ABSTRACT

This work aims to document the two-sided impact of the COVID-19 pandemic on online question and answer communities. It implements empirical analyses on subsidiary communities affiliating to the stack exchange network. Using a difference-in-difference approach to identify the impact of the pandemic on community volume (the counts of questions and answers) and responsiveness (the likelihood of questions to be answered), this work has the following discoveries. First, the community volume grows, both in questions and answers, driven by a prolonged time of staying at home during the pandemic. Second, the community responsiveness declines, driven by an influx of new community members during the pandemic, which is also a result of the prolonged time of staying at home. Theoretical and practical implications are discussed.

KEYWORDS

Community Responsiveness, Community Volume, COVID-19 Pandemic, Online Community, Q&A Community

1. INTRODUCTION

The COVID-19 pandemic has catalyzed digital transformation for various traditional industries. To sustain operations, those used to rely on the offline channel are enforced to adopt online channels to distribute products or services. For example, schools provide online courses (Mehla et al., 2022), restaurants accommodate online orders and takeaways (Raj et al., 2021), and hospitals facilitate online treatment inquiries (Sun & Wang, 2021). However, it is less documented about what platforms that are native to the online channel have experienced during the pandemic (Basavaraj et al., 2021; Han et al., 2021; Raj et al., 2021). Such documentation is important as it offers valuable lessons to social entities of what to expect for such an unprecedented health crisis to prepare for the next (Reinhart, 2020).

Although it is natural to expect that online platforms should be less affected by the pandemic, the pandemic may incur unexpected side effects. For example, although online retailers are robust in sales, they have suffered from severe logistics congestion (Han et al., 2021); Although food delivery platforms receive more orders, their incumbent small restaurants have been exposed to more intense competition (Raj et al., 2021); Although gig platforms have absorbed non-gig labors, the inequality among gig workers of different social groups are aggravated (Basavaraj et al., 2021). To add knowledge to this line of research, this work documents the opportunities and challenges of the online question and answer community (Q&A community for short) during the COVID-19 pandemic.
Q&A community has been an important source from which people absorb knowledge. There, questioners (community members who ask questions) can learn from the responding answers, and respondents (community members who answer questions) can also absorb knowledge through peer respondents’ answers (Jin et al., 2021; Stanko, 2016). The impact of the pandemic on the Q&A community is unclear. Intuitions may either suggest a positive effect as the offline channel of learning becomes restricted during the pandemic, or a negative one as people switch to more necessary and urgent issues (such as panic-buying) when their livelihoods are threatened in the hardship. Anyway, a convincing identification of this impact demands an empirical scrutinization. Moreover, the metrics to evaluate the Q&A community should be multidimensional. Aside from the community volume (e.g., number of questions and answers), the community responsiveness (e.g., response rate of questions) is equally vital because the latter greatly affects membership turnover (Butler, 2001; Butler & Wang, 2012). In addition, neither a volume growth (or decline) in questions nor in answers can, by itself, decide the way responsiveness change - rather, it should depend on how the volume of questions and answers relatively change (Butler, 2001; Butler & Wang, 2012). Therefore, a thorough understanding of the impact requires multifaceted analyses involving both community volume and responsiveness.

Then, a natural question is what drives the impacts of COVID-19 on community volume and responsiveness - such an in-depth exploration into the underlying mechanisms can be value-adding. First, the COVID-19 pandemic has devastated almost every aspect of daily life, entailing all-around disruption to people’s lifestyles (Giuntella et al., 2021). We nominate and test one of these aspects, namely a prolonged time of staying at home to be the behavioral mechanism underlying the changes in community volume. Second, we propose an influx of new members, which may break the balance of volume in questions and answers, as an additional antecedence of the change in response rate. Altogether, we specify and manage to figure out the following research questions: What is the impact of the COVID-19 pandemic on the volume and responsiveness of the online Q&A community, and what are the behavioral mechanisms of the impact?

To solve the research question, we situate the empirical analyses on 154 Q&A communities hosted by Stack Exchange (SE) network. To identify the main effect of COVID-19, we adopt a year-on-year difference-in-difference (DID) approach, which contrasts the time trend of community volume and responsiveness that have undergone sharp changes during the pandemic, with the natural trend obtained from the preceding year. To identify the behavioral mechanism, we implement multiple meticulous examinations either on the heterogeneity effects or with sub-samples.

We make several discoveries. First, we find that the community volume in questions and answers grow by 0.387 and 0.260 per day on average in the COVID-19 times, compared to the natural trend in the preceding year. Second, the growth of community volume can be explained by a behavioral shift to stay at home in daily lives. Third, the responsiveness falls, suggesting the growth rate of volume in questions exceeds that in answers so that the questions are less likely to be answered on average in the COVID-19 times relative to the previous year. The magnitude of the drop in likelihood varies from 1.9% for a question to be answered in 1 day, 4.4% in 7 days to 5.1% in 30 days. Forth, aside from the “home-staying” explanation, the relatively imbalanced growth rate should additionally ascribe to the influx of newly registered members during the pandemic, who contribute more to the volume in questions than answers. We also observed heterogeneity across communities with different topics.

2. RESEARCH BACKGROUND

2.1. The Consequences of the COVID-19 Pandemic

From the plague in the Middle Ages and Spanish influenza in the early twentieth century to the SARS, H1N1, and MERS in the latest 20 years, pandemics have never been rare in human history and now seem to outbreak more often in the age of globalization. Despite the sufferings, lessons should be learned from the consequences of the pandemics. However, the previous lessons may not be readily
applied to the recent and ongoing COVID-19 pandemic, as it distinguishes from the previous ones by its massive amount of cases, worldwide scope and unprecedented severity (Reinhart, 2020), as well as the evolving technological and socio-economic environment (Bhavya Alankar et al., 2022). These observations highlight the importance to analyze the consequences of the COVID-19 pandemic and incentivize us to undertake this explorative study.

Prior to us, these observations have already motivated a panoply of researches into the consequences of the COVID-19 pandemic. It has been documented how the pandemic strikes heavily on the development of the stock (Ding et al., 2021), the real estate (Stanton & Tiwari, 2021), the retailing (Fairlie & Fossen, 2021), and the labor markets (Sahin et al., 2021), so does of the primary and high education systems (Bulman & Fairlie, 2021). It has also aggravated the gender, racial and regional inequalities by doing more harm to the vulnerable (Albanesi & Kim, 2021; Andrasfay & Goldman, 2021; Perry et al., 2021).

The pandemic has also stimulated digital transformation in various industries. For example, as an alternative to classroom teaching, school, colleges, and universities now rely more on online courses (Mehla et al., 2022); Being restricted in the accommodation capacity, restaurants now take more online orders and offer take-aways (Raj et al., 2021); To avoid cross-infection, hospitals open up more room for online treatment inquiries (Sun & Wang, 2021). These examples are among the trend where public, private and social organizations embrace an online channel to distribute their products or services in replace of the traditional offline channel during the pandemic. Then, a natural question is how the platforms that are native to the online channel are affected by the pandemic.

