



Working (From Home) During a Crisis: Online Social Contributions by Workers During the Coronavirus Shock

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Prior research has documented that during mortality-related crises workers face psychic costs and are motivated to make social contributions. In addition, management practices that encourage workers to make social contributions during a crisis create value for firms. However, the coronavirus crisis of 2020 is unprecedented given conditions of social distancing. It raises the question of whether workers who continued to work (albeit from home) during this crisis were constrained in their ability to make social contributions and exhibited disproportionately greater psychic costs compared to workers who could not work from home. We exploit this shock to estimate differences in content contributions to an online community by workers who work from home (WFH) relative to workers who cannot work from home (CWFH). Online content contributions are especially pertinent in our context because social distancing constrained traditional forms of social contributions such as physical volunteering. Using data from a popular question-and-answer platform, we estimate a difference-in-differences specification and report nuanced results: while WFH workers made 19% fewer online contributions on average and contributed less to topics such as 'family', they made 148% more contributions on topics related to 'WFH best practices.' Using natural language processing tools, we also find that WFH workers exhibited greater psychic costs than CWFH workers. We provide evidence for a plausible mechanism, i.e. time allocation, and show that WFH workers attempted to catch up on social contributions at the end of their workday, suggesting time constraints. Our research contributes to literatures on managing workers during a crisis, WFH and online communities, and have several immediate implications for managing WFH and CWFH workers during the coronavirus crisis.

Keywords: crisis, social contributions, work from home (WFH), cannot work from home (CWFH), social distancing, online communities, coronavirus, COVID-19.

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1. Introduction

The coronavirus shock of 2020 is one of the most acute crises affecting companies and workers in recent times. In prior literature, Carnahan et al. (2017) highlight that a mortality-related crisis (in their paper, the 9/11 shock) leads to psychic costs for workers and motivates them to make pro-social contributions. In addition, management practices that encourage workers to make social contributions during a crisis create value for firms.² In fact, prior literature in strategic human capital has stressed that firms should motivate workers by offering them opportunities that increase worker satisfaction (Gambardella et al. 2015) and this insight is deeply relevant during a major crisis. However, the coronavirus crisis is unprecedented in that conditions of social distancing forced companies around the globe to ask millions of workers to work from home (Bodewits 2020). This created variation in work arrangements across industries as workers in some industries cannot work from home and raises the question of whether workers who continued to work (albeit from home) during this crisis were constrained in their ability to make social contributions. We also ask whether workers who made the drastic switch to working from home exhibited greater psychic costs and were constrained for time in the immediate aftermath of the crisis, compared to workers who could not work from home.³

Mandatory social distancing not only created variation in work arrangements for workers, it also constrained traditional forms of social contributions such as physical volunteering. However, workers could still make social contributions, albeit online. In today's digital economy, an important form of social contribution by workers relates to the unpaid content they contribute to online communities (Boudreau and Lakhani 2013; Zhang and Zhu 2006, 2011; Ghose and Han 2011; Luca 2015). Such content represents an example of a "positive spillover" from the internet to society as discussed by Chan et al. (2013). To quote Zhang and Zhu (2011), "Many public goods on the Internet today rely entirely on free user contributions. Popular examples include open source software development communities (e.g., Linux, Apache), open content production (e.g., Wikipedia, Open Courseware), and content sharing

² Carnahan et al. (2017) document that incentivizing social contributions by workers creates value for firms in the form of reduced turnover of workers. Prior literature on pro-social behavior by workers has focused on contributions such as physical volunteering hours and pro-bono cases (Bénabou and Tirole 2006; Exley 2018).

³ It is possible that in the longer term, workers who can and cannot work from home will be affected differently by factors such as forced turnover and it is not the intention of the paper to claim that the patterns observed will be sustained over time.

networks (e.g., Flickr, YouTube).” (ibid, page 1601). Thus, we adopt a broad definition of social contribution to mean any free contribution to an online public good.

We exploit the coronavirus shock and provide causal evidence of how workers who work from home (WFH) differ from workers who cannot work from home (CWFH) with respect to content contributed to online communities. The online community of interest is one of China’s largest online question and answer communities. In prior literature, Wang et al. (2013) study online question and answer communities such as Quora and Stack Overflow and conclude that “community question and answer sites provide a unique and invaluable service to its users” (ibid, 1350). Thus, our measure of individual worker output (i.e., the number of answers contributed to the online community) meets the characterization of social contributions (i.e. “helping others”) articulated by Carnahan et al. (2017).

Our pre-period comprises the Chinese New Year holidays when most workers are on vacation in their hometowns. In the post-period, all workers were under mandatory lockdown facing social distancing. However, while individuals working in certain industries (such as the internet industry and the software industry) were asked to WFH, workers in industries such as airlines, computer hardware, and manufacturing could not work from home under lockdown. We estimate a difference-in-differences specification comparing content contributions of individuals working from home in the post-period to contributions made by individuals who cannot work from home in the post-period.

We report several results. On average, WFH workers posted 19% fewer answers than CWFH workers. However, WFH workers provided more answers in certain socially helpful categories such as advice on how to work from home. Using natural language processing tools, we also document evidence of greater psychic costs exhibited by WFH workers compared to CWFH workers. Additionally, we explore a key mechanism (i.e. time allocation) and analyze hourly contributions by WFH and CWFH workers. This reveals that while during work hours WFH workers contributed less than CWFH workers, they contributed equally between 8pm and midnight. In other words, WFH workers tried to “catch-up” on the social contributions at the end of the workday, suggesting disproportionate constraints on their time. Our findings contribute to several streams of the strategic human capital literature and have implications for how managers and firms should manage WFH and CWFH workers during a major crisis.

2. Setting and Data

2.1. Work-From-Home during COVID-19 Lockdown

In December 2019, several cases of pneumonia emerged near the Huanan seafood market in Wuhan, China. Later, it was revealed to be triggered by a novel coronavirus that is both highly contagious and deadlier than the common flu (Huang et al. 2020). The Chinese New Year public holiday lasted from January 24 to February 2, 2020.⁴ In order to enforce social distancing and slow the diffusion of the virus, provincial governments across mainland China implemented a household lockdown across the country, and barred companies from resuming physical work until February 10. The government also encouraged companies to adopt WFH arrangements starting February 3.⁵ On Monday, February 3, 2020, workers in certain industries (such as software development) began to work from home (Liang 2020). The weekly downloads of business and remote work applications on the iOS App Store increased from 2.4 million in late January to 14 million in the week of February 3 (Liao 2020). In contrast, workers in other industries for which remote work is unfeasible (such as airlines, computer hardware, and manufacturing) stayed home and could not work. A detailed timeline of major events is shown in Table A1 in the Appendix.

We screened meticulously for evidence indicating that certain industries had started WFH at scale on February 3. The information was obtained through outlets such as news portals, forums, and blogposts. Specifically, industries that started WFH on February 3 include E-Commerce, Internet, and Software Development.⁶ Workers from these industries form our treatment group. Next, we screened for industries that almost certainly did not start remote work on February 3. These industries include traditional industries that would require physical work as well as industries for which we found concrete evidence for a later start date. Industries where workers could not work at home after February 3 include Airlines, Automobile, Banking, Computer Hardware, Construction Tools, Education, Electronics, Indoor Decoration, Machinery, Manufacturing, and Restaurants. These workers form our control group.

