Polarized Protective Behaviors in Response to the COVID-19 Pandemic: An Empirical Study of Changes in Time Spent Socializing

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Abstract

This paper investigates the existence of polarized protective behaviors in response to the pandemic using empirical analysis of data from the American Time Use Survey (ATUS). The study finds that the proportion of people without daily social interaction increased significantly during the pandemic compared to the same period in 2019. Additionally, based on a counterfactual distribution estimated using the method developed by Chernozhukov et al. (2013), the study shows that people socializing during the pandemic would have spent similar amounts of time socializing if there were no pandemic. These findings provide evidence supporting the existence of polarization in which some people chose safety first and stopped socializing, while others chose to live as usual without reducing their social time during the pandemic.

1 Introduction

The COVID-19 pandemic has undoubtedly had a significant impact on the world in many ways. One of the consequences is that it may have increased the division and polarization of society, leading to heightened social conflict and unrest. According to the Armed Conflict Location & Event Data Project (ACLED), as of March 4, 2022, there have been 61,830 pandemic-fueled violent demonstrations, public protests, or riots worldwide. Among these, approximately two-thirds were protests against anti-coronavirus measures taken by authorities, while one-third were for more protection and attention. This indicates that people seem to be sharply divided in their views on how they should behave or what policies should be implemented in response to the pandemic.

In terms of protective measures against COVID-19, we have also observed a tendency of polarization, where most individuals take either maximal protective measures or none at all. A typical example of this is the face mask debate, where people advocate for either always wearing a mask in public or never wearing one. Figure 1 shows the mask-wearing behavior of residents in four major European capitals during the early stages of the pandemic in April 2020, highlighting this polarization. A striking similarity is observed across the four cities, with over 70 percent of residents opting for the extreme options of either "always wearing a mask in public" or "never wearing a mask in public."

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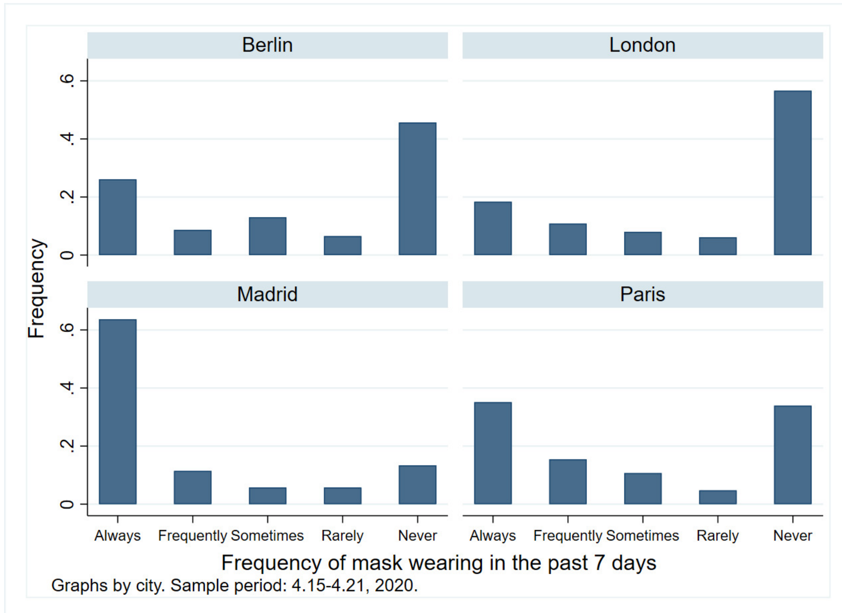

Figure 1: People's mask-wearing frequency in four cities

The above examples only provide a general overview of people's polarized behavior in response to the pandemic. This paper seeks to investigate whether statistical evidence supports the existence of such polarized behavior. To achieve this, we conduct an empirical study that formally documents people's polarized protective behaviors in response to the pandemic. Our analysis uses data from the American Time Use Survey (ATUS) to study how people changed their time spent on face-to-face socializing during the pandemic in the absence of stay-at-home orders. Our empirical findings are twofold. First, the proportion of people without daily social interaction increased significantly during the pandemic compared to the same period in 2019. Second, based on the method developed by Chernozhukov et al. (2013), we estimate the counterfactual distribution of time that people who socialized in 2020 pandemic would have spent socializing if they followed their behavioral mode in 2019 without the pandemic. It turns out that the estimated counterfactual distribution is not significantly different from the fitted distribution of time spent socializing in 2020. This means that people socializing during the 2020 pandemic would have spent similar amounts of time socializing if there were no pandemic. To the best of our knowledge, our findings are the first to provide evidence supporting the existence of polarization in which some people chose safety first and stopped socializing, while others chose to live as usual without reducing their social time during the pandemic.