This question is relatively less attended to in recent researches. At first thought, one may speculate that the online platforms should be less affected, or even enhanced, by the pandemic. However, recent researches find that the impact is two-sided. For example, online retailers have shown resilience while also suffering from more severe logistics congestion (Han et al., 2021); Food delivery platforms have received increasing orders while exposed incumbent small restaurants with more intense competitions (Raj et al., 2021); Gig platforms have absorbed non-gig labors while aggravated inequality among gig workers of different social groups (Basavaraj et al., 2021). In this work, we join the discussion by documenting the consequence of the COVID-19 pandemic on Q&A communities.

2.2. Online Q&A Communities

Online Q&A communities are the venue where people ask and respond to questions on specific topics (Shah et al., 2009). They are an important source of knowledge. Through the wisdom of crowd, they are only capable to find all-around solutions to complex and open-ended questions (Khansa et al., 2015), but channel the knowledge to the population in need but could have no access (Goh et al., 2016).

Previous literature on the Q&A communities has proposed various internal factors to member engagement (Wu et al., 2019; Y. Zhao et al., 2021). Khansa et al. (2015) categorize these factors into artifacts, membership, or habits related. Zhao et al. (2016) add that they can be substitutive or complemental in their effects. Qiao et al. (2021) propose approaches to mitigate the adverse effects when factors are substitutive. In addition, external factors also drive member engagement. For example, Khurana et al. (2019) find community members contribute for real-world fame. In this work, we add to this literature by proposing the COVID-19 outbreak as another external factor that prompts member engagement.

To further underpin the theoretical foundations for our empirical analyses, we draw on the general theories of online communities (Butler, 2001; Faraj et al., 2011; Marquis & Battilana, 2009; O’Mahony & Lakhani, 2011; Seidel & Stewart, 2011) to introduce some relevant features of the online Q&A communities. First of all, communities are defined as “collections of actors whose membership in the collective provides social and cultural resources that shape their action” (Marquis et al. 2011, p. xvi)” The membership here can derive from, but not limited to, a commitment to a common goal (Bateman et al., 2011; Marquis et al., 2011). In online Q&A communities, for example, community members gather to advance knowledge on a specific theme, which should be demarcated to garner members’
commitments (Kim et al., 2018). In this work, the themes differentiate the various communities in our empirical context.

Second, the entering and exiting the community are prone to exogenous shocks. A prevalent perspective to study online communities is to take it as a distinctive form of organizations (O’Mahony & Lakhani, 2011; Seidel & Stewart, 2011). According to Faraj et al. (2011), the distinctiveness of online communities lies in fluidity, which implies that the organizational boundaries of online communities are highly permeable so that anyone can obtain the community membership if commits to the common goal, and abandon the membership otherwise. In this work, we emphasize the first half of this argument, that is, there are hardly any barriers to obtain community membership in general. It implies that new members can freely join the community so long as they want to, or being stimulated by like the pandemic.

Third, volume and responsiveness are two important resources. A fundamental element for the online community is the resources that are mostly virtual (Butler, 2001; Marquis & Battilana, 2009), such as passion, time and identities (Faraj et al. 2011), etc. In online Q&A communities, the resources are the knowledge. Then, the answers are the carriers of knowledge and the questions are the indispensable showcases to organize and present knowledge. In light of this, the community volume in questions and answers (the count of questions and answers) is the typical measurement for the quantity of resources (Butler, 2001). Aside from the volume, another resource-related indicator is community responsiveness, which is specific to Q&A communities. According to Butler (2001), a partial accumulation of resources may entail side effects that make its members difficult to benefit from the resources. Applied to Q&A communities, commitment to the community will be lost in the long run if questions are frequently unanswered (Butler & Wang, 2012). In this case, community responsiveness (the likelihood of questions to be answered) becomes another resource-related indicator in specific to Q&A communities. In essence, it measures the balance between volume in questions and answers.

Forth, new and senior members are fundamentally difference. Seidel and Stewart (2011) envision the interior structure of online communities as the transection of an onion: the less and highly committed members reside on the peripheral and core layers respectively. These layers, the same as the organization boundary, are permeable, which infers that any peripheral members can head into the core if want to (Faraj et al. 2011). In the meantime however, the only approach to get promoted into the core layers is to contribute resources to the community. It indicates that any member, if at the core layers, must have contributed more resources to the community than members at peripheral. To adapt these theories to Q&A communities, we follow Butler (2001) and define community members as those who have formally registered. Then, any member should reside more closely to the core than the new members that have just registered, who, consequently, have contributed less knowledge. Therefore, the new members are more likely to engage in the communities from making, rather than answering questions.

3. EMPIRICAL SETTING

3.1. The Stack Exchange Network

We situate the empirical analyses on the subsidiary online Q&A communities affiliating to the Stack Exchange (SE) network. Established in 2010, the Stack Exchange (SE) network comprises a collection of Q&A communities. Over the years, it breeds myriads of subsidiary communities, where crowds collaborate on sharing and learning knowledge through making and solving questions. Throughout the years, it has mobilized approximately 12 million registered members from all around the world, who generate over 6 million questions and 9 million answers in total.

Despite the large size and long history that makes the subsidiary communities to the SE network representative of other Q&A communities, they are a suitable empirical context for our analyses.
for two reasons. First, the way it functions meets our needs. All the subsidiaries to the SE network conform to the typical form of Q&A communities, that is, any registered members can make questions and others can answer, regardless of the experience or the status in the community. More important, unregistered visitors are barred from generating any content and moderators regularly inspect the community and remove spam. This naturally excludes the possibility that the community volume grows out of spamming somewhat than learning and sharing knowledge. Second, the SE network offers fine-grained data so that we have access to detailed information about the open activities in the communities. Third, the SE network incorporates an abundance of subsidiary communities, which can be used to construct a rich panel, and that ensures the results are not diverted by some special effects particular to a few communities.

3.2. Empirical Design

Figure 1 depicts the research design. We exploit the outbreak of COVID-19 as an exogenous shock to the community volume and responsiveness in 2020. We implement a year-on-year DID approach (Bandiera et al., 2005) to identify the treatment effect of COVID-19 on community volume and responsiveness. It eliminates some parametrically-intractable trends that emerge every year in some communities, such as the rise of member activities in health-related communities during the influenza seasons and the drop of activities in technology-related communities during the Christmas seasons. An alternative design to estimate the treatment effect of the COVID-19 pandemic is to take observations from a typical period that precedes the outbreak of the pandemic as the control group, as in Perry et al. (2021) for example. We suspect this approach is improper to this work. Imagine an observation period from January 1, 2020 to April 30, 2020, the time trend between January 1 to February 29 should not be taken as the natural trend had it not been the pandemic for the trend between March 1 to April 30, because of the community-specific seasonality effect for example. In other words, we believe a “community and day of year-wise” comparison is necessary to correctly identify the treatment effect of the COVID-19 pandemic in this work. To suit the research design into such an empirical framework, we recognize several problems and solve them as follows.

First, the first community affiliating to the SE network could date back to 2010, so that it has experienced various events that aroused global upheaval. These events may alter member contributions to the online communities (Kummer et al., 2020), and therefore confound the treatment effect of interest. With this regard, we prefer a short observation period to exclude these irrelevant events. Specifically, we restrict the observation period to two years - 2020 as the year of treatment and 2019 as the year of control.