To emphasize, our research question relates to how WFH workers differ from workers who cannot work from home (CWFH) with respect to their content contributions to online social communities. In the past, identifying a causal relationship between WFH and community contributions

⁴ The Lunar New Year holiday was originally to end on January 30 and later extended to February 2 to contain COVID-19 outbreak (Xinhua, 2020).

⁵ We study provincial government policies, based on news reports such as China News Services (2020).

⁶ For more information on group assignment, please see the last footnote under Appendix Table A1.

was challenging because workers' choices of work arrangements would likely be endogenous and affected by unobservable worker characteristics and by social and economic conditions. In this study, we use the coronavirus-induced variation in work arrangements to construct a natural experiment. Since the government policy to prohibit return to *physical* work until February 10 was driven by the rapid spread of coronavirus across the country, it creates an exogenous shock where workers in the treatment group are asked to WFH and workers in the control group cannot work from home. Additionally, the online platform we focus on did not implement any major design changes or marketing campaigns to differentially affect WFH workers' and CWFH workers' content contributions in that window of time.

2.2. Data and Methods

We acquired the data from a popular question-and-answer platform based in China. In 2019, the platform had about 200 million registered participants, similar in size to its American counterpart, Quora. On this platform, participants mainly engage in two activities: answer others' questions and ask their own questions.⁷ They also engage in activities such as "liking" a question or answer, following an account, publishing an article, and posting a photo. To acquire data on worker behavior and characteristics, we used nine newly registered accounts to scroll down a total of 151,000 questions recommended by the platform. Among the 664,000 workers who contributed to these questions, we randomly selected 30,000 workers with the restriction that at least 3,000 workers (10%) were from Wuhan. For these 30,000 workers, we crawled down their historic platform contribution, including the content and time-stamp of every answer and every question they posted, the content and the number of likes, follows, visits, and comments on every answer and every question they posted, as well as background information and worker characteristics such as location, industry, gender, and number of fans.

We focus on analyzing workers' answers because answering a community's questions is a form of online social contribution. The main dataset contains 3.7 million answers posted by the 30,000 workers from when they registered their accounts until February 15, 2020. We then collapse the data to form a panel dataset at the worker-date level. We focus on two periods: 1) the pre-period is from January 24 to February 2, when workers were at home on vacation during the Chinese New Year holiday; 2) the post-period is from February 3 to February 7, when workers in the treatment group started WFH and workers

⁷ Hereon, we refer to all platform users as "workers" to stay consistent with the rest of the paper.

in the control group could not work.⁸ Our final dataset contains daily information on 100,680 worker-dates: 6,712 unique workers posted 18,065 answers from January 24 to February 7, 2020. WFH and CWFH workers comprise 64% and 36% of the sample, respectively. The main dependent variable is *Answers* (number of answers posted by a worker on a given day). Additionally, we investigate the characteristics of workers' contributions – specifically, the popularity of the questions they choose to answer, the topics (e.g., family and WFH), and workers' sentiment expressed in their answers. We control for the following variables: the number of *New Infections* of COVID-19 reported in a worker's city on a given day, the numbers of *Fans* a worker has, times a worker has helped the platform *Edit* public content, times a worker's post is *Featured* by the platform, times a worker is publicly *Recognized* by other top contributors, as well as a worker's *Gender* (0 = female; 1 = male).⁹ Table A2 in the Appendix shows the summary statistics and pairwise correlations.

We use the Poisson quasi-maximum likelihood (QML) estimator with conditional fixed effects to estimate the main models with count dependent variables, and we run ordinary least squares (OLS) regressions for other dependent variables. Poisson QML with conditional fixed effects accommodates over-dispersion and autocorrelated error terms (Wooldridge 2010). The following regression illustrates the specification in our main models:

$$\log(E[y_{iact} | \mathbf{X}_{iact}]) = \beta \text{WFH}_d \times \text{Post}_t + \boldsymbol{\gamma}' \mathbf{Z}_{ict} + \alpha_d + \lambda_t,$$

where i indexes individual worker, d indexes industries, c indexes cities, and t indexes days. α_d and λ_t are the industry and date fixed effects, respectively. $\text{WFH}_d \times \text{Post}_t$ is the treatment indicator, which equals 1 if a worker-date is in a *WFH* industry on or after February 3. \mathbf{Z}_{ict} is the vector of control variables. Finally, all standard errors are clustered at the industry level, which is the level of treatment (Bertrand et al. 2004). We also use worker fixed effects in robustness tests.

3. Results

3.1. Effects of WFH on the Level and Heterogeneity of Content Contributions

⁸ We excluded February 8 and 9 from the post-period because they were weekend days. We excluded all student contributors because they do not abide by the traditional work schedule.

⁹ We take the natural logarithms of all control variables except for Gender. Data on daily infected cases is from *The Paper*, a Chinese news portal that published daily city-level numbers of infections after consolidating data from the local ministries of health and local news channels. Count data at the worker level (e.g., *Fans*, times *Recognized*) are values from February 16.

We first test whether, and to what extent, WFH affected workers' social contributions. Figure 1a illustrates these results: WFH workers' contribution level barely changed in the post-period, but CWFH workers displayed a visible increase in contribution. When both groups had no work prior to February 3, the average treated worker answered 0.16 questions per day and the average control worker answered 0.18 questions per day. After February 3, the average treated worker answered 0.18 questions per day and the average control worker answered 0.25 questions per day. Regressions in Table 1, Models 1-3 show that, after February 3, the average treated worker (WFH) generated about 19% fewer answers than the average control worker (CWFH) ($\exp(-0.211) - 1 = -0.19$). In terms of the economic effects for the entire platform, the reduction in answer count among WFH workers amounts to a decrease of roughly 260,000 answers per day and 8.8 million views per day on the platform – about 4.4% of all platform activities (see Appendix Note N3 for details on the calculation).

Our results are driven mainly by the intensive margin, as opposed to the extensive margin; the lower relative contribution among WFH workers can be mainly attributed to active workers answering relatively fewer number of questions, as opposed to active workers becoming inactive in the post-period. Additionally, Figure 1b shows the dynamics of treatment effects before and after February 3. To generate this graph, we created a set of dummy variables indicating the days before and after February 2 (from $t = -5$ to $t = +5$). We then interact those dummy variables with the WFH indicator and regress the interaction terms against our dependent variables with control variables and fixed effects included. The graph shows that the WFH effect is close to zero in the pre-period, suggesting that the parallel trends assumption is likely to be valid. In the post-period, the WFH effect becomes negative, which supports our main result.