Our estimation methodology is related to the fast-growing literature that applies counterfactual analysis to investigate the influences of the pandemic. Some studies focus on the impacts of the pandemic itself, such as the impacts on job search (Hensvik et al. 2021), on economic growth across countries (Chudik et al. 2021), on income inequality (Bonacini et al. 2021), and on college student experiences and expectations (Aucejo et al. 2020). More studies use counterfactual analysis to assess the effectiveness and consequences of policy interventions. For example, through counterfactual experiments controlling for information and people's behavioral responses, (Chernozhukov et al. 2021) find that mandating face coverings for employees early in the pandemic could have significantly reduced the weekly growth rate of cases and deaths in the U.S. Other counterfactual studies on the effectiveness and side effects of anti-epidemic measures include Aum et al. (2021),Hsiang et al. (2020) , Fang et al. (2020), Baron et al. (2020), Brodeur et al. (2021), Agostinelli et al. (2022), among others.

Unlike the existing literature that mostly examines counterfactual effects on the mean of the variable of interest, our empirical study focuses on the distributional effects of the pandemic on people's social time.

In particular, our analysis found that compared to 2019, the proportion of individuals who did not socialize significantly increased during the pandemic, while the distribution of social time among those who continued to socialize remained unchanged. This indicates that some individuals opted for one extreme by abstaining from socializing, while others chose the opposite extreme and continued to socialize as before, without reducing their social time. This finding provides evidence for the polarization in people's socializing behaviors during the pandemic. It also highlights the limitation of representative agent models with interior equilibrium, which implies that socially active individuals will continue their socializing activities but reduce their social time.

2 The dataset

We utilize the American Time Use Survey (ATUS) data, which measures the amount of time people spend on various daily activities. The ATUS data possesses several advantages that are appropriate for our research objectives. Firstly, the "time spent on various activities" variable has a sufficiently wide range of fluctuations, which can prevent false polarization results due to limited data variation. This is in contrast to binary choices data collected by surveys, which are naturally polarized and unsuitable for our analysis. Secondly, ATUS provides individual behavior data, which is useful for examining polarized individual choices. It is worth noting that aggregated regional data may obscure polarization at the individual level. Therefore, commonly used data such as Safegraph, which only provides aggregate behavioral data at the census block group level, is unsuitable for our analysis. Thirdly, the ATUS dataset has a long time span that covers individuals' behavior both before and during the pandemic. This enables us to eliminate temporal factors, such as seasonal effects, and attribute behavioral changes directly to the pandemic.

Among various activities, our study examines how people adjust their daily time spent on face-to-face socializing during the pandemic in the absence of stay-at-home orders. We specifically investigate face-to-face social activities for several reasons. Firstly, they significantly increase the risk of infection since the virus is transmitted through exposure to infectious respiratory fluids, including inhalation of fine respiratory droplets and aerosol particles.[1] Secondly, reducing face-to-face socializing results in a loss of utility, so individuals face a trade-off between the utility obtained from socializing and the increased risk of infection. Studying face-to-face socializing allows us to see how individuals adjust their behaviors in light of the risk of infection. Lastly, modern communication technologies make face-to-face social interaction relatively dispensable compared to behaviors necessary for survival, such as purchasing food at a supermarket. Thus, it is possible for a person to temporarily stop face-to-face socializing, which allows us to understand people's choices regarding this extreme option.

Our baseline analysis focuses specifically on face-to-face social activities captured by the two subcategories under category 12 of the ATUS: socializing and communicating (1201) and attending or hosting social events (1202). These subcategories capture face-to-face social activities with a high risk of infection, such as conversing with people dining at a restaurant (coded as 1201) or attending a meeting or festival party (coded as 1202). It is important to note that communications over telephone or the internet, which carry no risk of infection, are excluded from these subcategories and are therefore not classified as social activity in our analysis. Moreover, we include additional activity types in our analysis for robustness checks. The ATUS data also provides information on the location and "with whom" during the activities, as well as the characteristics of the respondents, including age, family income, education, employment status, number of children, and child's age. A descriptive summary of the data is included in the Online Appendix.