Figure 1. The year-on-year difference-in-difference design
Second, the COVID-19 pandemic comes in multiple waves (Fan et al., 2021). It retreats and then resurges, and each time varies in severity so that the pandemic should be interpreted as a repeated treatment. To simplify the identification of its impact, we focus on the first wave so that the treatment variable signifies the sharpest change from null to a serious outbreak. To do so, we truncate the sample for both treatment and control group to May 31 - the date taken as the end of the first wave (Fan et al., 2021).

Third, the outbreak time of COVID-19 varies across countries. In this work, we unify the country-specific treatment by taking March 11, the date when the World Health Organization (WHO) declared the COVID-19 to become a global pandemic, as the onset of the pandemic.

Fourth, a necessary precondition to the validity of the year-on-year approach is that the time trend is linear. Besides, if the time trend is marginally increasing (decreasing), the year-on-year estimator is expected to overestimate (underestimate) the treatment effect. Since an underestimated treatment effect will not negate our results, we concern more about whether the time trend is marginally increasing. Figure 2 offers the intuition. The time effect accumulated linearly in the left panel, the natural increment of the time trend during a given time period \( \tau \), for the year 2019 \( \gamma_{2019} \), equals to that of the year 2020 \( \gamma_{2020} \), so that the year-on-year DID estimator \( \hat{d} \) identify the treatment effect \( \delta \). In the right panel, the time effect accumulated in a marginally increasing manner, the year-on-year DID estimator is wrongly obtained through an estimated linear curve whose slope is smaller than the actual slope, so the \( \hat{d} \) is larger than the treatment effect \( \delta \). We prove these arguments in Appendix D.

Since communities usually expand rapidly in infancy and then slow down when matured, their trend is mostly marginally increasing in the preceding years and become steady later on. Against this backdrop, we restrict the sample within communities established before 2017 to exclude the communities that are growing in a marginally increasing manner. Further, we conduct a placebo test to verify the trend does not negate our results. As in Figure 1, we assume the pandemic outbreaks in
2019 and repeat the year-on-year DID analyses with the restricted sample. If no effect is found, the trend is unlikely to drive our results.

3.3. DATA

We collect granular data from all the subsidiary communities affiliating to the SE network. We aggregate the data into a daily time series and construct it into a DID analysis framework as described in the previous section. The final dataset consists of 154 Q&A communities, covers the first five months in 2019 and 2020.

We generate the following dependent variables. For each day of year \( t \) in year \( g \) and each subsidiary Q&A community \( i \) from the SE network, we measure community volume with \( Questions_{igt} \) - the number of questions posted, and \( Answers_{igt} \) - the number of answers posted. To measure responsiveness, we have \( RespRate_{igt}^n \) - the response rate of questions posted on day \( t \) in year \( g \) and community \( i \) during an answer-waiting period of \( n \) days. We alter the answer-waiting period from 1, 7 to 30 days, thereby having \( RespRate_{igt}^1 \), \( RespRate_{igt}^7 \) and \( RespRate_{igt}^{30} \). Longer answer-waiting period takes account of the time and effort it consumes to answer difficult questions.

As to the independent variable, we set a group indicator \( Year_g \) which equals 1 for 2020 and 0 for 2019, as well as a treatment indicator \( COVID_t \) which equals 1 after March 11 and 0 otherwise.

### Table 1. Summary statistics

|                          | 2019 (Year\(_g\) = 0) | 2020 (Year\(_g\) = 1) |
|--------------------------|------------------------|------------------------|
|                          | Mean | SD  | Min | 50% | Max | Mean | SD  | Min | 50% | Max |
| Pre-treatment Stage \(COVID_t = 0\) |     |     |     |     |     |     |     |     |     |     |
| Questions\(_{igt}\)       | 12.47 | 21.56 | 0 | 5 | 185 | 11.16 | 20.49 | 0 | 4 | 218 |
| Answers\(_{igt}\)        | 17.33 | 25.93 | 0 | 7 | 202 | 14.67 | 23.31 | 0 | 6 | 208 |
| RespRate\(_{igt}^1\)     | 0.62  | 0.27  | 0 | 0.67 | 1 | 0.59  | 0.29  | 0 | 0.63 | 1 |
| RespRate\(_{igt}^7\)     | 0.75  | 0.24  | 0 | 0.80 | 1 | 0.74  | 0.27  | 0 | 0.80 | 1 |
| RespRate\(_{igt}^{30}\)  | 0.79  | 0.23  | 0 | 0.83 | 1 | 0.78  | 0.25  | 0 | 0.83 | 1 |
| CumQuestions\(_{igt}\)   | 9.30  | 1.40  | 6.72 | 9.19 | 12.86 | 9.45 | 1.39  | 6.90 | 9.32 | 12.95 |
| CumAnswers\(_{igt}\)     | 9.83  | 1.38  | 7.22 | 9.71 | 13.28 | 9.97 | 1.37  | 7.36 | 9.93 | 13.34 |
| CumMembers\(_{igt}\)     | 10.13 | 1.20  | 7.53 | 9.93 | 13.50 | 10.36 | 1.19  | 7.77 | 10.12 | 13.67 |
| Age\(_{igt}\)            | 7.86  | 0.39  | 6.76 | 7.86 | 8.26  | 7.90  | 0.33  | 7.12 | 7.99 | 8.35 |
| Post-treatment Stage \(COVID_t = 1\) |     |     |     |     |     |     |     |     |     |     |
| Questions\(_{igt}\)       | 12.55 | 4.5  | 0 | 4.5 | 192 | 14.72 | 29.99 | 0 | 5 | 313 |
| Answers\(_{igt}\)        | 16.89 | 25.76 | 0 | 7 | 190 | 15.71 | 26.47 | 0 | 6 | 232 |
| RespRate\(_{igt}^1\)     | 0.60  | 0.28  | 0 | 0.65 | 1 | 0.55  | 0.29  | 0 | 0.57 | 1 |
| RespRate\(_{igt}^7\)     | 0.74  | 0.26  | 0 | 0.79 | 1 | 0.68  | 0.28  | 0 | 0.72 | 1 |
| RespRate\(_{igt}^{30}\)  | 0.77  | 0.24  | 0 | 0.83 | 1 | 0.72  | 0.27  | 0 | 0.75 | 1 |
| CumQuestions\(_{igt}\)   | 9.34  | 1.40  | 6.75 | 9.22 | 12.88 | 9.48 | 1.39  | 9.35 | 6.92 | 12.97 |
| CumAnswers\(_{igt}\)     | 9.87  | 1.38  | 7.24 | 9.77 | 13.30 | 9.99 | 1.37  | 7.38 | 9.96 | 13.36 |
| CumMembers\(_{igt}\)     | 10.17 | 1.20  | 7.60 | 9.98 | 13.55 | 10.34 | 1.20  | 7.84 | 10.15 | 13.71 |
| Age\(_{igt}\)            | 7.78  | 0.38  | 6.85 | 7.89 | 8.28  | 7.92  | 0.32  | 7.17 | 8.01 | 8.37 |
We also incorporate some control variables. Including these variables not only control for the factors that potentially confound the time trends, but also improve the estimation precision. These control variables include the accumulated number of registered community members \( (Year_g = 0) \), questions \( (Year_g = 1) \) and answers \( ((COVID) = 0) \), as well as the age of the community in days \( (Questions_{igt}) \). Table 1 provides the descriptive statistics for the dependent and control variables for the treatment and control groups against pre and post-treatment stages.