Next, we explore the heterogeneity of worker contributions – what types of questions workers tend to answer. To test this, we use data on the tags associated with each answered question to construct six topic categories that are most popular on the platform: Arts, Business, Education, Emotions, Entertainment, and Family. We include one additional category which is relevant to our setting, WFH Best Practices, to gauge if workers helped address questions regarding how to work from home (e.g., what software to use, how to do video conferencing).¹⁰ We run seven regressions to compare the number

¹⁰ Appendix Note N2 provides more information on the keywords used to categorize the topic categories.

of answers belonging to different categories between WFH workers and CWFH workers (Table 2). The results show that WFH workers answered significantly fewer questions in the categories of Arts, Emotions, and Family than CWFH workers after February 3. In the post-period, relative to the pre-period, WFH workers answered 43%, 21%, and 26% fewer questions related to arts, emotions, and family, respectively, than CWFH workers. These results suggest that contributions were particularly depressed in categories that are arguably more related to maintaining work-life and work-family balance. However, WFH workers answered *148% more* questions related to WFH best practices than CWFH workers in the post-period. This result suggests that WFH workers were educating the community about the details of remote work.

3.2. Mechanism: Time Allocation

Building on the literature on time budget allocation by workers (Perlow 1999), we propose a mechanism that may plausibly explain the observed patterns: differences in time budget allocation. Whereas the mechanism may seem straightforward, it is important to empirically examine 1) its validity and 2) how it plays out. We first categorize all answers into two types – answers during working hours (8am-12pm; 1-7pm) and answers outside of working hours.¹¹ At the worker-date level, we construct two variables, number of *Working-Hour Answers* and number of *Non-Working-Hour Answers*. Regressions of those two variables over the $WFH \times Post$ interaction term show that WFH led to a more drastic decrease in contributions during working hours (21% decrease) than during non-working hours (17%) (Table 3, Models 1-2).

This result provides support for the time substitution mechanism that WFH workers likely took time away from social contributions due to the onset of remote work. It also highlights an interesting phenomenon: not only did workers reduce their contribution level due to WFH, they also *redistributed* their contributions over different hours of the day. To further investigate this phenomenon, we examine the hourly effects of WFH. Specifically, we generate 24 dependent variables corresponding to the number of answers posted within each one-hour period and run 24 regressions over the $WFH \times Post$ interaction term. Figure 2 combines the coefficients in an hourly graph. It shows that, relative to CWFH workers, WFH workers experienced a drop in contributions during all working hours in the post-period. The most

¹¹ There is one unified time zone in all of China.

significant drops occurred at around 2am, 2pm, and 6pm. This is likely because in the post-period WFH workers could no longer stay up too late, needed to resume work after lunchbreak, and needed to finish work at around 6pm. Starting at around 8pm till midnight, there are no differences in contributions between WFH and CWFH workers, suggesting that WFH workers might have been “cramming in” their online contributions after work before bedtime.

3.3. Effects on Worker Sentiment

While the crisis imposes psychic costs on all workers (Carnahan et al., 2017), challenges in managing time (Perlow 1999) and transitioning between work, life and social roles (Ashforth et al. 2000) might have led to disproportionately higher psychic costs for WFH workers in the immediate aftermath of the crisis. In the WFH literature, Gajendran and Harrison (2007) have documented that workers who practice WFH on a temporary or ad-hoc basis (such as the workers in our sample) might be less effective at managing work-life boundaries leading to greater conflicts and psychic costs, compared to workers who practice WFH on a regular basis.

We test WFH’s effects on worker sentiment by conducting a sentiment analysis of all answer texts using natural language processing techniques. We use JiebaR, the latest Chinese word segmentation program in R, to intelligently segment the text into words (Qin and Wu 2019). Using sentiment dictionaries compiled by Tsinghua University (Li 2011), we calculate the sentiment scores by counting the number of words indicating positive and negative sentiment in each answer.¹² Then, we regress the sentiment scores over the interaction term. Results show that, in the post-period, WFH workers’ answers displayed 6.6% less positive sentiment than CWFH workers’ answers relative to the pre-period (Table 3, Models 3-4).

3.4. Physical Work as an Alternative Baseline

Here we explore whether the WFH and CWFH conditions affect social contributions differently from physical, in-office work. To do that, we need to find a counterfactual worker group who are similar to the WFH and CWFH groups but start physical work instead of remote work or remaining workless at home. Since we observe workers’ historic contribution, we analyze the behavior of the same groups of workers from February 4 to February 15, 2019 – the same period one year earlier. The 2019 period also

¹² Appendix Note N1 provides more information on the sentiment dictionaries.

includes a pre-period (seven days during the Chinese New Year holiday) and a post-period (five days after workers resumed physical work post-holiday). By looking at WFH and CWFH workers' contributions from 2019, we are able to construct a scenario in which workers transition from vacation to physical work. Regressions show that, in the post-period, whereas CWFH workers generated 87% higher contributions in the post-period than they did last year, the contributions among WFH workers were also 73% higher than last year (Appendix Table A5, Panel C). This result could be affected by time trends and context differences, and it should be treated as correlational. The large effect sizes, however, offer some support for the statement that both WFH and CWFH generate more contributions than physical work.

3.5. Robustness Checks and Limitations

As robustness checks for empirical design, we modify the industries in the treatment and the control groups to test alternative group compositions. First, we exclude e-commerce workers, who could have been more familiar with WFH than other types of workers due to the nature of their work, from the WFH treatment group. Then, we exclude the bank and airline industries from the control group because a small percentage of workers in these two industries could have been engaging in physical work during the lockdown in order to keep essential services running for the public. Results remain highly similar with those changes (Appendix Table A6, Panel A). Additionally, we re-estimate our main results using different model specifications such as worker fixed effects and negative binomial regressions with unconditional fixed effects (Allison and Waterman 2002; Wooldridge 2010). Results remain similar (Appendix Table A6, Panel B; Appendix Figures A1-A2 show DID and hourly graphs with worker FE).

Our study has several limitations. First, we do not know if we would observe similar patterns if the workers were not under social distancing and/or had more time to prepare for WFH. Second, the workers in our sample are likely to be those who were particularly active during our window of observation. It is unlikely to affect our main results, but it may bias our results on WFH and CWFH's comparison to physical work one year earlier. Finally, it is *not* our intent to state that making social contributions are the *only* driver of worker utility and/or these patterns would be observed with a prolonged crisis. Long periods of not working and/or unemployment during a crisis might negatively and severely affect worker utility and future research should compare productivity and psychic costs of WFH and CWFH workers using a broader set of measures and over a longer time frame.

4. Contributions and Conclusion

The coronavirus shock is arguably the biggest crisis facing firms and workers in recent times. The prior literature, notably Carnahan et al. (2017), has documented that during a crisis, workers are motivated to make social contributions, and management practices that encourage workers to make social contributions during a crisis create value for firms. However, the coronavirus shock is unprecedented because unlike prior crisis, social distancing created variation in work arrangements for workers. While workers in certain industries continued to work (albeit from home), other workers could not work from home. Given these conditions, we estimate a causal difference in an important social contribution, i.e. content contributions to online communities, between WFH and CWFH workers. This form of social contribution is particularly salient in our context, given that social distancing constrained the ability of workers to engage in traditional forms of social contribution such as physical volunteering. We report a nuanced set of causal results: while WFH workers made 19% fewer online contributions on average and contributed less to socially helpful topics such as “family”, they made 148% more contributions on socially helpful topics related to “remote work best practices”.

