, $ORDER_{it} \times LOCCOMS_i$, and $ORDER_{it} \times COMS_i$ are all found to be statistically insignificant. This outcome implies that the implementation of stay-at-home orders in the US does not have a significant influence on developers' OSS contributions.

Table B1
T-tests in the overall and alternative matched samples for the US lockdowns.

	Before matching			After matching		
	Mean		*T*-test	Mean		*T*-test
	Treatment group	Control group	Difference	Treatment group	Control group	Difference
Weeks	237.195	251.904	−14.710***	236.515	232.990	3.525
Student	0.177	0.160	0.016	0.177	0.181	−0.004
Employee	0.391	0.407	−0.016	0.390	0.391	−0.002
Contact	1.000	1.000	0.000	1.000	1.000	0.000
Number of projects	18.946	19.269	−0.323	18.651	18.921	−0.270
Commits	2072.852	2039.565	33.286	2058.688	1822.745	235.943
Stars received	48.550	71.115	−22.565	48.081	39.739	8.342
Issues received	14.561	15.009	−0.448	13.848	11.662	2.186

(*continued on next page*)

Table B1 (*continued*)

	Before matching			After matching		
	Mean		*T*-test	Mean		*T*-test
	Treatment group	Control group	Difference	Treatment group	Control group	Difference
Comments received	44.084	47.101	−3.017	42.707	32.934	9.773
Stars sent out	53.217	53.018	0.199	45.862	49.546	−3.684
Issues sent out	25.280	26.767	−1.487	23.762	24.065	−0.303
Comments sent out	138.069	163.793	−25.723	133.803	138.307	−4.504
C	0.019	0.025	−0.006	0.019	0.021	−0.001
C++	0.033	0.043	−0.011**	0.033	0.034	−0.001
C#	0.055	0.047	0.008	0.055	0.055	0.001
Go	0.011	0.017	−0.006*	0.011	0.009	0.002
Java	0.101	0.115	−0.014*	0.102	0.103	−0.001
JavaScript	0.211	0.188	0.023**	0.208	0.217	−0.009
PHP	0.039	0.051	−0.012**	0.040	0.037	0.003
Python	0.123	0.133	−0.011	0.123	0.124	−0.001
Ruby	0.025	0.025	−0.000	0.025	0.027	−0.002
Scala	0.002	0.004	−0.002	0.002	0.002	0.000
TypeScript	0.018	0.020	−0.001	0.018	0.015	0.003
collaborators	1225.186	1203.774	21.412	1074.696	1118.728	−44.032
Local collaborators	1.377	2.207	−0.830***	1.354	1.384	−0.030
Average age of projects	89.021	95.269	−6.249***	88.861	87.490	1.370
Number of projects with GPL	1.081	1.181	−0.100	1.075	1.127	−0.052

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table B2
Regression results for alternative sample for the US lockdowns.

	Dependent variable: $CONTRIBUTION_{it}$		
	(1)	(2)	(3)
$ORDER_{it}$	0.000	0.000	0.000
	(0.007)	(0.007)	(0.007)
$ORDER_{it} \times LOCCOMS_i$		0.001	
		(0.001)	
$ORDER_{it} \times COMS_i$			0.000
			(0.000)
$REPO_{it}$	0.225*	0.225*	0.225*
	(0.120)	(0.120)	(0.120)
$TENURE_{it}$	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)
$STARR_{it}$	0.012*	0.012*	0.012*
	(0.007)	(0.007)	(0.007)
$STARS_{it}$	−0.006**	−0.006**	−0.006**
	(0.003)	(0.003)	(0.003)
$ISSUER_{it}$	0.012	0.012	0.012
	(0.029)	(0.029)	(0.029)
$ISSUES_{it}$	0.089***	0.089***	0.089***
	(0.028)	(0.028)	(0.028)
$COMMENTR_{it}$	0.036***	0.036***	0.036***
	(0.009)	(0.009)	(0.009)
$COMMENTS_{it}$	0.075***	0.075***	0.075***
	(0.017)	(0.017)	(0.017)
$CASE_{it}$	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Constant	−0.593	−0.592	−0.593
	(0.451)	(0.451)	(0.451)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	220,848	220,848	220,848
R-squared	0.049	0.049	0.049

Robust standard errors in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

References

Airbnb, 2022. Airbnb's Design for Employees to Live and Work Anywhere. https://news.airbnb.com/airbnbs-design-to-live-and-work-anywhere/.

Asay, M., 2020. COVID-19 Isn't Slowing Open Source—Watch for Developer Burnout. https://www.techrepublic.com/article/covid-19-isnt-slowing-open-source-watch-for-developer-burnout/.