Figure 3 plots the trend for the \( Answers_{igt} \), \( RespRate_{igt}^1 \) and \( RespRate_{igt}^7 \) for both treatment and control year. The x-axis presents the day of year and y-axis presents the value of each dependent variable averaged on each day. We use a 7-day moving average to smooth the daily time-series to highlight the trend. We find that the pretreatment trend (trend before 11 March) reveals no systematic difference between the treatment and control year. Moreover, we also notice a sharp change around the treatment in the treatment year, which corresponds to the treatment effect we are to identify. In addition, we also plot the trend of 2018 and find it identical to the trend of 2019, which re-confirms the validity of using 2019 as the control year.

4. IMPACT OF THE COVID-19 PANDEMIC ON COMMUNITY VOLUME

4.1. Main Effect of the COVID-19 Pandemic on Community Volume

As indicated from Figure 3, the community volume is sharply expanded. To make rigorous conclusions, we apply the year-on-year DID specification to identify the treatment effect of the COVID-19 pandemic.
on the counts of questions and answers from the Q&A communities affiliating to the SE network. To account for the skewness and the likely over-dispersion relative to Poisson in the distribution of the counts of questions and answers, we adopt a negative binomial regression (Hausman et al., 1984). Specifically, we estimate:

\[ \text{RespRate}_{igt}^{30} \]

In Equation (1), \( \text{CumQuestions}_{igt} \) represents either \( \text{CumAnswers}_{igt} \) or \( \text{CumMembers}_{igt} \), which measures the volume in questions or answers of community \( Age_{igt} \) in year \( (COVID_t = 1 \) and day of year \( Questions_{igt} \). \( Answers_{igt} \) presents the set of controls, including \( \text{RespRate}_{igt}^{1} \), \( \text{RespRate}_{igt}^{7} \), \( \text{RespRate}_{igt}^{30} \) and \( \text{CumQuestions}_{igt} \). \( \text{CumAnswers}_{igt} \) and \( \text{CumMembers}_{igt} \) are the community and day-of-year fixed effects. \( Age_{igt} \) is the group indicator, which equals 1 if the observation is in the year 2020. \( CumMember_{igt} \) is the indicator of treatment, which equals 1 after March 11. The main effect of \( \text{CumQuestions}_{igt} \) is collinear with the day of year dummy \( \text{CumAnswers}_{igt} \), and therefore omitted. The coefficient of interest is \( Age_{igt} \), which captures the difference in the changes in volume before and after 11 March, between 2019 and 2020.

Table 2 presents the estimation of Equation (1). It can be taken as a parametric analogy to the upper and middle panel in Figure 3. In column 1 and 2, we observe a statistically significant positive coefficient \( Questions_{igt} \) for both \( Answers_{igt} \) and \( \text{RespRate}_{igt}^{1} \). It indicates that the counts of questions and answers have grown by 1.26 (\( Volume_{igt} = \alpha Year_{igt} + \beta Year_{igt} \times COVID_t + X_{igt} \delta + \gamma_i + \lambda_t + \varepsilon_{igt} \# (1) \)) and 1.10 (\( Volume_{igt} \)) per day in 2020 after the pandemic compared to 2019, which equates to about 11.3% and 7.50% growth relative to the pre-COVID time in 2020. The growth in questions and answers suggests that the COVID-19 pandemic positively influenced community volume.

It may be that the trend of community volume is marginally increasing in itself, thereby explaining the growth in community volume. Although this possibility can be negated by the fact that trends of volume in 2018 and 2019 do not differ, we re-confirm it with a placebo test, which assumes the COVID-19 pandemic outbreaks in 2019 and use 2018 as the control year. As shown in column 3 and 4, we observe no detectable effect between 2018 and 2019. It assures us that, for the Q&A community in our sample, the trend of volume grows at the same speed since 2018, thereby verifying the validity of the year-on-year DID estimator.

Moreover, the negative binominal estimator from Hausman et al. (1984) is inconsistent as it derives the fixed effect from the conditional mean in contrast to the original distribution of dependent variables. This drives some weird properties of the Hausman et al. (1984) estimator, making the fixed-effects from Hausman et al. (1984) deviate from its common sense (Greene, 2017). For example, the coefficient of time-invariant variables can still be identified conditional on time-fixed effects. With this regard, we follow the suggestions from Wooldridge (1999), where the Poisson estimator can be a feasible alternative that attains consistency. Additionally, we also offer a linear estimator, using the logarithms of the volume plus one as dependent variables. The results are shown in Appendix A and stay unchanged.
4.2. Home-staying and the Growth in Community Volume

Now that we have documented how the COVID-19 pandemic impacts community volume, we next explore its behavioral mechanism. Worldwide, people now stay home longer than ever before to stem the spread of COVID-19. We speculate this behavioral shift explains the rise in community volume during the pandemic: when offline channels of knowledge learning and sharing are restricted, they resort to the online channel. We provide two pieces of supporting evidence to confirm this explanation.

The first piece of evidence relates to the effect of stay-at-home orders on community volume during the first wave of the COVID-19 pandemic. We utilize the variation in the effective time of stay-at-home orders among US states to identify the impact of staying at home on community volume generated by US community members. To implement the analyses, we should first identify the US community members. We extract the location information from the self-reported location texts from community member profiles. However, the location texts are mostly too simple and ambiguous. Against this background, we integrate multiple geolocation services and K-means clustering algorithms to extract the location information and provide the details in Appendix C. Then we acquire the effective date of the stay-at-home orders for each state from Christopher et al. (2021). We also collect the daily and accumulated number of COVID-19 infections and fatalities for each state from the Johns Hopkins Coronavirus Resource Center as controls. Since the US states enact stay-at-home orders in a staggered manner, we construct the model in the fashion of event study analyses (Athey & Imbens, 2018):

\[ Questions_{igt} \]

In Equation (2), \( Answers_{igt} \) is given by \( i \) for states that have enacted SAH orders and 0 otherwise. Here, \( g \) refers to the date when SAH order in state \( t \) starts, so that the coefficients \( X_{igt} \) signify the treatment effect on \( CumMember_{igt} \) days leading or lagging to the \( CumQuestions_{igt} \). In particular, the day of treatment is taken as the baseline and \( CumAnswers_{igt} \) is thus omitted to avoid perfect collinearity. With \( Age_{igt} \), we control for the daily and accumulated number of COVID-19 infections and fatalities. \( \gamma_t \) and \( \lambda_t \) stand for the state and day fixed effect respectively. The observation period starts at January 1, 2020 and last till the first cancelation of the SAH order for the states that have enacted such orders, or May 31, 2020 otherwise.

|                  | Main Results: 2019-2020 | Placebo Test: 2018-2019 |
|------------------|-------------------------|-------------------------|
|                  | Questions | Answers | Questions | Answers |
| **Year**         | -0.193     | -0.241   | -0.082     | -0.142    |
|                  | (0.008)    | (0.008)  | (0.006)    | (0.007)   |
| **COVID * Year** | 0.235      | 0.094    | -0.006     | -0.002    |
|                  | (0.008)    | (0.008)  | (0.008)    | (0.008)   |
| **N**            | 47,414     | 47,414   | 47,414     | 47,414    |
| **Forum FEs**    | YES        | YES      | YES        | YES       |
| **Day FEs**      | YES        | YES      | YES        | YES       |
| **Controls**     | YES        | YES      | YES        | YES       |
We estimate the Year's simultaneously and plot them in Figure 4. We find the COVIDs prior to treatment do not significantly differ from 0, which indicates that the pre-treatment trend may not be a major factor to confound the treatment effect. Moreover, we find positive and significant effect of the stay-at-home orders on the community volume generated by US community members, which indicates a behavioral shift to home-staying may be the cause to make community volume rise during the pandemic.