Using natural language processing tools, we also document greater psychic costs faced by WFH workers compared to CWFH workers in the immediate aftermath of the crisis. We also provide evidence around a key mechanism and using hourly contributions show that WFH workers tried to catch-up on social contributions at the end of the workday. This suggests that WFH workers were plausibly experiencing conditions of “time famine”, i.e. a “pervasive feeling of having insufficient time in daily life” (Perlow, 1999; page 244) that leads to stress, anxiety and psychic costs. These results speak to a prior literature in strategy on worker well-being and firm productivity (e.g. Lee and Miller 1999) and is especially salient to how firms should manage worker well-being during a crisis.

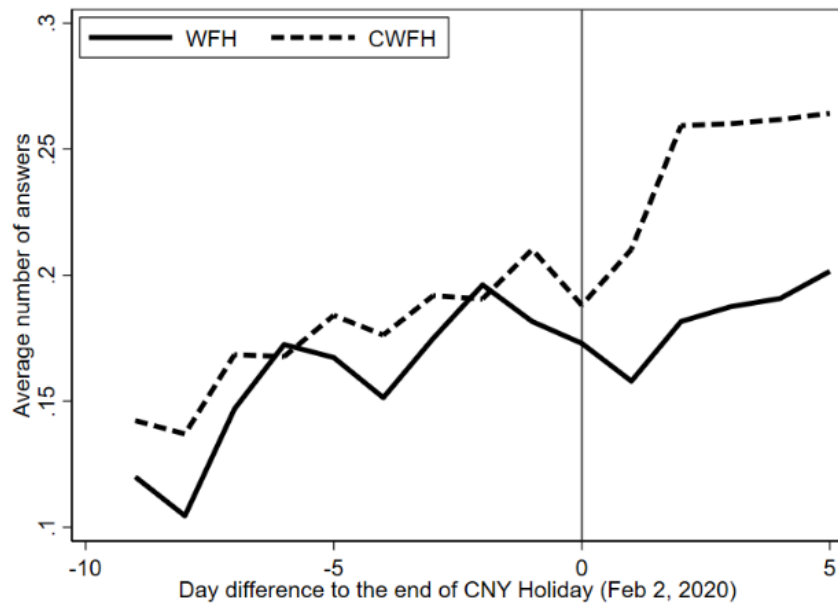
Our study also contributes to the remote work literature. While prior literature (Bloom et al. 2015; Choudhury et al. 2019) has compared output of workers under conditions of WFH and physical work, to the best of our knowledge, this is the first study to compare individual contributions of WFH and CWFH workers. Also, while we have prior literature on how physical isolation from the office (Bartel et al., 2012) and professional isolation (Cooper and Kurland 2002) affects WFH workers, to the best of

our knowledge, this is the first study that documents output of WFH workers under conditions of social distancing.

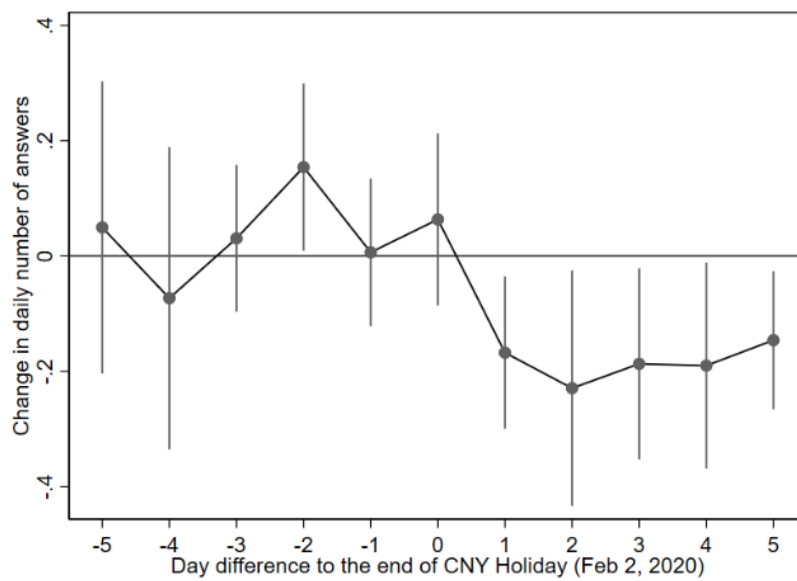
In this paper, we underscore three immediate managerial and policy implications of our study. First, given that our study demonstrates that WFH workers make disproportionately greater online contributions to socially helpful topics such as remote work best practices and yet face disproportionately higher psychic costs and possibly time famine, managers might consider awarding WFH workers temporal flexibility in the form of a few “free hours” to engage in online contributions and other “virtual watercoolers” in order to deal with work-social and work-life balance. In fact, Katherine Maher, CEO of Wikimedia, the nonprofit organization behind Wikipedia announced that workers can work 20 hours per week and still get paid for 40 hours during the crisis (Gardeman 2020).

Second, our result on the greater psychic costs of WFH workers compared to CWFH workers is important to highlight: while current debate is centered around the psychic costs of CWFH workers (such as gig workers who cannot work, e.g. Scott, 2020), managers should also consider strategies to mitigate the psychic costs of workers who have made a drastic switch to WFH and might have insufficient time to fulfill their work, social and family roles. Third, while there have been widespread concerns at the loss of human capital returns for idle workers, especially for workers who cannot work at home during this coronavirus shock (Morona, 2020), a silver lining in this very dark cloud is that CWFH workers may continue to generate social returns to their human capital by contributing free content to online communities. In conclusion, our paper advances literatures on managing workers during a crisis, WFH and online contributions and have several immediate managerial and policy implications for managing workers during the coronavirus shock.

Figures and Tables



(a) Average daily contributions of WFH (work-from-home) workers versus CWFH (cannot-work-from-home) workers.



(b) Daily effects of *WFH* on contribution differences between WFH and CWFH workers. “1” on the x-axis indicates the first day of remote work for WFH workers (95% Confidence Intervals).