The COVID-19 outbreak divided the 2020 ATUS data into two periods: a pre-pandemic period including January and February 2020 and a pandemic period from July to December 2020. We excluded data from March to May 2020 because data collection was suspended during this time. Data for June 2020 was also excluded because the stay-at-home policy was still in effect in more than 10% of U.S. counties[2], restricting people's freedom to socialize. Additionally, we used data from the same months in 2019 as a reference for behaviors under normal circumstances. Comparing data from January and February 2019 to 2020, we did

[1] https://www.cdc.gov/coronavirus/2019-ncov/science/science-briefs/sars-cov-2-transmission.html

[2] Our hypothesis testing results are robust to the inclusion of the data for June 2020

not find any annual trend or systematic change in people's social behavior in the absence of the pandemic. Therefore, changes in social time from July to December 2020 relative to the same period in 2019 can be attributed to the pandemic. We also excluded data beyond 2020 to eliminate the effect of vaccination[3] on behavioral changes, ensuring that changes relative to 2019 were purely a result of the pandemic.

3 Empirical results

This section presents an empirical analysis of how people adjusted their socializing behaviors during the pandemic and documents the polarized pattern of their adjustments in response to the pandemic. It is important to note that the daily time spent socializing is a nonnegative variable that follows a distribution with a point mass at zero and a roughly continuous density over positive values. By examining the impact of the pandemic on the proportion of individuals without socializing and the distribution of social time for individuals who do socialize, we can gain insights into people's behavioral changes during the pandemic from different perspectives. Hence, we will analyze the point mass at zero and the continuous part of the distribution separately.

First, we will consider the proportion of individuals with zero daily social time. It is worth noting that the dataset contains observations with zero social time even before the pandemic, as a respondent may not have any social activities on the day of the interview. Therefore, we aim to study how this proportion changes prior to and during the pandemic by examining two scenarios.

- Scenario 1: Individuals who previously socialized choose to stop socializing during the pandemic, resulting in an increase in the proportion of people with zero daily social time compared to the same period in 2019. This scenario suggests that some individuals prioritize their safety and choose the extreme option to pause their socializing.
- Scenario 2: People choose to continue socializing but reduce their social time, and the proportion of people with zero social time relative to the same month in 2019 is expected to remain roughly the same. This scenario implies that people tend to choose moderate options to reduce their social time instead of completely stopping socializing.

As a result, we can investigate these two competing scenarios by testing the following hypotheses:

$$\begin{array}{rcl} H_0^1: N_1^t & = & N_2^t \\ H_1^1: N_1^t & < & N_2^t, \end{array} \tag{1}$$

where H_0^1 and H_1^1 correspond to Scenarios 2 and 1, respectively, and N_1^t and N_2^t denote the proportions of individuals with nonzero daily social time during month t in 2019 and 2020, respectively. Figure 2 plots N_1^t and N_2^t in different months and reports the p-values for the null hypothesis H_0^1. The data show that the proportion of observations with zero social time in January and February 2020 did not change significantly relative to 2019. In contrast, the proportion of observations with zero social time between July and December 2020 was significantly higher than during the same period in 2019. This suggests that pandemic is responsible for the rise in the proportion of individuals without socializing, which aligns with Scenario 1 where some people opted to halt their social activities.

[3] According to data from ourworldindata.org, less than 1% of the population were vaccinated in the U.S. by the end of 2020.

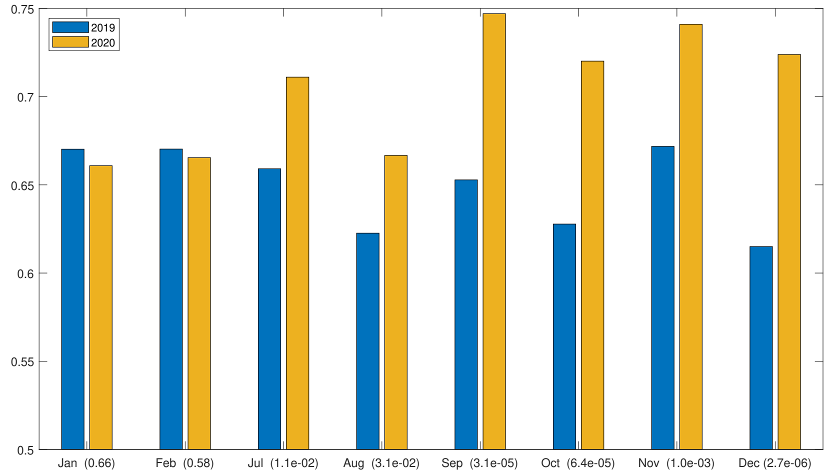

Figure 2: The proportions of people with zero social time in 2019 and 2020.