The second piece of evidence is drawn from the intuition that, the daytime should be more affected by the COVID-19 because people could have been in office or schools at this time of the day, but now they are at home because of the pandemic. Then, the impact of the COVID-19 pandemic on community volume should be more compelling in the daytime. To test, we analyze the heterogeneity in the treatment effect found in Equation (1). In particular, we estimate:

\[
COVID_t
\]

In Equation (3), we split \( \lambda_t \) into the 24 hours of a day and generate \( \beta \) - the volume of community \( \beta \). on hour \( Questions_{igt} \) from day of year \( Answers_{igt} \) in year \( e^{0.235} \) and allow the year-on-year DID estimator \( e^{0.094} \) to vary with the hours of a day. In generating

\[
Volume_{it} = \beta_k \sum_{k=-4}^{7} (SAH \ Order)_{it+k} + X_{it} \delta + \gamma_s + \lambda_t + \varepsilon_{it}\# (2)
\]

the locations of community members are reused to convert the originally coordinated universal time (UTC)-formatted timestamps to local time.
Figure 5 plots the estimations from Equation (3). The x-axis stands for the hour of the day (\(SAH\ Order_{s,t+k}\)) and y-axis the hour-specific treatment effects (\(1[t \leq SAH\ Order_{s,t+k}, k = -3\), \(1[t = SAH\ Order_{s,t+k}, -3 < k < 7\). The shaded area indicates a 95% confidence interval for each \(SAH\ Order_{s}\). We find that most of the detectable effects concentrate in the daytime, thereby underpins our explanation to the rise of community volume during the pandemic.

4.3. Alternative Explanations to the Growth in Community Volume

Despite the prolonged home staying, the growth in community volume may also be ascribed to a surge of contents related with the COVID, or a need of spiritual handholds from peer community members to ease emotional struggle\(^7\). We test these alternative explanations as follows. First, we ensure that our findings persist in removal of contents on the pandemic. To do so, we collect a list of pandemic-related words and present them in Appendix E. This list covers a wide range of topics that people concern about. We remove all the questions and answers that have mentioned these words and re-estimate Equation (1).

Second, we examine whether the sentiment in content change after the pandemic. If the increasing activities on the communities are attribute to the seeking of psychological remedy to emotional struggle during the COVID, then the textual sentiments of questions and answers are both affected: the sentiments of questions should turn negative because the questions express the emotional struggle, and the sentiments of answers should turn positive because the answers convey emotional support.
To test, we conduct a sentiment analyses on the contents aggregated at a day level and examine the sentiment change.

Shown in Appendix E, the volume in questions and answers still rise but in a lesser degree, which indicates that, although the pandemic-related topics contributes to the growth in community volume, they cannot negate our findings. Moreover, we find the the sentiments remain stable after the pandemic. One reason for this is that questions and answers from the SE communities, targeting at knowledge learning and sharing, have to be expressed in a reasonable, calm and objectively tone.

5. IMPACT OF THE COVID-19 PANDEMIC ON COMMUNITY RESPONSIVENESS

5.1. Main Effect of the COVID-19 Pandemic on Community Responsiveness

We estimate the effect on community responsiveness using the following specification:

\[
\text{Responsiveness}_{igt} = \alpha \text{Year}_g + \beta Year_g \times COVID_t + X_{igt} \delta + \gamma_i + \lambda_t + \varepsilon_{igt} \tag{4}
\]

The notations in Equation (4) is the same with those of Equation (1) except for the dependent variable. Here, \( \beta_k \) stands for either \( k \), \( SAH \ Order \) or \( \beta_0 \), which infers to the responsive rate of questions posted on community \( X_{igt} \) in year \( \gamma_i \) and day of year \( \lambda_t \) in an answer-waiting period of 1, 7, or 30 days respectively. The coefficient of interest is still \( \beta_k \), which can be interpreted as the difference in the changes in response rate before and after March 11, between the 2020 and 2019. We estimate Equation (3) with a linear model. In addition, we avoid an overlap between the answer-wating period with both pre- and post-treatment stage, we exclude 1, 7 or 30 days prior to treatment when \( \beta_k \), \( Volume_{igt} = \alpha \text{Year}_g + \beta Year_g \times COVID_t + X_{igt} \delta + \gamma_i + \lambda_t + \varepsilon_{igt} \tag{3} \) or \( Volume_{igt} \) is the dependent variable.

Table 3. The impact of COVID-19 pandemic on community responsiveness

|                | Main Results: 2019-2020 | Placebo Test: 2018-2019 |
|----------------|-------------------------|-------------------------|
|                | 1 day       | 7 days    | 30 days | 1 day       | 7 days    | 30 days |
| **Year**       | -0.047      | -0.024    | -0.020  | -0.018      | -0.007    | -0.002  |
|                | (0.022)     | (0.023)   | (0.023) | (0.006)     | (0.015)   | (0.014) |
| **COVID * Year**| -0.019      | -0.044    | -0.051  | -0.012      | -0.009    | -0.010  |
|                | (0.007)     | (0.007)   | (0.008) | (0.006)     | (0.006)   | (0.007) |
| **N**          | 40,541      | 38,676    | 32,678  | 40,975      | 39,075    | 33,104  |
| **Forum FEs**  | YES         | YES       | YES     | YES         | YES       | YES     |
| **Day FEs**    | YES         | YES       | YES     | YES         | YES       | YES     |
| **Controls**   | YES         | YES       | YES     | YES         | YES       | YES     |

Table 3 presents the estimations from Equation (2). According to column 1-3, the response rate drops in 2020 after the pandemic compared to 2019, whichever the answer-waiting period. In particular, a 1.9% decline in the likelihood of a question to be answered by at least once within 1 day should ascribe to the COVID-19 pandemic, and the magnitude becomes 4.4% and 5.1% within
an answer-waiting period of 7 and 30 days respectively. Column 4-6 show the results of the placebo test assuming the COVID-19 pandemic outbreaks in 2019. It reassures us that the pretreatment trend do not confound the estimation of the treatment effect on community responsiveness under our empirical design.

In Appendix B, we replicate Equation (4) using the average number of answers received by a question within a given answer-waiting period as an alternative proxy for community responsiveness. We find the results stay consistent: the average number of answers per question drops by 0.024 to 0.045.