Figure 1. Contribution Differences Between WFH and CWFH Workers

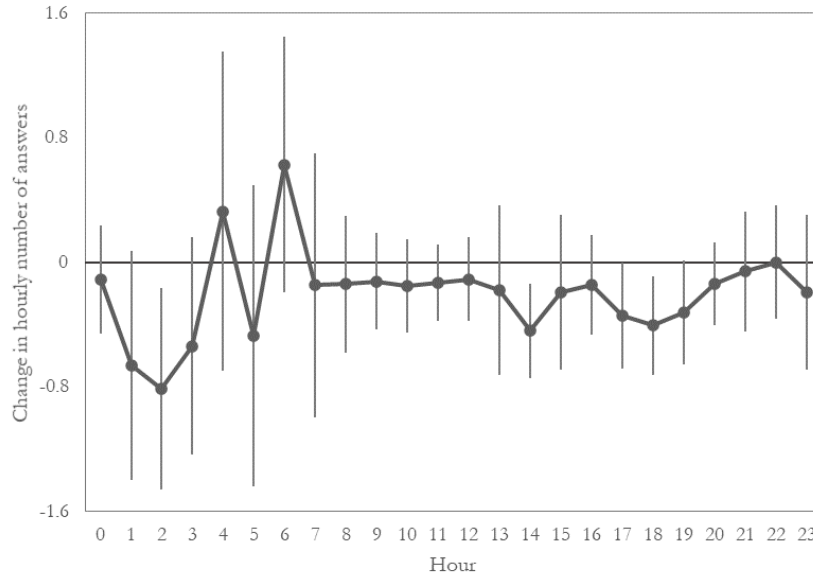


Figure 2. Hourly Effects of WFH on Contribution Differences (95% Confidence Intervals)

Table 1. WFH Effects on the Level of Content Contribution

Dependent variable	<i>Answers</i>			
	(1)	Full Sample (2)	(3)	Intensive Margin (4)
<i>WFH × Post</i>	-0.211*** (0.050)	-0.210*** (0.055)	-0.211*** (0.055)	-0.205*** (0.054)
<i>Post</i>	0.357*** (0.046)	0.397*** (0.050)		
<i>New Infections</i>		-0.083*** (0.021)	-0.100*** (0.024)	-0.062*** (0.020)
<i>Fans</i>		0.073*** (0.009)	0.073*** (0.009)	0.008 (0.010)
<i>Edit</i>		0.114*** (0.024)	0.114*** (0.024)	0.020 (0.020)
<i>Featured</i>		-0.165 (0.116)	-0.164 (0.117)	-0.015 (0.112)
<i>Recognized</i>		0.187* (0.104)	0.185* (0.105)	0.027 (0.094)
<i>Gender</i>		0.165 (0.125)	0.165 (0.126)	0.037 (0.113)
Industry FE	No	Yes	Yes	Yes
Date FE	No	No	Yes	Yes
Observations	100,680	91,995	91,995	28,780
Log-likelihood	-60,117.3	-54,022.1	-53,828.9	-35,491.8

Notes: Models are estimated using the Poisson QML estimator with conditional fixed effects. “Intensive margin” sample includes only active workers with at least one answers per period. Standard errors in parentheses are clustered at the industry level. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$. Robust to inclusion of worker FEs.

Table 2. WFH Effects on Contribution Topics

Dependent variable	<i>Arts Answers</i> (1)	<i>Business Answers</i> (2)	<i>Education Answers</i> (3)	<i>Emotions Answers</i> (4)	<i>Entertainment Answers</i> (5)	<i>Family Answers</i> (6)	<i>WFH Best Practices Answers</i> (7)
<i>WFH × Post</i>	-0.554** (0.248)	-0.084 (0.163)	-0.050 (0.101)	-0.234** (0.107)	0.033 (0.069)	-0.301** (-0.111)	0.918** (0.405)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,441	8,396	8,441	8,441	8,441	8,441	8,374
Log-likelihood	-2,749.1	-1,902.4	-4,789.7	-4,405.9	-7,608.5	-2,742.5	-1,053.1

Notes. Models are estimated using Poisson QML. Sample excludes worker-date observations with no answers. Standard errors in parentheses are clustered at the industry level. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$.

Table 3. Sentiment Difference and Time Allocation Mechanism

Dependent variable	<i>Working-hour Answers</i> (1)	<i>Non-working-hour Answers</i> (2)	<i>Positive Sentiment</i> (3)	<i>Negative Sentiment</i> (4)
<i>WFH × Post</i>	-0.233*** (0.071)	-0.185*** (0.059)	-0.068*** (0.022)	-0.037 (0.024)
Controls	Yes	Yes	All controls + <i>Answer Length</i>	
Industry FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	91,995	91,995	8,412	8,412
Log-likelihood	-32,871.9	-30,269.0		
Adjusted R2			0.705	0.620

Notes. Models 1-2 are estimated using Poisson QML. *Working-hour Answers* is defined as the number of answers posted during 8 am - 12 pm and during 1 - 7 pm. *Non-working-hour Answers* is defined as the number of answers posted during all other hours. Models 3-4 are estimated using OLS. Standard errors in parentheses are clustered at the industry level. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$.

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Appendix

Table A1. Timeline of the Coronavirus Outbreak in China¹³ *

*Dates highlighted in gray comprise our window of observation (Jan 24 – Feb 7, 2020)

Date	Event
<hr/>	
2019	
Dec 8	<ul style="list-style-type: none"> • First cluster of patients reported symptoms, near the Huanan Seafood Market in Wuhan, China.
Dec 30	<ul style="list-style-type: none"> • Rumors of a SARS-like virus started to spread on social media platforms (these rumors originated from WeChat groups of doctors). Information sources include Doctor Wenliang Li, who passed away due to the infection.¹⁴ • Wuhan Municipal Health Commission (WMHC) issued the “Emergency Notice on the Treatment of Viral Pneumonia of Unknown Causes” to hospitals. This notice was leaked to the public on the same day.
Dec 31	<ul style="list-style-type: none"> • The first public notice from WMHC confirmed 27 cases of pneumonia of unknown causes.¹⁵ • Local government conducted a large-scale disinfection of the Huanan Seafood Market, which is a cluster of the confirmed cases.
<hr/>	
2020	
Jan 1	Huanan Seafood Market was closed.
Jan 3	WMHC confirmed 44 cases in a second public notice. ¹⁶
Jan 5	WMHC confirmed 59 cases and ruled out possible known causes such as MERS and SARS. ¹⁷
Jan 11	WMHC confirmed 41 cases. ¹⁸
Jan 13	First oversea case reported in Thailand. ¹⁹
Jan 14	WMHC confirmed possible human-to-human infection. ²⁰ ²¹ ²²
Jan 18	WMHC confirmed 17 new cases

¹³ Sources of information include: Wuhan Health Commission, local newspaper in Hubei Province such as *Chutian Metropolis Daily*, and national and international news agencies such as *Xinhua*, *People’s Daily*, *China News Service*, *The Paper*, *Caixin*, *Yicai*, *Guancha*, *Phoenix New Media*, *BBC*, *Reuters*, and *Wall Street Journal*.