The numbers in parentheses are the p-values for the null hypothesis that the proportion in 2020 remains the same compared to the same month in 2019.

Next, we investigate the impact of the pandemic on people's daily social time density conditional on that they socialized. Two additional scenarios will be considered.

- Scenario 3: Individuals who socialized in 2020 will live a normal life without reducing their level of social activity compared to the pre-pandemic period in 2019. This represents the extreme option where the pandemic has no impact on people's behavior, resulting in the same amount of time spent socializing in both 2020 and 2019.

- Scenario 4, individuals who chose to continue socializing reduced their time spent doing so due to the risk presented by the pandemic in 2020. This scenario contrasts with Scenario 3, where people maintain their pre-pandemic level of social activity.

Scenario 3 represents the opposite extreme option to that mentioned in Scenario 1, where individuals would cease socializing. It can be inferred that under Scenario 3, the density of social time in 2020 would be comparable to that of the pre-pandemic period in 2019, assuming that the same population is tracked over both years. In contrast, under Scenario 4, individuals do not choose the extreme options of no socializing in Scenario 1 or spending the same amount of time socializing during the pandemic in Scenario 3. Instead, they choose a moderate option between these two extremes.

To test these two competing scenarios, we introduce the following notations. Let X_1 and X_2 represent the personal characteristics of the respondents in 2019 and 2020, respectively, and let Y_1 and Y_2 denote the amount of time they spent socializing each day in 2019 and 2020, respectively. $F_{X_2}(x|Y_2 > 0)$ denotes the distribution of X_2 conditional on $Y_2 > 0$. Following Chernozhukov et al. (2013), we consider the following distributions

$$F_Y(y)_{t,2} \equiv \int F_{Y_t|X_t,Y_t>0}(y|x)\, dF_{X_2}(x|Y_2 > 0) \tag{2}$$

for $t = 1, 2$, where $F_{Y_t|X_t,Y_t>0}(y|x)$ represents the conditional distribution of Y_t given X_t and $Y_t > 0$, which captures the dependence of daily social time on people's characteristics in year t given that they socialized. $F_Y(y)_{2,2}$ denotes the fitted distribution of Y conditional on $Y > 0$ in 2020, while $F_Y(y)_{1,2}$ denotes the counterfactual distribution of Y. The counterfactual distribution integrates the conditional distribution of

Y given X and $Y > 0$ in 2019 with respect to the distribution of characteristics X given $Y > 0$ in 2020. Thus, $F_Y(y)_{1,2}$ represents the distribution of social time that people who socialized in 2020 would have spent socializing if they followed their behavioral mode in 2019 without the pandemic.

Recal that the extreme option in Scenario 3 suggests that those who continued to socialize during the pandemic would have spent a similar amount time socializing in 2019. Conversely, Scenario 4 suggests that those who continued to socialize would have spent more time doing so if the pandemic had not occurred. Namely, $F_Y(y)_{1,2}$ is expected to be smaller than $F_Y(y)_{2,2}$ for a given y (i.e., $F_Y(y)_{1,2}$ has larger quantile values than $F_Y(y)_{2,2}$). To test these competing implications, we compare the difference

$$\delta(y) = F_Y(y)_{2,2} - F_Y(y)_{1,2}.$$

Under Scenario 3, $\delta(y)$ is expected to be close to zero for all $y \in \mathcal{Y}$ with $\mathcal{Y} \subseteq \mathbb{R}^+$. Thus, we test the following hypotheses:

$$\begin{aligned} H_0^2 : \sup_{y\in\mathcal{Y}} |\delta(y)| &= 0 \\ H_1^2 : \sup_{y\in\mathcal{Y}} |\delta(y)| &\neq 0. \end{aligned} \tag{3}$$

The null hypothesis in (3) is restrictive in that it requires the empirical distance between $F_Y(y)_{1,2}$ and $F_Y(y)_{2,2}$ to be close to zero for all y values.