Bao, L., Li, T., Xia, X., Zhu, K., Li, H., Yang, X., 2022. How does working from home affect developer productivity? – a case study of Baidu during COVID-19 pandemic. SCIENCE CHINA Inf. Sci. 65, 1–15.

Barber, B.M., Jiang, W., Morse, A., Puri, M., Tookes, H., Werner, I.M., 2021. What explains differences in finance research productivity during the pandemic? J. Financ. 76, 1655–1697.

Bergiel, B.J., Bergiel, E.B., Balsmeier, P.W., 2006. The reality of virtual teams. Competition Forum 4, 427–432.

Boden, D., Molotch, H.L., 1994. The compulsion of proximity. In: Friedland, R., Boden, D. (Eds.), Nowhere: Space, Time and Modernity. University of California Press, Berkeley, pp. 257–286.

Brandtzæg, P.B., Nov, O., 2011. Facebook use and social capital—a longitudinal study. In: Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media, Barcelona, Spain, pp. 454–457.

Brucks, M.S., Levav, J., 2022. Virtual communication curbs creative idea generation. Nature 605, 108–112.

Butler, J., Jaffe, S., 2021. Challenges and gratitude: a diary study of software engineers working from home during COVID-19 pandemic. In: 2021 IEEE/ACM 43rd International Conference on Software Engineering: Software Engineering in Practice. IEEE, Madrid, Spain, pp. 362–363.

Chen, S., Ma, H., Wu, Q., 2019. Bank credit and trade credit: evidence from natural experiments. J. Bank. Financ. 108, 105616.

Chen, J., Chen, W., Liu, E., Luo, J., Song, Z.M., 2022a. The Economic Cost of Lockdown in China: Evidence from City-to-city Truck Flows.

Chen, X., Guo, M., Shangguan, W., 2022b. Estimating the impact of cloud computing on firm performance: an empirical investigation of listed firms. Inf. Manag. 59, 103603.

Cochran, W.G., Rubin, D.B., 1973. Controlling bias in observational studies: a review. Sankhya: Indian J. Stat. Ser. A 35, 417–446.

Columbro, G., 2020. Open Source and COVID-19: Open Source Will Come Out Stronger on the Other Side of the Pandemic. https://www.finos.org/blog/open-source-and-covid-19-open-source-will-come-out-stronger-on-the-other-side-of-the-pandemic.

Cramton, C.D., 2001. The mutual knowledge problem and its consequences for dispersed collaboration. Organ. Sci. 12, 346–371.

Cramton, C.D., Webber, S.S., 2005. Relationships among geographic dispersion, team processes, and effectiveness in software development work teams. J. Bus. Res. 58, 758–765.

Crowston, K., Howison, J., Masango, C., Eseryel, U.Y., 2007. The role of face-to-face meetings in technology-supported self-organizing distributed teams. IEEE Trans. Prof. Commun. 50, 185–203.

Cui, R., Ding, H., Zhu, F., 2022. Gender inequality in research productivity during the COVID-19 pandemic. Manuf. Serv. Oper. Manag. 24, 707–726.

Daft, R.L., Lengel, R.H., 1986. Organizational information requirements, media richness and structural design. Manag. Sci. 32, 554–571.

Daniel, S., Stewart, K., 2016. Open source project success: resource access, flow, and integration. J. Strateg. Inf. Syst. 25, 159–176.

Davidson, J., Mannan, U., Naik, R., Dua, I., Jensen, C., 2014. Older adults and free/open source software: a diary study of first-time contributors. In: Proceedings of the International Symposium on Open Collaboration. Association for Computing Machinery, New York, NY, United States, pp. 1–10.

Dennis, A.R., Fuller, R.M., Valacich, J.S., 2008. Media, tasks, and communication processes: a theory of media synchronicity. MIS Q. 32, 575–600.

DiMaggio, P., Hargittai, E., Neuman, W.R., Robinson, J.P., 2001. Social implications of the internet. Annu. Rev. Sociol. 27, 307–336.

Fang, Y., Neufeld, D., 2009. Understanding sustained participation in open source software projects. J. Manag. Inf. Syst. 25, 9–50.

Fang, H., Wang, L., Yang, Y., 2020. Human mobility restrictions and the spread of the novel coronavirus (2019-nCoV) in China. J. Public Econ. 191, 104272.

Foerderer, J., 2020. Interfirm exchange and innovation in platform ecosystems: evidence from Apple's worldwide developers conference. Manag. Sci. 66, 4772–4787.

Ford, D., Storey, M.-A., Zimmermann, T., Bird, C., Jaffe, S., Maddila, C., Butler, J.L., Houck, B., Nagappan, N., 2021. A tale of two cities: software developers working from home during the COVID-19 pandemic. ACM Trans. Softw. Eng. Methodol. 31, 1–37.