5.2. The Influx of New Community Members and the Drop in Responsiveness

Now that we have documented the drop in community responsiveness, we next explore its behavioral mechanism. Beforehand, we acknowledge that the explanation to the growth of community volume cannot be directly applied to change in community responsiveness, as it fails to take account of the imbalance between the volume growth in questions and answers. In this case, we search for an intermediate mechanism that lies in between the prolonged time of staying at home and the decline of community responsiveness.

We speculate that an influx of new community members explains the imbalanced growth of community volume in questions and answers because new members usually start by asking, rather than answering questions, and the influx of new members itself is another consequence of a prolonged time of staying at home. Figure 6 offers some intuitions. The x-axis marks the day of year and y-axis marks the proportion of community volume generated by members on the registration day, smoothed by a 7-day moving average. We find that the trend of the proportion of questions from new members deviates from its trend in 2019 in the COVID-19 times, and this statistical pattern does not appear in the trend of the proportion of answers.

Figure 6. The pre- and post-treatment trend on the volume generated on registration day

![Figure 6](image-url)
To verify the speculation, we take on three steps. First, we test whether the number of new registered members grows during the COVID-19 pandemic. Second, we compare new and senior members against the likelihood of making questions and answers. Third, we ask, had it not been the new registering members, whether the community responsiveness still drops.

We adhere to the year-on-year DID design and re-estimate Equation (1), using the count of new registers in community $Volume_{ith}$ on each day of year $i$ in year $h$ as dependent variable, denoted by $t$. As shown in Column 1 Table 4, the COVID-19 pandemic contributes to 1.25 ($g$) new daily registrations per community, relative to the trend of 2019. It indicates that new members increasingly enrolled into the community during the pandemic, who, we speculate, generate more questions than answers.

To test, we regress the proportion of volume from new community members in community $\beta_h$ on each day of year $Volume_{ith}$ in year $h$ - denoted by $\beta_h$ and $\beta_h$ - on the the DID interactions. In Column 2, the coefficient of $Responsiveness_{igt} = \alpha Year_g + \beta Year \times COVID_t + \gamma_i + \lambda_t + \varepsilon_{igt} \# (4)$ is significantly positive on $Responsiveness_{igt}$. It indicates that the new members, those on their first day of registration in particular, generate more questions than their senior peers. In Column 3, the coefficient of $RespRate_{igt}^1$ is still positive but not significant at 5% level. It indicates that the new members do not differ with their senior peers in generating answers. Put together, the marginally increasing number of new members give rise to a growing number of questions rather than answers, which end up with the drop in community responsiveness.

To test, we remove all the community volumes generated by members on their registration day, re-compute $RespRate_{igt}^7$ and re-estimate Equation (4). The results are shown in Column 4. We find that, had it not been these new members, the impact of the COVID-19 pandemic becomes insignificant at 5% level. To conclude the findings from Table 4, the drop in community volume should ascribe to an influx of new community members during the pandemic, who break the previous balance between the volume in questions and answers, which further reduces the community responsiveness.

6. ADDITIONAL FINDINGS

Aside from the impact of the COVID-19 on Q&A communities, and its mechanism, we also explore the heterogeneity across different SE community subsidiaries. We split the sample into 6 categories,
according to the design of the SE community, and re-estimate Equation (1) and (4). These categories are business, culture, life, professional, science, and technology. The results are presented in Table 5.

Table 5. Heterogeneous impact on subsidiaries communities of different categories

|                  | Business | Culture | Life    | Professional | Science | Technology |
|------------------|----------|---------|---------|--------------|---------|------------|
| **Panel A. Questions** |          |         |         |              |         |            |
| COVID * Year     | 0.441 (0.107) | 0.089 (0.015) | 0.188 (0.019) | -0.089 (0.052) | 0.283 (0.013) | 0.256 (0.007) |
| N                | 906      | 12,986  | 7,248   | 1,812        | 5,436   | 19,026     |
| **Panel B. Answers** |          |         |         |              |         |            |
| COVID * Year     | 0.262 (0.084) | 0.014 (0.012) | 0.082 (0.014) | -0.085 (0.054) | 0.645 (0.013) | 0.097 (0.006) |
| N                | 906      | 12,986  | 7,248   | 1,812        | 5,436   | 19,026     |
| **Panel C. Response Rate** |          |         |         |              |         |            |
| COVID * Year     | -0.098 (0.049) | -0.014 (0.009) | -0.039 (0.125) | 0.041 (0.023) | -0.038 (0.014) | -0.058 (0.007) |
| N                | 668      | 10,329  | 6,009   | 1,234        | 5,023   | 17,130     |

We find the subsample results remain consistent, with a few exceptions. In particular, subsidiaries of the business and science category have grown the most in questions and answers respectively. It implies that people become more interested in business topic and experts in specific scientific area have more time to share knowledge during the pandemic. Moreover, the business category has witnessed the largest reduction in response rate, thanks to its largest growth of volume in question and median growth of volume in answer. The only exception is the professional category. Its volume and response rate remains stable. One explanation is that people interested in these topics, such as freelancing, writing and open source, are flexible in workplace, so that they are least affected by the pandemic.

Figure 7. Summary of the findings
7. CONCLUSIONS AND DISCUSSIONS

7.1. Summary of Findings

Figure 7 summarizes the findings. In this work, we have empirically tested the impact of the COVID-19 pandemic on online Q&A communities as an example. We draw on two critical indicators to the Q&A community - community volume and responsiveness - to evaluate the impact of the pandemic. We find the community volume has grown during the pandemic, with respect to both questions and answers. The impact on volume is driven by a prolonged time of staying at home. However, we also find the community responsiveness drops during the pandemic. It should be ascribed to an influx of new members into the community, who are also stimulated by the longer time of staying at home. In additional analyses, we also observe a heterogeneity across different categories of subsidiary communities. Altogether, we conclude that the impact of the COVID-19 pandemic on the online Q&A community is mixed as it stimulates the growth of community volume but engenders community responsiveness.

7.2. Theoretical Implications

This work makes theoretical contributions to multiple fields. First, it contributes to the growing body of work in Q&A communities and adds insights into the factors that affect the development of these communities. While extant literature has underlined the importance of subjective factors to drive content generation from a psychological perspective (Khansa et al., 2015; Qiao et al., 2021; L. Zhao et al., 2016), we propose an external factor, the COVID-19 pandemic, can also play a role as an exogenous shock to impact the community volume and responsiveness.

In a broader sense, this work is also relevant to the general online communities in terms of membership turnover. In particular, previous studies have noted how a blend of new and senior members realize the common goal of the online community (Ransbotham & Kane, 2011), we join the discussion by offering an instance in which an exogenous influx of new members can have a negative effect on the community. Moreover, while it has been documented how an attraction of new members and retention of senior members are both important to the sustainability of online communities (Butler et al., 2014), our findings imply that, at least in a short run, the senior members are more valuable than the new members in terms of response rate. However, we do not deny the importance of attracting new members in a long run, because some of them will turn senior in the future.

Second, this work is also among the researches on the consequences of the COVID-19 pandemic. Given its unprecedented numbers of cases, scope and severity, as well as the social and economic upheaval it entails, the importance to understand its consequences are self-evident. While previous research has largely documented how organizations attain resilience through a switch to digital channel (Basavaraj et al., 2021; Raj et al., 2021), we illustrate how Q&A communities, being native to the digital channel, are affected in a two-sided way. This is counter-intuitive: online platforms, being native to the online channel, should obtain opportunities from the pandemic, since offline alternatives are mostly disabled.