We estimate $F_Y(y)_{t,2}$ using the estimator developed by Chernozhukov et al. (2013)[4] and compute the deciles of $F_Y(y)_{1,2}$ and $F_Y(y)_{2,2}$ with bootstrap uniform confidence bands. Since social time has mass points at rounded minute values, we estimate the conditional distribution $F_{Y_t|X_t,Y_t>0}(y|x)$ using distribution regression (Foresi and Peracchi 1995; Han and Hausman 1990); with a probit link function. The covariates X in our baseline specification include age, squared age, family income, employment status, presence of children, number of children, age of the youngest child, and dummy variables for Monday through Saturday. Adding additional controls, such as dummy variables for months, did not significantly alter the results. The sample consists of 542 (521) from January and Feburary 2020 (2019) and 1417 (1634) observations from July to December 2020 (2019).

Figure 3 displays the deciles of $F_Y(y)_{2,2}$ and $F_Y(y)_{1,2}$ with the 95% level uniform confidence band of $F_Y(y)_{1,2}$ for the period before the pandemic (January and February 2020, upper left panel) and the period during the pandemic (July to December 2020, lower left panel). The right upper and right lower panels plot the difference between the deciles of $F_Y(y)_{1,2}$ and $F_Y(y)_{2,2}$ for the periods before and during the pandemic, respectively. The fitted distribution is always within the 95% confidence band of the counterfactual distribution before and during the pandemic. Moreover, the horizontal axis is within the 95% confidence band of the difference between the deciles of $F_Y(y)_{1,2}$ and $F_Y(y)_{2,2}$ in both periods. The p-values of the Kolmogorov-Smirnov statistics for testing H_0^2 are 0.75 and 0.9 before and during the pandemic, respectively. These results indicate that the difference between $F_Y(y)_{1,2}$ and $F_Y(y)_{2,2}$ is not significantly different from zero for all y. Based on these findings, we accept the null hypothesis in (3), which means that people who socialized during the 2020 pandemic would have spent a similar amount of time socializing if they behaved the same way as they did in 2019, in the absence of pandemic. This suggests that these people choose the "life as usual" option, which is in line with Scenario 3.

[4]A related method is the unconditional quantile regression developed by Firpo et al. (2009), which provides a first order approximation to counterfactual effects. In contrast, Chernozhukov et al. (2013)'s approach can measure the exact size of counterfactual effects.