Forsgren, N., 2020. Octoverse Spotlight: An Analysis of Developer Productivity, Work Cadence, and Collaboration in the Early Days of COVID-19. https://github.blog/2020-05-06-octoverse-spotlight-an-analysis-of-developer-productivity-work-cadence-and-collaboration-in-the-early-days-of-covid-19/.

Foss, N.J., Jeppesen, L.B., Rullani, F., 2021. How context and attention shape behaviors in online communities: a modified garbage can model. Ind. Corp. Chang. 30, 1–18.

GitHub, 2022a. GitHub Language Support. https://docs.github.com/en/get-started/learning-about-github/github-language-support.

GitHub, 2022b. Where the World Builds Software. https://github.com/about.

Hambrick, D.C., Davison, S.C., Snell, S.A., Snow, C.C., 1998. When groups consist of multiple nationalities: towards a new understanding of the implications. Organ. Stud. 19, 181–205.

Hertel, G., Niedner, S., Herrmann, S., 2003. Motivation of software developers in open source projects: an internet-based survey of contributors to the linux kernel. Res. Policy 32, 1159–1177.

Howard, P.E., Rainie, L., Jones, S., 2001. Days and nights on the internet: the impact of a diffusing technology. Am. Behav. Sci. 45, 383–404.

Hu, J., Hu, D., Yang, X., Chau, M., 2023. Can firms improve performance through external contributions to their open-source software projects?. In: Proceedings of the 31th European Conference on Information Systems (ECIS), Kristiansand, Norway.

Huang, L., Zheng, D., Fan, W., 2022. Do social networking sites promote life satisfaction? The explanation from an online and offline social capital transformation. Inf. Technol. People 35, 703–722.

Khalis, A., Mikami, A.Y., 2018. Talking face-to-facebook: associations between online social interactions and offline relationships. Comput. Hum. Behav. 89, 88–97.

Kock, N., 2004. The psychobiological model: towards a new theory of computer-mediated communication based on darwinian evolution. Organ. Sci. 15, 327–348.

Kraut, R.E., Lewis, S.H., Swezey, L.W., 1982. Listener responsiveness and the coordination of conversation. J. Pers. Soc. Psychol. 43, 718–731.

Kraut, R., Kiesler, S., Boneva, B., Cummings, J., Helgeson, V., Crawford, A., 2002. Internet paradox revisited. J. Soc. Issues 58, 49–74.

von Krogh, G., Haefliger, S., Spaeth, S., Wallin, M.W., 2012. Carrots and rainbows: motivation and social practice in open source software development. MIS Q. 36, 649–676.

Lau, D.C., Murnighan, J.K., 1998. Demographic diversity and faultlines: the compositional dynamics of organizational groups. Acad. Manag. Rev. 23, 325–340.

Leslie, E., Wilson, R., 2020. Sheltering in place and domestic violence: evidence from calls for service during COVID-19. J. Public Econ. 189, 104241.

Lipnack, J., Stamps, J., 1999. Virtual teams: the new way to work. Strateg. Leadersh. 27, 14–19.

Miller, C., Widder, D.G., Kästner, C., Vasilescu, B., 2019. Why do people give up flossing? A study of contributor disengagement in open source. In: IFIP International Conference on Open Source Systems. Springer, pp. 116–129.

Miller, C., Rodeghero, P., Storey, M.-A., Ford, D., Zimmermann, T., 2021. "How was your weekend?" Software development teams working from home during COVID-19. In: IEEE/ACM 43rd International Conference on Software Engineering. IEEE, pp. 624–636.

Moqri, M., Mei, X., Qiu, L., Bandyopadhyay, S., 2018. Effect of "following" on contributions to open source communities. J. Manag. Inf. Syst. 35, 1188–1217.

Muralidharan, K., Prakash, N., 2017. Cycling to school: increasing secondary school enrollment for girls in India. Am. Econ. J. Appl. Econ. 9, 321–350.

Negoita, B., Vial, G., Shaikh, M., Labbe, A., 2019. Code forking and software development project sustainability. In: Evidence from GitHub, Fortieth International Conference on Information Systems, Munich, Germany.

Neto, P.A.d.M.S., Mannan, U.A., de Almeida, E.S., Nagappan, N., Lo, D., Singh Kochhar, P., Gao, C., Ahmed, I., 2021. A deep dive into the impact of COVID-19 on software development. IEEE Trans. Softw. Eng. 48, 3342–3360.

NicCanna, C., Razzak, M.A., Noll, J., Beecham, S., 2021. Globally distributed development during COVID-19. In: 2021 IEEE/ACM 8th International Workshop on Software Engineering Research and Industrial Practice. IEEE, pp. 18–25. Virtual Conference.

Ocker, R., Fjermestad, J., Hiltz, S.R., Johnson, K., 1998. Effects of four modes of group communication on the outcomes of software requirements determination. J. Manag. Inf. Syst. 15, 99–118.