¹⁴ <https://www.bbc.com/zhongwen/simp/chinese-news-51371586>

¹⁵ <http://wjw.wuhan.gov.cn/front/web/showDetail/2019123108989>

¹⁶ <http://wjw.wuhan.gov.cn/front/web/showDetail/2020010309017>

¹⁷ <http://wjw.wuhan.gov.cn/front/web/showDetail/2020010509020>

¹⁸ <http://wjw.wuhan.gov.cn/front/web/showDetail/2020011109035>

¹⁹ <http://wjw.wuhan.gov.cn/front/web/showDetail/2020011509040>

²⁰ <http://wjw.wuhan.gov.cn/front/web/showDetail/2020011509040>

²¹ <https://www.yicai.com/news/100476157.html>

²² <https://www.bbc.com/zhongwen/simp/world-51116985>

(Continued)

Jan 20	<ul style="list-style-type: none">• Human-to-human transmission confirmed on China's national TV channel, CCTV, by renowned epidemiologist Nanshan Zhong.• Wuhan established the Headquarter of Coronavirus Prevention and Control²³ and provided a list of designated medical institutions for the treatment of coronavirus.
Jan 21	WMHC confirmed the first death.
Jan 22	Citizens in Wuhan were required to wear masks in public spaces. ²⁴
Jan 23	<ul style="list-style-type: none">• Wuhan and 5 neighboring cities in Hubei Province (Ezhou, Xiantao, Zhijiang, Qianjiang, and Tianmen) started lockdown.^{25,26,27}• Zhejiang²⁸, Guangdong²⁹, and Hunan³⁰ Provinces started level 1 alarm, the highest level of emergency alarm.
Jan 24	<ul style="list-style-type: none">• 13 More provinces started level 1 alarm: Hubei, Beijing, Tianjin, Anhui, Shanghai, Chongqing, Sichuan, Jiangxi, Yunnan, Guizhou, Shandong, Fujian, Guangxi.³¹• 11 Other cities in Hubei started home lockdown.³²
Jan 25	13 more provinces started level 1 alarm: Henan, Hainan, Xinjiang, Henan, Heilongjiang, Gansu, Liaoning, Shanxi, Shaanxi, Qinghai, Jilin, Ningxia, and Inner Mongolia. ³³
Jan 26	Chinese New Year Holiday was extended to Feb 2, 2020. ³⁴
Jan 28	One more city in Hubei province, Xiangyang, started home lockdown.
Jan 29	All other provinces have started level 1 alarm.
Jan 31	Regions outside Hubei province started home lockdown: Wuzhong, Yinchuan, and Chongqing. ³⁵
Feb 2	Wenzhou started home lockdown, allowing only essential outdoor activity. ³⁶
Feb 3	Employees in some industries started work from home. ³⁷
Feb 4 –	
Feb 14	Most provinces and cities started home lockdown. ^{38,39}

23 http://news.southcn.com/china/content/2020-01/21/content_190107762.htm.

24 <http://www.chinanews.com/gn/2020/01-22/9067622.shtml>.

25 <http://society.people.com.cn/n1/2020/0123/c1008-31560436.html>.

26 <https://web.archive.org/web/20200124203401/https://www.reuters.com/article/us-china-health-who-idUSKBN1ZM1G9>.

27 https://www.thepaper.cn/newsDetail_forward_5696966.

28 http://www.xinhuanet.com/2020-01/23/c_1125497886.htm.

29 <http://www.bjnews.com.cn/news/2020/01/23/678604.html>.

30 <https://www.yicai.com/news/100480181.html>.

31 <http://news.ifeng.com/c/7tUoW6aZsa8>.

32 https://www.thepaper.cn/newsDetail_forward_5631188.

33 <http://news.ifeng.com/c/7tUoW6aZsa8>.

34 http://www.gov.cn/zhengce/content/2020-01/27/content_5472352.htm.

35 http://www.nx.xinhuanet.com/newscenter/2020-02/01/c_1125517685.htm.

36 http://www.wenzhou.gov.cn/art/2020/2/2/art_1219304_41867473.html.

37 <https://zhuanlan.zhihu.com/p/104849984>; <https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/a-blueprint-for-remote-working-lessons-from-china>.

38 <http://finance.eastmoney.com/a/202002101378386028.html>.

39 A long list of large internet companies such as Alibaba, Baidu, Dingding, JD, and Xiaomi started remote work on February 3. For more information regarding the work arrangements of internet, software, and e-commerce companies (Economic News Daily 2020; Yang 2020). We also collected qualitative evidence from interviewing 15 employees in the following industries: internet, software, e-commerce, banking, finance, and education. The qualitative evidence was used to corroborate the work arrangements in these industries. The earliest date for schools and colleges to start online

courses was February 10. Most school staff started working (remotely or physically) on February 17. Our interviews with bank staff show that banks throughout the country resumed work on February 17, with little to no remote work before that date. According to a report from Chinese Restaurant Association, 97% restaurant only resumed operation after February 24 (Xinhua 2020b).

Table A2. Summary Statistics and Correlation Matrix

Panel A. Full sample (91,955 worker-date observations, including 6,133 workers)

Variable	Mean	Median	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1 <i>Answers</i>	0.18	0	0.884	0	58	1										
2 <i>Working-hour answers</i>	0.10	0	0.583	0	26	0.80	1									
3 <i>Non-working-hour answers</i>	0.09	0	0.544	0	32	0.77	0.23	1								
4 <i>WFH</i>	0.64	1	0.479	0	1	-0.02	-0.02	-0.01	1							
5 <i>Post</i>	0.33	0	0.471	0	1	0.02	0.02	0.02	0	1						
6 <i>New Infections (log)</i>	2.62	2.64	1.736	0	7.59	-0.03	-0.03	-0.02	0.04	0.16	1					
7 <i>Fans (log)</i>	5.33	5.30	2.903	0	13.69	0.06	0.05	0.04	0.05	0.00	-0.08	1				
8 <i>Edit (log)</i>	2.57	2.71	1.679	0	10.19	0.06	0.04	0.04	0.07	0.00	-0.03	0.32	1			
9 <i>Featured (log)</i>	0.07	0	0.357	0	5.05	0.02	0.02	0.02	0.00	0.00	-0.03	0.36	0.22	1		
10 <i>Recognized (log)</i>	0.05	0	0.301	0	5.24	0.04	0.03	0.03	-0.04	0.00	-0.03	0.31	0.17	0.65	1	
11 <i>Gender</i>	0.73	1	0.45	0	1	0.02	0.02	0.00	0.09	0.00	0.02	-0.01	0.14	0.03	0.04	1

Panel B. Sample Excluding Worker-Dates with No Answers (8,441 worker-date observations, including 2,565 workers)