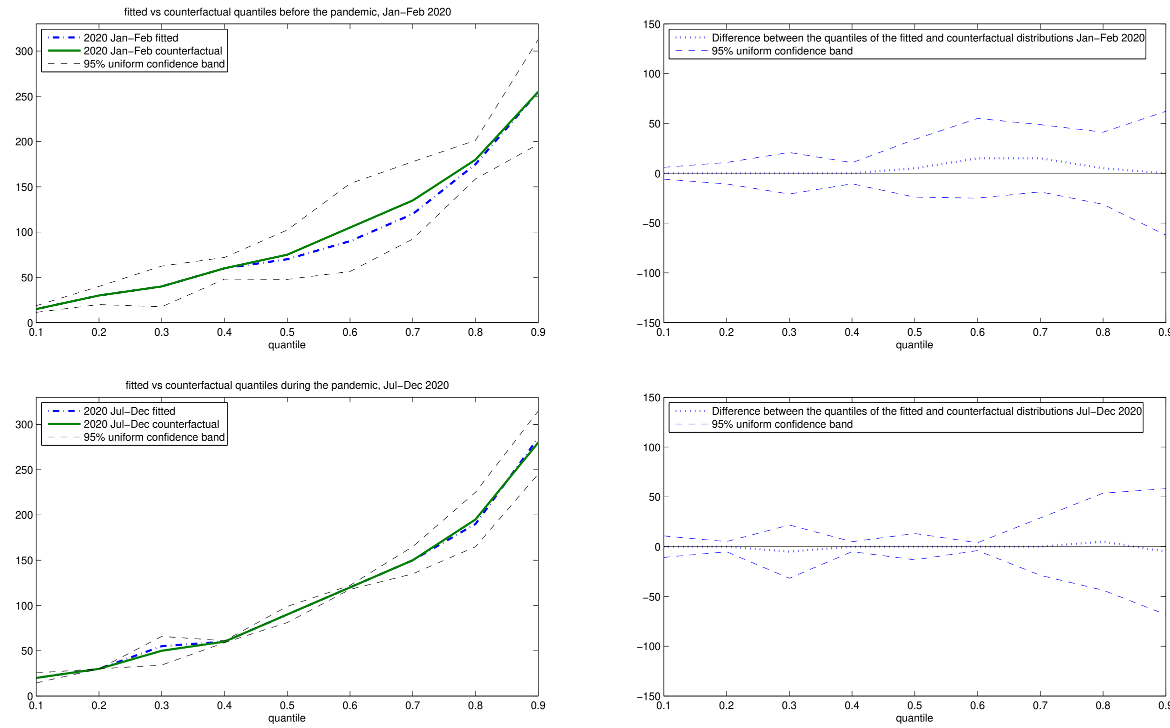

Figure 3: Fitted versus counterfactual quantiles of time spent socializing for people who socialized in 2020.

The p-values of the Kolmogorov-Smirnov statistic for testing H_0^2 are 0.75 and 0.9 before and during the pandemic, respectively.

To ensure the robustness of our results, we conducted further analysis of the total time respondents spend per day on a wider range of behaviors. Our analysis included dining in restaurants and bars and exercising in public indoor spaces, in addition to socializing, in the absence of orders for closing these establishments[5]. These additional behaviors are associated with high risks of infection and can be avoided at the cost of utility loss during the pandemic. Incorporating these types of behaviors in our empirical analysis has two advantages. Firstly, it increases the sample size, making the test more powerful. Secondly, if a person avoids some risky behaviors (e.g., socializing) but continues some other risky behaviors (e.g., exercising in a gym), then the total time spent would be nonzero but less than if there were no pandemic. This means that moderate choices mentioned in Scenario 4 are more likely to be observed when we consider the total time spent on multiple activities. These two reasons render the null hypothesis H_0^2 more likely to be rejected if it is false. In other words, if we still cannot reject H_0^2 using the augmented data, then it provides stronger evidence that people chose the extreme option in Scenario 3.

The estimated distributions using the augmented data are plotted in Figure 4, and the results are similar to those shown in Figure 3. The p-values of the Kolmogorov-Smirnov statistics for testing H_0^2 are 0.87 (Jan-Feb) and 0.79 (Jul-Dec) during the two subperiods in 2020. Therefore, the fitted distribution is not significantly different from the counterfactual distribution, which is again consistent with Scenario 3.

[5]To be specific, we consider time spent eating in public places including restaurants, bars, malls, and grocery stores. Our analysis excluded the purchase of takeout, as it is a relatively low-risk activity if people wear masks and the dwell time is short. For sport, we only consider excercises in indoor public spaces because exercising in the open air or in a private place (such as at home) is much less risky. These two additional types of activities are highly risky because it is difficult or even impossible for people to wear masks during these activities.

To summarize, our findings show that compared to 2019, there was a significant increase in the proportion of people who did not socialize (Scenario 1) during the pandemic. However, among those who continued to socialize, the distribution of social time spent remained unchanged (Scenario 3). This suggests that the pandemic caused some individuals to prioritize safety and limit their social activities, while others continued to choose "life as usual" without reducing their social time. This finding demonstrates that people displayed polarized behaviors when adjusting their socializing habits during the pandemic.