O'Mahony, S., Ferraro, F., 2007. The emergence of governance in an open source community. Acad. Manag. J. 50, 1079–1106.

Ralph, P., Baltes, S., Adisaputri, G., Torkar, R., Kovalenko, V., Kalinowski, M., Novielli, N., Yoo, S., Devroey, X., Tan, X., Zhou, M., Turhan, B., Hoda, R., Hata, H., Robles, G., Fard, A.M., Alkadhi, R., 2020. Pandemic programming. Empir. Softw. Eng. 25, 1–35.

Shah, S.K., 2006. Motivation, governance, and the viability of hybrid forms in open source software development. Manag. Sci. 52, 1000–1014.

Sheridan, A., Andersen, A.L., Hansen, E.T., Johannesen, N., 2020. Social distancing laws cause only small losses of economic activity during the COVID-19 pandemic in Scandinavia. Proc. Natl. Acad. Sci. 117, 20468.

Smite, D., Moe, N.B., Klotins, E., Gonzalez-Huerta, J., 2023. From forced working-from-home to voluntary working-from-anywhere: two revolutions in telework. J. Syst. Softw. 195, 111509.

Sproull, L., Kiesler, S., 1986. Reducing social context cues: electronic mail in organizational communication. Manag. Sci. 32, 1492–1512.

Stam, W., 2009. When does community participation enhance the performance of open source software companies? Res. Policy 38, 1288–1299.

Straus, S.G., McGrath, J.E., 1994. Does the medium matter? The interaction of task type and technology on group performance and member reactions. J. Appl. Psychol. 79, 87–97.

Suphan, A., Mierzejewska, B.I., 2016. Boundaries between online and offline realms: how social grooming affects students in the USA and Germany. Inf. Commun. Soc. 19, 1287–1305.

Suphan, A., Feuls, M., Fieseler, C., 2012. Social media's potential in improving the mental wellbeing of the unemployed. In: Eriksson-Backa, K., Luoma, A., Krook, E. (Eds.), Exploring the Abyss of Inequalities. Springer, Berlin, pp. 10–28.

Tanaka, T., Okamoto, S., 2021. Increase in suicide following an initial decline during the COVID-19 pandemic in Japan. Nat. Hum. Behav. 5, 229–238.

Townsend, A.M., DeMarie, S.M., Hendrickson, A.R., 1998. Virtual teams: technology and the workplace of the future. Acad. Manag. Perspect. 12, 17–29.

Wakefield, R.L., Leidner, D.E., Garrison, G., 2008. Research note—a model of conflict, leadership, and performance in virtual teams. Inf. Syst. Res. 19, 434–455.

Walters, C., Mehl, G.G., Piraino, P., Jansen, J.D., Kriger, S., 2022. The impact of the pandemic-enforced lockdown on the scholarly productivity of women academics in South Africa. Res. Policy 51, 104403.

Wang, G., 2022. Stay at home to stay safe: effectiveness of stay-at-home orders in containing the COVID-19 pandemic. Prod. Oper. Manag. 31, 2289–2305.

Wang, Y., Cai, H., Li, C., Jiang, Z., Wang, L., Song, J., Xia, J., 2013. Optimal caliper width for propensity score matching of three treatment groups: a Monte Carlo study. PLoS One 8, e81045.

Warren, T., 2020. Microsoft Is Letting More Employees Work From Home Permanently. https://www.theverge.com/2020/10/9/21508964/microsoft-remote-work-from-home-covid-19-coronavirus?fbclid=IwAR0H_roHhjyjmbFnfwYAvpH8CdRVK5sVs52qTYaAUyc6BQRSYrmKtXxToQ4.

Wellman, B., Salaff, J., Dimitrova, D., Garton, L., Gulia, M., Haythornthwaite, C., 1996. Computer networks as social networks: collaborative work, telework, and virtual community. Annu. Rev. Sociol. 22, 213–238.
Wikipedia, 2022. Han Chinese. https://en.wikipedia.org/wiki/Han_Chinese.
Wu, J., Smith, S., Khurana, M., Siemaszko, C., DeJesus-Banos, B., 2020. Stay-at-home Orders Across the Country. https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736.
Xu, B., Jones, D.R., Shao, B., 2009. Volunteers' involvement in online community based software development. Inf. Manag. 46, 151–158.
Yang, X., Li, X., Hu, D., Wang, H.J., 2021. Differential impacts of social influence on initial and sustained participation in open source software projects. J. Assoc. Inf. Sci. Technol. 72, 1133–1147.
Zhang, X.M., Zhu, F., 2011. Group size and incentives to contribute: a natural experiment at Chinese Wikipedia. Am. Econ. Rev. 101, 1601–1615.