Variable	Mean	Median	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 <i>Arts</i>	0.10	0	0.38	0	7	1															
2 <i>Business</i>	0.06	0	0.32	0	11	0.00	1														
3 <i>Education</i>	0.22	0	0.60	0	12	0.05	0.03	1													
4 <i>Entertainment</i>	0.39	0	1.27	0	15	0.12	-0.03	0.01	1												
5 <i>Life</i>	0.53	0	1.07	0	22	0.04	0.03	0.15	0.38	1											
6 <i>Psychology</i>	0.08	0	0.32	0	6	0.03	0.01	0.13	0.06	0.30	1										
7 <i>Workplace</i>	0.08	0	0.32	0	6	-0.01	0.21	0.15	0.02	0.17	0.10	1									
8 <i>Tag Frequency (log)</i>	7.63	8.00	1.98	0	10.96	0.12	0.07	0.10	0.13	0.25	0.15	0.06	1								
9 <i>WFH</i>	0.60	1	0.49	0	1	-0.03	0.00	-0.12	0.06	0.01	-0.02	0.01	0.03	1							
10 <i>Post</i>	0.38	0	0.49	0	1	-0.06	0.01	0.03	-0.03	-0.01	0.00	0.02	-0.01	0.01	1						
11 <i>New Infections (log)</i>	2.42	2.64	1.52	0	7.59	-0.03	0.01	0.02	-0.02	-0.03	0.00	-0.01	0.00	-0.04	0.14	1					
12 <i>Fans (log)</i>	6.35	6.48	2.92	0	13.69	0.02	0.03	-0.02	-0.12	-0.08	-0.02	0.03	0.08	-0.07	-0.01	0.00	1				
13 <i>Edit (log)</i>	3.08	3.18	1.75	0	9.54	-0.01	-0.01	-0.03	-0.10	-0.06	0.00	0.00	0.04	-0.08	-0.03	-0.03	0.36	1			
14 <i>Featured (log)</i>	0.12	0	0.47	0	4.61	-0.01	0.01	-0.01	-0.03	-0.02	-0.01	0.01	0.06	-0.04	0.00	0.01	0.40	0.26	1		
15 <i>Recognized (log)</i>	0.11	0	0.41	0	4.16	-0.01	0.00	-0.01	-0.03	-0.03	-0.02	0.02	0.05	0.02	0.01	0.00	0.40	0.21	0.66	1	
16 <i>Gender</i>	0.76	1	0.43	0	1	0.02	0.02	-0.03	0.03	-0.10	-0.08	-0.01	-0.04	-0.04	-0.01	0.00	0.03	0.14	0.04	0.06	1

Table A3. WFH Effects on Question Popularity, Answer Length and Number of Photos

Dependent variable	<i>Question Popularity</i>	<i>Answer Length</i>	<i>Number of Photos in Answer</i>
	(1)	(2)	(3)
<i>WFH</i> × <i>Post</i>	-0.134** (0.049)	-0.054 (0.109)	0.027 (0.037)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Observations	8,440	8,412	8,441
Adjusted-R ₂	0.010	0.193	0.107

Notes: Models are estimated using OLS with logged dependent variable in the answer sample (excluding worker-date with no answers). Question Popularity is measured by the frequency at which a question's main tag appears in other questions. Answer Length is measured by the number of Chinese characters in an answer. Standard errors in parentheses are clustered at the industry level. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$.

Table A4. Sub-sample Analysis on Wuhan/Non-Wuhan and Infection Level

Dependent variable			<i>Answers</i>	
	Non-Wuhan (1)	Wuhan (2)	Low Infections (3)	High Infections (4)
<i>WFH</i> × <i>Post</i>	-0.207*** (0.056)	-0.254** (0.124)	-0.159** (0.078)	-0.281*** (0.072)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	79,980	12,015	43,920	48,075
Log-likelihood	-49,924.2	-3,536.2	-26,373.1	-27,173.5

Notes: Models are estimated using Poisson QML. Standard. Low infections sample includes cities with fewer daily new infections than median, while high infections sample refers to the subsample with more new infections than median (inclusive). Standard errors in parentheses are clustered at the industry level. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$.

Table A5. Physical Work as a Baseline

Panel A. Summary Statistics and Correlation Matrix of WFH group in 2019 and 2020 (N = 92,964)

Variable	Mean	Median	SD	Min	Max	1	2	3	4	5	6	7	8
1 <i>Answers</i>	0.13	0	0.75	0	58	1							
2 <i>WFH</i>	0.51	1	0.50	0	1	0.06	1						
3 <i>Post</i>	0.21	0	0.41	0	1	0.04	0.51	1					
4 <i>Fans (log)</i>	5.44	5.46	2.90	0	13.69	0.07	0.00	0.00	1				
5 <i>Edit (log)</i>	2.66	2.77	1.69	0	10.19	0.06	0.00	0.00	0.33	1			
6 <i>Featured (log)</i>	0.07	0	0.33	0	4.28	0.04	0.00	0.00	0.37	0.23	1		
7 <i>Recognized (log)</i>	0.04	0	0.25	0	3.81	0.05	0.00	0.00	0.29	0.16	0.58	1	
8 <i>Gender</i>	0.76	1	0.43	0	1	0.01	0.00	0.00	-0.06	0.12	0.02	0.02	1.00

Panel B. Summary Statistics and Correlation Matrix of CWFH group in 2019 and 2020 (N=52,524)

Variable	Mean	Median	SD	Min	Max	1	2	3	4	5	6	7	8
1 <i>Answers</i>	0.16	0.79	0	0	24	1							
2 <i>CWFH</i>	0.50	0.50	0	0	1	0.07	1						
3 <i>Post</i>	0.21	0.41	0	0	1	0.06	0.51	1					
4 <i>Fans (log)</i>	5.13	2.90	0	5.00	13.59	0.08	0.00	0.00	1				
5 <i>Edit (log)</i>	2.41	1.65	0	2.49	8.99	0.08	0.00	0.00	0.30	1			
6 <i>Featured (log)</i>	0.07	0.40	0	0	5.05	0.01	0.00	0.00	0.36	0.19	1		
7 <i>Recognized (log)</i>	0.07	0.37	0	0	5.24	0.02	0.00	0.00	0.34	0.18	0.74	1	
8 <i>Gender</i>	0.67	0.47	0	1	1	0.04	0.00	0.00	0.05	0.16	0.04	0.07	1.00

Panel C. Comparison Between WFH/CWFH (in 2020) and Physical Work (in 2019)

Dependent variable	<i>Answers</i>			
	Full Sample		Active Workers Only	
	WFH vs. Physical Work (1)	CWFH vs. Physical Work (2)	WFH vs. Physical Work (3)	CWFH vs. Physical Work (4)
<i>WFH</i> × <i>Post</i>	0.550*** (0.052)		0.173*** (0.013)	
<i>CWFH</i> × <i>Post</i>		0.626*** (0.092)		0.234** (0.108)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Day Difference FE	Yes	Yes	Yes	Yes
Observations	92,964	52,524	28,872	18,744
Log-likelihood	-43,000.0	-27,458.5	-29,962.1	-19,739.6

Notes. For Models 1 and 3 (2 and 4), the baseline is the contributions of the same group of WFH (CWFH) workers around CNY holiday in 2019. Models are estimated using Poisson QML. For the sample of “Active Workers Only”, we only include workers in the WFH and CWFH industries who posted at least one answer in both 2019 and 2020 periods. Standard errors in parentheses are clustered at the industry level. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$.

Table A6. Robustness Checks

Panel A. Industry Modification in Treatment/Control Group Formation

Dependent variable	<i>Answers</i>		
	E-commerce excluded	Airline and Bank excluded	Airline, Bank, E-commerce excluded
<i>WFH</i> × <i>Post</i>	-0.209*** (0.056)	-0.172*** (0.045)	-0.170*** (0.046)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Observations	86,955	89,100	84,060
Log-likelihood	-50,241.2	-52,211.9	-48,625.3

Notes: Models are estimated using Poisson QML with conditional fixed effects. Standard errors are clustered at the industry level and appear in parentheses. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$.