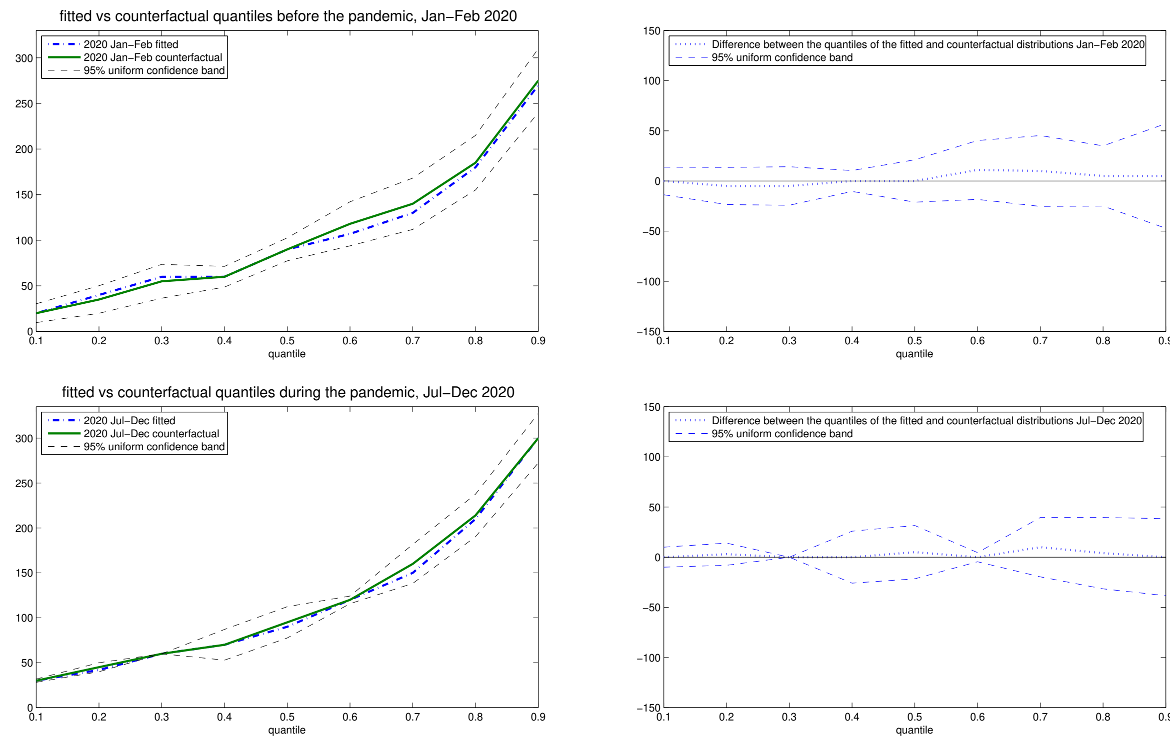

Figure 4: Fitted versus counterfactual quantiles of daily time spent socializing, dining in restaurants, and exercising in public indoor spaces for people who engaged in these activities in 2020

The p-values of the Kolmogorov-Smirnov statistic for testing H_0^2 are 0.87 and 0.79 before and during the pandemic, respectively.

4 Conclusion

This paper uses data from the American Time Use Survey (ATUS) to investigate how people changed their time spent on face-to-face socializing during the pandemic. The analysis found that the proportion of people without daily social interaction significantly increased during the pandemic compared to the same period in 2019. Additionally, the distribution of social time among those who did socialize remained unchanged, indicating that some people chose "safety first" and stopped socializing, while others continued with their daily social activities without reducing their social time. These findings provide evidence for the polarization of people's socializing behaviors during the pandemic. Our result also highlights the limitations of representative agent models with interior equilibrium.

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Appendix

Table A1 presents a descriptive summary of the duration data used for counterfactual analysis in Section 3. Panels A and B demonstrate a substantial decrease in the proportion of respondents with zero socializing time during July to December, from 33.8% in 2019 to 26.7% in 2020, while only a slight reduction was observed during January to February, from 31.5% in 2019 to 30.1% in 2020. Furthermore, the average durations of non-zero socializing from July to December are similar between 2019 (123.62) and 2020 (123.91). Panels C and D report similar results for more communicable behaviors.

Table A1. Descriptive statistics of durations of socializing, outdining and exercising

month	variable	obs.	mean	s.d.	min	max
	A. socializing, 2019					
1-2	duration	1,580	34.67	78.51	0	625
	duration (>0) (share:31.5%)	497	109.58	106.66	1	625
7-12	duration	4,561	41.82	90.67	0	861
	duration (>0) (share:33.8%)	1,543	123.62	119.14	1	861
	B. socializing, 2020					
1-2	duration	1,609	34.88	88.46	0	990
	duration (>0) (share:30.1%)	498	112.70	128.57	2	990
7-12	duration	5,002	33.15	81.13	0	720
	duration (>0) (share:26.7%)	1,338	123.91	115.60	1	720
	C. socializing, outdining, exercising in public spaces, 2019					
1-2	duration	1,580	52.52	93.74	0	720
	duration (>0) (share:44.4%)	702	118.20	109.63	1	720
7-12	duration	4,561	62.62	105.95	0	861
	duration (>0) (share:47.7%)	2,176	131.25	120.52	1	861
	D. socializing, outdining, exercising in public spaces, 2020					
1-2	duration	1,609	50.41	97.66	0	990
	duration (>0) (share:43.0%)	693	117.04	119.79	2	990
7-12	duration	5,002	44.55	93.19	0	750
	duration (>0) (share:34.0%)	1,701	130.99	119.23	1	750

Table A2 reports the descriptive statistics for the control variables used in the distributional regression, including age, employment status (a dummy indicating whether the respondent is employed), family income (classified into 16 categories ranging from "less than $5,000" to "$150,000 and over"), number of children under 18, age of the youngest child under 18, and a dummy variable indicating the absence of children under 18, as well as the day of the week of the diary day (coded from 1 to 7 for Monday to Sunday). The mean and standard deviation (in parentheses) of each variable are reported for respondents with zero/non-zero socializing time during January to February (pre) and July to December (post), for 2019 and 2020, respectively. The results indicate that respondents with non-zero socializing time during the pandemic are slightly younger and have higher family income than those in the other groups.