Moreover, this work joins the emerging discussion on how online platforms substitute their offline alternatives during the pandemic to maintain people’s normal life. These discussions have covered almost every necessary aspects of people’s lives, including food-ordering, shopping and working (e.g., Raj et al., 2021; Sun & Wang, 2021), this work focus on a unique field - online Q&A communities, which satisfies people’s need of absorbing and sharing knowledge. Therefore, this work also add new insights to this line of researches and is unique from its peers amid the discussion.

In a broader sense, the contents of the Q&A communities are essentially public goods. Therefore, our findings also add knowledge to literature on public good provision during crisis. With this regard, this work is close to Kummer et al. (2020), who find the growing unemployment during the 2008 economic crisis stimulates public good provision, in terms of content creation and revision on Wikipedia. In comparison, this work further looks at the public good consumption during the hardship.
In particular, aside from the growth of community volume in answers being a provision of public good, we have also observed the growth of volume in questions which can be seen as consumption of public good.

7.3. Practical Implications

This work has practical implications for the operators of online Q&A communities. It informs both the positive and negative sides of the pandemic to the community, so that acknowledge the operators to react to the resurgent pandemic and other crisis in the futures. For example, they can improve the server stability and capacity to deal with the volume growth. They can also take actions to stimulate members to answer more questions to attenuate the decline of community responsiveness.

Notably, while barring new community members to contribute any contents can attenuate the decline of community responsiveness, it should not be taken as a feasible strategy. On the one hand, the questions and answers generated by members on the day of registration occupy approximately 40% and 20% of all. Therefore, imprudently remove all these volumes should entail a loss to the community. On the other hand, if an individual realize that it is impossible to making questions until the second day of registration, he or she may not register in the first place. Thus, the attenuated decline in community responsiveness are not resulted from an appropriate counterfactual situation. Besides, although these implications are derive from an analyses on the COVID-19 pandemic, they should also apply to regional epidemics, which may also entails a prolonged time of staying at home.

7.4. Limitations and Future Research

This work is subject to limitations that offer opportunities for future research. In this work, we analyze the immediate impact of the COVID-19 pandemic on online Q&A communities. However, the impact in a long run, especially when the pandemic is over, should be different. As the community responsiveness drop, those new registered community members are less likely to commit to the community, which should incur a heavier loss of members and that may eventually harms the community volume. We believe this threat is realistic to the communities, but demands rigorous test when data becomes available.

A finer-grained analyses are also value-adding. Although we have noted how new and senior members change their behaviors in terms of posting questions and answers during the pandemic, more can be found through individual-level analyses. For example, the pandemic may also make members to leave the community, especially for the senior members, and that may also explain the drop in response rate.

Besides, we restrict community members to those who have formally registered. Alternative in some studies, the unregistered visitors are also taken as members of the communities (Seidel & Stewart, 2011). We adopt the narrow definition because we do not observe the activity of those unregistered while future researches, if accessible to the click stream data, can undertake a more thorough examination on the impact of the COVID-19.

Lastly, this work stops by documenting a phenomena, while not offering meaningful solutions. However, a feasible cannot be found less the problem is well-documented. In this regard, our findings can be taken as the first-step for solution finding research in the future. Moreover, it is currently not possible to propose a reliable solution, because the SE community or other Q&A communities have not taken action to the decreasing response rate. For example, we have assumed the community to block new members to post questions and find it helps to prevent the loss of response rate. However, it should be taken as feasible solution as it does not happen in reality.

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REFERENCES

Alankar, Kaur, Ahsaan, Sharma, & Chang. (2022). Towards Reviewing an Immediate Impact of COVID-19 on the integrative world economy- An Evolving perspective. *Journal of Global Information Management, 30*(2). 10.4018/JGIM.20220701oa01

Albanesi, S., & Kim, J. (2021). The Gendered Impact of the COVID-19 Recession on the US Labor Market (No. w28505). National Bureau of Economic Research. doi:10.3386/w28505

Andrasfay, T., & Goldman, N. (2021). Reductions in 2020 US life expectancy due to COVID-19 and the disproportionate impact on the Black and Latino populations. *Proceedings of the National Academy of Sciences of the United States of America, 118*(5), e2014746118. doi:10.1073/pnas.2014746118 PMID:33446511

Athey, S., & Imbens, G. (2018). *Design-based analysis in difference-in-differences settings with staggered adoption*. Academic Press.

Bandiera, O., Barankay, I., & Rasul, I. (2005). Social Preferences and the Response to Incentives: Evidence from Personnel Data. *The Quarterly Journal of Economics, 120*(3), 917–962.

Bulman, G., & Fairlie, R. (2021). The Impact of COVID-19 on Community College Enrollment and Student Success: Evidence from California Administrative Data (No. w28715). National Bureau of Economic Research. doi:10.3386/w28715

Butler, B. S. (2001). Membership Size, Communication Activity, and Sustainability: A Resource-Based Model of Online Social Structures. *Information Systems Research, 12*(4), 346–362. doi:10.1287/isre.12.4.346.9703

Butler, B. S., Bateman, P. J., Gray, P. H., & Diamant, E. I. (2014). An Attraction-Selection-Attrition Theory of Online Community Size and Resilience. *Management Information Systems Quarterly, 38*(3), 699–728. doi:10.25300/MISQ/2014/38.3.04

Christopher, A., Kenya, A., Bree, B.-J., Nancy, F., Beatrice, M., Grace, R., & John, W. (2021). Governor partisanship explains the adoption of statewide mandates to wear face coverings. *Journal of Health Politics, Policy and Law, 46*(2), 211–233. PMID:32955556

Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics, 141*(2), 802–830. doi:10.1016/j.jfineco.2021.03.005 PMID:34580557

Goh, J. M., Gao, G., & Agarwal, R. (2016). The Creation of Social Value: Can an Online Health Community Reduce Rural-Urban Health Disparities? *Management Information Systems Quarterly, 40*(1), 247–263. doi:10.25300/MISQ/2016/40.1.11

Greene, W. H. (2017). *Econometric Analysis* (8th ed.). Pearson Education.
Han, B. R., Sun, T., Chu, L. Y., & Wu, L. (2021). COVID-19 and E-commerce Operations: Evidence from Alibaba. Academic Press.

Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric Models for Count Data with an Application to the Patents–R & D Relationship. *Econometrica, 52*(4), 909–938. doi:10.2307/1911191

Jin, Y., Lee, H. C. B., Ba, S., & Stallaert, J. (2021). Winning by Learning? Effect of Knowledge Sharing in Crowdsourcing Contests. *Information Systems Research*. 10.1287/isre.2020.0982

Khansa, L., Ma, X., Liginlal, D., & Kim, S. S. (2015). Understanding Members’ Active Participation in Online Question-and-Answer Communities: A Theory and Empirical Analysis. *Journal of Management Information Systems, 32*(2), 162–203. doi:10.1080/07421222.2015.1063293

Khurana, S., Qiu, L., & Kumar, S. (2019). When a Doctor Knows, It Shows: An Empirical Analysis of Doctors’ Responses in a Q&A Forum of an Online Healthcare Portal. *Information Systems Research*. 10.1287/isre.2019.0836

Kim, Y., Jarvenpaa, S. L., & Gu, B. (2018). External Bridging and Internal Bonding: Unlocking the Generative Resources of Member Time and Attention Spent in Online Communities. *Management Information Systems Quarterly, 42*(1), 265–283. doi:10.25300/MISQ/2018/13278

Kummer, M., Slivko, O., & Zhang, X. (2020). Unemployment and Digital Public Goods Contribution. *Information Systems Research, 31*(3), 801–819. doi:10.1287/isre.2019.0916

Marquis, C., & Battilana, J. (2009). Acting globally but thinking locally? The enduring influence of local communities on organizations. *Research in Organizational Behavior, 29*, 283–302. doi:10.1016/j.ori.2009.06.001

Marquis, C., Lounsbury, M., & Greenwood, R. (2011). Introduction: Community as an Institutional Order and a Type of Organizing. In C. Marquis, M. Lounsbury, & R. Greenwood (Eds.), *Research in the Sociology of Organizations* (Vol. 33, pp. ix–xxvii). Emerald Group Publishing Limited. doi:10.1108/S0733-558X(2011)0000033003

Mehla, L., Sheorey, P. A., Tiwari, A. K., & Behl, A. (2022). Paradigm Shift in the Education Sector Amidst COVID-19 to Improve Online Engagement: Opportunities and Challenges. *Journal of Global Information Management, 30*(5), 1–21. doi:10.4018/JGIM.290366

O’Mahony, S., & Lakhani, K. R. (2011). In C. Marquis, M. Lounsbury, & R. Greenwood (Eds.), *Organizations in the Shadow of Communities* (Vol. 33, pp. 3–36). Emerald. doi:10.1108/S0733-558X(2011)0000033004

Perry, B. L., Aronson, B., & Pescosolido, B. A. (2021). Pandemic precarity: COVID-19 is exposing and exacerbating inequalities in the American heartland. *Proceedings of the National Academy of Sciences of the United States of America, 118*(8), e2020685118. doi:10.1073/pnas.2020685118 PMID:33547252

Qiao, D., Lee, S.-Y., Whinston, A. B., & Wei, Q. (2021). Mitigating the Adverse Effect of Monetary Incentives on Voluntary Contributions Online. *Journal of Management Information Systems, 38*(1), 82–107. doi:10.1080/07421222.2021.1870385

Raj, M., Sundararajan, A., & You, C. (2021). COVID-19 and Digital Resilience: Evidence from Uber Eats. *SSRN Electronic Journal*. 10.2139/ssrn.3625638

Ransbotham & Kane. (2011). Membership Turnover and Collaboration Success in Online Communities: Explaining Rises and Falls from Grace in Wikipedia. *Management Information Systems Quarterly, 35*(3), 613. doi:10.2307/23042799

Reinhart, C. (2020). This time truly is different. https://www.project-syndicate.org/commentary/covid19-crisis-has-no-economic-precedent-by-carmen-reinhart-2020-03

Sahin, A., Tasci, M., & Yan, J. (2021). Unemployment in the Time of COVID-19: A Flow-Based Approach to Real-time Unemployment Projections (No. w28445). National Bureau of Economic Research. doi:10.3386/w28445

Seidel, M.-D. L., & Stewart, K. J. (2011). An Initial Description of the C-Form. In C. Marquis, M. Lounsbury, & R. Greenwood (Eds.), *Research in the Sociology of Organizations* (Vol. 33, pp. 37–72). Emerald Group Publishing Limited. doi:10.1108/S0733-558X(2011)0000033005
Shah, C., Oh, S., & Oh, J. S. (2009). Research agenda for social Q&A. *Library & Information Science Research*, 31(4), 205–209. doi:10.1016/j.lisr.2009.07.006

Stanko, M. A. (2016). Toward a Theory of Remixing in Online Innovation Communities. *Information Systems Research*, 27(4), 773–791. doi:10.1287/isre.2016.0650

Stanton, C., & Tiwari, P. (2021). Housing Consumption and the Cost of Remote Work (No. w28483). National Bureau of Economic Research. doi:10.3386/w28483

Sun, S., & Wang, G. (2021). *Does Telehealth Reduce Rural-Urban Care Access Disparities? Evidence from Covid-19 Telehealth Expansion*. Academic Press.

Wooldridge, J. M. (1999). Distribution-free estimation of some nonlinear panel data models. *Journal of Econometrics*, 90(1), 77–97. doi:10.1016/S0304-4076(98)00033-5

Wu, M., Kang, L., Shi, Y., Zhao, J. L., & Liang, L. (2019). Why People are Involved in and Committed to Online Knowledge-Sharing Communities: An Expectancy-Value Perspective. *Journal of Global Information Management*, 27(2), 78–101. doi:10.4018/JGIM.2019040105

Zhao, L., Detlor, B., & Connelly, C. E. (2016). Sharing Knowledge in Social Q&A Sites: The Unintended Consequences of Extrinsic Motivation. *Journal of Management Information Systems*, 33(1), 70–100. doi:10.1080/07421222.2016.1172459

Zhao, Y., Wu, L., Zhang, J., & Le, T. (2021). How Question Characteristics Impact Answer Outcomes on Social Question-and-Answer Websites. *Journal of Global Information Management*, 29(6), 1–21. doi:10.4018/JGIM.20211101.oa20
ENDNOTES

1 Although it also makes sense if we follow Butler (2001) and theorize the resources of online Q&A communities as the time and energy that community members spend on learning and sharing knowledge, we prefer to theorize the resources as the knowledge to make the logic more straightforward.

2 Spamming is a real threat to this work because people may become idle and are likely to pour useless information into the communities as the unemployment rate continuously rises in the COVID-19 times.

3 To enable balanced pairwise comparisons, we exclude the observations on 29 February, 2020.

4 Each subsidiary community has a concomitant “Meta” community, where community members can discuss the workings and policies on the main community. We exclude these “Meta” communities because they are significantly smaller in volume.

5 For example, if 10 questions are posted on sometime on 1st Jan (the day of year ) in Superuser.net (the community ), 5 of them are responded to in 1 day (sometime in 2st Jan 2020). Then the equals 0.5. Similarly, we can also generate and , by setting the period to 7 and 30 days.

6 In other words, the identical trend for the year 2018 and 2019 implies that the trend of 2020 would have developed in the way of 2018 and 2019, had it not been the pandemic.

7 We are grateful to an anonymous reviewer for suggesting these two alternative explanation.

8 For example, image a question is posted on March 8, with two answers responded to it. The first another is on March 9 and the second on March 14. In this case, the first one is unaffected by the COVID-19 whereas the second one affected. It occurs when we use or as the dependent variable.

9 In fact, the exogeneity of COVID-19 pandemic on community responsiveness is self-evident conditional on the exogeneity of COVID-19 on community volume, because community responsiveness is fully determined by the number of questions and answers.

10 We have empirically corroborated the influx of new members during the pandemic. The results can be offered upon request.