Panel B. Main Results Re-estimated with Worker Fixed Effects and Negative Binomial Regressions

Dependent variable	<i>Answers</i>			
	Poisson QML		Negative Binomial	
	(1)	(2)	(4)	(5)
Estimation				
<i>WFH</i> × <i>Post</i>	-0.211*** (0.055)	-0.212*** (0.055)	-0.253*** (0.065)	-0.232*** (0.060)
Controls	Yes	Yes	Yes	Yes
Worker FE	No	Yes	No	Yes
Industry FE	Yes	No	Yes	No
Date FE	Yes	Yes	Yes	Yes
Observations	28,780	38,475	91,995	91,995
Log-likelihood	-35,491.8	-24,339.012	-38,668.5	-38,949.0

Notes: Model 1 is our baseline result in Table 1 in the article. For models with worker fixed effects, the only control variable that is not omitted is *New Infections*. Standard errors in parentheses are clustered at the industry level. $p < 0.1^*$; $p < 0.05^{**}$; and $p < 0.01^{***}$.

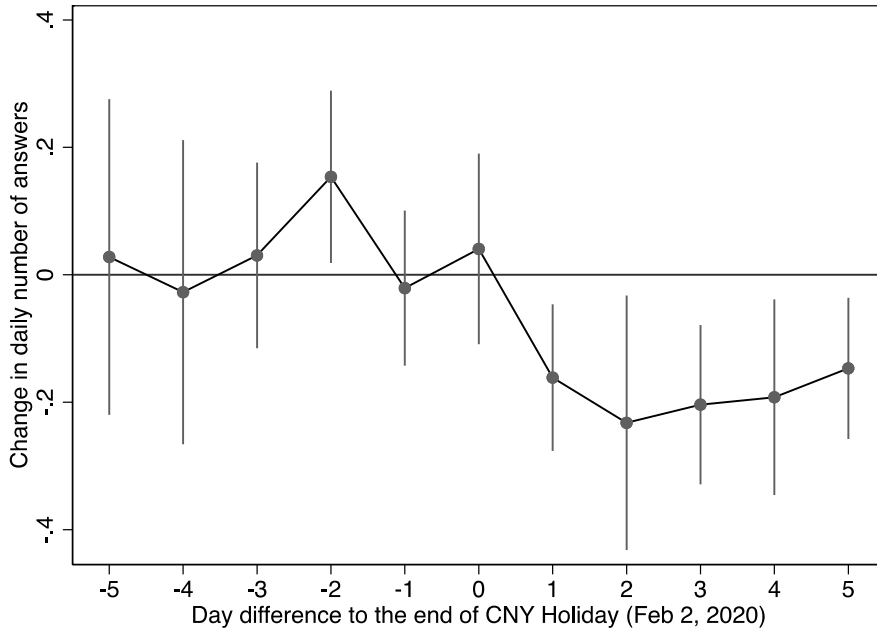


Figure A1. Difference-in-Differences Graph (with Worker FE)

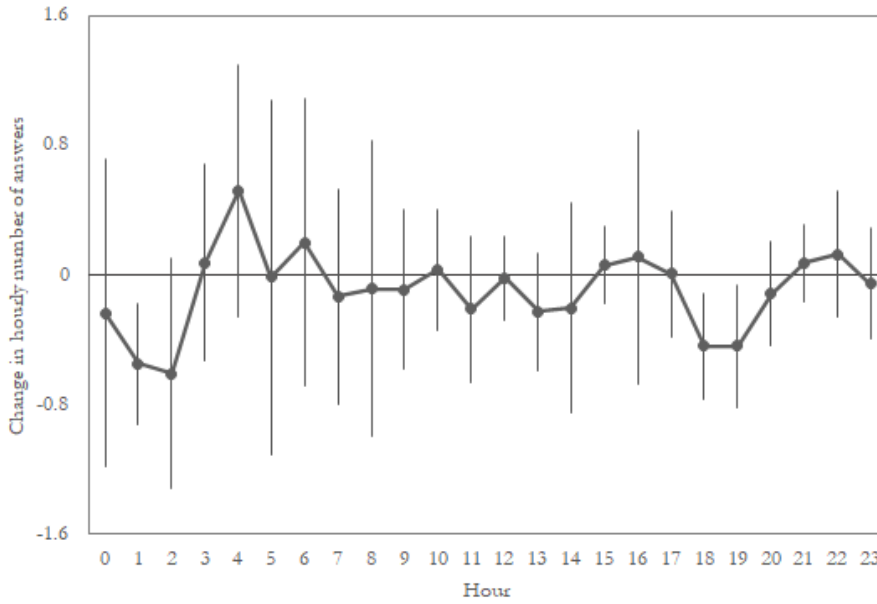


Figure A2. Hourly Effects of WFH on Contribution Differences (with Worker FE)

Note N1. Sentiment Dictionaries

The positive-sentiment and the negative-sentiment dictionaries contain 8,011 and 8,274 words/phrases, respectively. The positive-sentiment words/phrases express a general sense of success, happiness, optimism, gratitude, approval, and excitement. Examples include: “success,” “hero,” “responsible,” and “bring on the food.” The negative-sentiment words/phrases express a general sense of failure, fear, sadness, despair, disapproval, and anger. Examples include: “low-tier,” “suspicion,” “seek help,” “assassination,” and a long list of expletives.

Note N2. Keywords for Topic Categories

The Emotions category includes tags like “love,” “happiness,” “anger,” and “emotions.” The Family category includes tags such as “parents,” “children,” “family members,” and “marriage.” The Remote Work category includes tags such as “remote work,” “video conferencing,” “DingTalk,” “WeChat Work,” “webcam,” and “cloud storage.”

Note N3. Back-of-the-Envelope Calculation of Economic Effects

In our sample period, workers in WFH and CWFH industries cover 34.3% of the full sample (101K/293K). In that sample, 36.4% are CWFH workers, and 63.6% are WFH workers. Among the CWFH workers, the average daily answer count is 0.20, so a 19% daily drop would be 0.04 answers. There are 30 million daily active users per data revealed by the platform. Assuming a similar industry makeup on the platform as in our sample, the reduction in answers due to WFH should be around $34.3\% \times 63.6\% \times 30 \text{ million workers} \times 0.04 \text{ reduced answers/day} = \mathbf{262K \text{ answers/day}}$. This reduction is approximately **4.4% of the total** answer count on the platform ($262K \div (0.2 \times 30\text{million})$). Next, we investigate the drop in views due to WFH. In our sample period, the average number of views for a question is 5.4 million, and the average question has been created for 270 days. Thus, the average number of views per day per question is $5.4 \text{ million views/question} \div 270 \text{ days} = 20K \text{ views/day/question}$. On average, there are 597 answers per question. Assuming viewers scroll down to the answers underneath a question, each answer gets $20K \text{ views/day/question} \div 597 \text{ answers/question} = 33.6 \text{ views/day/answer}$. Thus, the reduction in view count due to WFH is roughly $262K \text{ answers} \times 33.6 \text{ views/day/answer} = \mathbf{8.8 \text{ million views/day}}$.

References for Appendix

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