Table A2. Descriptive statistics of control variables

	2019				2020			
variable	0 pre (obs:824)	0 post (obs:2,253)	>0 pre (obs:756)	>0 post (obs:2308)	0 pre (obs:856)	0 post (obs:3,175)	>0 pre (obs:753)	>0 post (obs:1,827)
age	51.49	51.49	50.35	51.04	51.50	52.22	50.61	49.75
	(17.91)	(17.77)	(18.08)	(18.33)	(17.72)	(18.35)	(18.25)	(18.03)
emp	0.58	0.58	0.57	0.57	0.58	0.53	0.56	0.56
	(0.49)	(0.49)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)
faminc	11.16	11.03	11.66	11.91	11.14	11.71	12.16	12.27
	(4.04)	(4.09)	(3.85)	(3.81)	(4.01)	(3.79)	(3.78)	(3.53)
childnum	0.68	0.68	0.72	0.69	0.64	0.62	0.72	0.68
	(1.10)	(1.10)	(1.06)	(1.05)	(1.04)	(1.02)	(1.12)	(1.07)
kidage	3.72	3.73	4.06	3.95	3.71	3.52	3.99	3.85
	(5.90)	(5.90)	(6.04)	(6.01)	(5.93)	(5.78)	(6.08)	(5.99)
nokid	0.65	0.65	0.61	0.62	0.65	0.66	0.63	0.64
	(0.48)	(0.48)	(0.49)	(0.49)	(0.48)	(0.47)	(0.48)	(0.48)
diaryday	3.75	3.84	3.75	3.99	3.99	3.90	4.08	4.05
	(2.25)	(2.30)	(2.36)	(2.39)	(2.29)	(2.32)	(2.37)	(2.43)

Figure A1 reports the results for testing (1) using augmented data for three types of daily activities: socializing, dining in restaurants, and exercising in public indoor spaces. The null hypothesis H_1^0 cannot be rejected when comparing the pre-pandemic period of 2020 to the same months in 2019 (i.e., January and February). However, the null hypothesis is strongly rejected in favor of H_1^1 when comparing the second half of 2020 to the same period in 2019. This finding supports the results presented in Section 3.

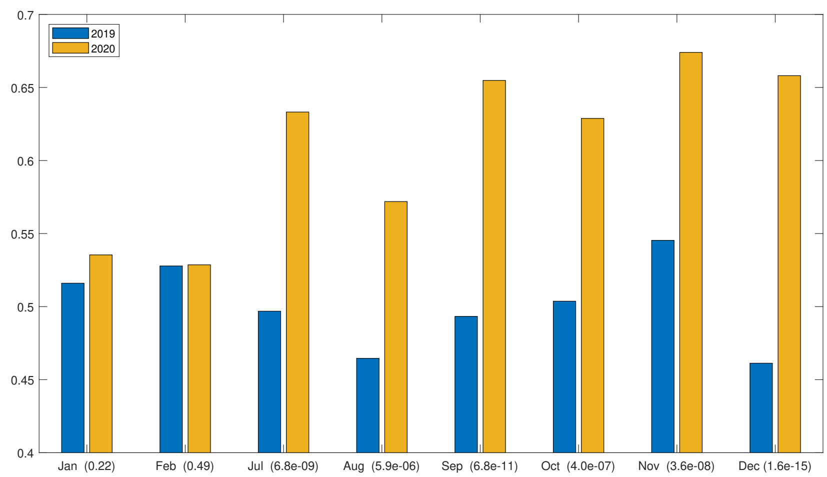

Figure A1: The proportions of people spending no time on socializing, dining in restaurants, and exercising in public indoor spaces in 2019 and 2020

The numbers in paretheses are the p-values for the null hypothesis that the proportion in 2020 remains the same compared to the same month in 2019.