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The Impact of the COVID-19 Pandemic on the Use of Remote Meeting Technologies

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Abstract

We evaluate the impact of the COVID-19 pandemic on the volume and quality of firms' daily usage of remote (video) meeting technologies. While per-firm daily meeting volume (minutes, number of meetings, and total participants) increase significantly (between 15\% and 48\%), the average meeting is more crowded (+15\%), shorter (-30\%, or 10 minutes) and of significantly poorer (video/audio) quality (-59\%). Firms in the service sector experience the most notable increases in volume usage, while effects on the duration, size and quality of meetings is experienced by firms in all industries.

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1 Introduction

COVID-19 expanded quickly. The U.S. declared a public health emergency on February 3rd and a national emergency on March 13. In tandem, many states issued stay-at-home orders as well as additional restrictions such as schools and non-essential business closures.[1] As a result, most people faced the unprecedented situation of not being able to leave home. Unlike prior pandemics, however, workers' inability to physically go to work might have been mitigated by technology. Many workers were able to continue their routines aided by remote (video) meeting technologies provided by their employer.

While there seems to be an agreement that remote communication technologies have been key in keeping the economy moving during the locked down phase (and afterwards), precise quantifications of their impact are only starting to emerge. Before one can answer such type of question, it is important to understand whether and how the pandemic affected the usage of such technologies. In this paper, we seek to measure how firms' usage patterns of remote (video) meeting technologies were impacted by the pandemic in the U.S. Importantly, our data allows us to speak about the impact on the overall usage volume as well as on other more specific aspects of usage such as meeting duration, size of meetings (number of participants) and (video/audio) quality.

Further, we study how such impacts vary by industry. While remote communication technologies are generally regarded as beneficial for the operation of businesses, in the event of a mandatory transition to remote work its impact will depend on how adaptable firms are to the technology. Specifically, the substitutability between remote and on-site operations depends on the type of business; for example construction cannot be done remotely but many services (consulting, banking) can. Further, an effective transition to remote work depends on firms' current operations structure: some firms may have had the technology and the logistics in place for a rapid transition while others may have had a much more difficult time to adjust.

In terms of volume usage, we find that the total number of daily meetings per firm increased by approximately 33% in the 12-week period after the stay-at-home orders were enacted. Similarly, the number of total daily meeting participants per firm increased by 48%, while total daily meeting minutes per firm saw a 19% increase. Since the number of total daily meeting minutes increased by less than the total number of daily meetings, the average meeting length (duration) experienced a decrease (30%). Meeting size (average number of

[1] See https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020 and https://www.nga.org/state-COVID-19-emergency-orders/

participants per meeting) grew by 15%, a result of a stronger growth in the number of daily participants than in the number of daily meetings. Meeting quality, measured by the ratio of meeting minutes with good (video/audio) connection over meeting minutes with poor connection, experienced the greatest of all effects: a reduction of 59%.

The effects vary by industry (sector). We divide firms in eight SIC sectors: Finance, Government, Manufacturing, Mining & Oil, Retail, Services, Utilities and Wholesale Trade.[2] Only firms in the Service sector experience a substantial and statistically significant increase in usage (meetings, meeting minutes and number of participants). Consequently, firms in the Service sector are the primary driver of the overall volume usage effect described in the prior paragraph. Conversely, in terms of meeting duration, size and quality, the effects are sizable and significant across all but the Retail sector.[3] In terms of timing, we observe that the effects, when they occur, take place gradually but quickly: effects grow substantially for the initial 3-5 weeks and stabilize thereafter until the end of our data (12 weeks after stay-at-home orders).

Our study focuses on usage of remote meeting technologies licensed to and used by companies. These technologies are part of a broader business-solution often known as unified communications (UC). In a nutshell, UC are applications that run on top of high-speed networks, providing the means for firms' employees to interact in a much more effective way than with traditional voice-only communications. These systems have been used for several years by many companies as a means to reduce costs and enhance the interaction between teams.[4] The use and development of UC had been growing steadily prior to the pandemic. It is important to differentiate UC from videoconferencing software (e.g. Zoom). UC is a more general concept that includes a variety of tools to communicate (for example multiple videoconferencing softwares, or interaction tools, integrated over a single platform).[5]

UCs are often integrated and managed by software platforms. The main purpose of these platforms is to monitor and perform analyses of UC environments. These platforms are capable of measuring the quality and intensity of use of the communications transmitted over

[2] We follow the the Standard Industry Classification (SIC)

[3] Another exception is the average number of participants per meeting in the Government sector, for which there is a positive but statistically insignificant effect.

[4] While UC providers have diversified business models, they often provide their customers (companies) with solutions (features) that are customized to their clients' needs. Examples of UC providers include Microsoft, Cisco, Google, among others.

[5] With UC many communications tools as instant messaging, presence information, voice, video conferencing, data sharing, and call control are integrated to provide a consistent unified interface for user experience across multiple devices and media types. Essentially, UC could encompass all forms of communications that are exchanged via IP networks.

UC applications.[6] Our data provider, Vyopta, is one of the leading providers of performance and analytic platforms for UC usage. Our data consists of de-identified records that display the behavior (usage intensity and quality) of each client's UC platform across all remote (video) communications. The resulting dataset includes a daily panel of firms (our data provider's clients) spanning the first half of 2019 and the first half of 2020.[7] While firms remain anonymous, they carry a unique identification code that allows us to track them over time and categorize them by industry sector.

Our work contributes to the rapidly growing literature on the economic effects of the pandemic. While this body of work is by now quite large, there has, to our knowledge, been only one other attempt to measure the effect of COVID-19 on the usage of remote communications. DeFilippis et al. (2020) study employees' digital communication patterns for 16 large metropolitan areas in North America, Europe and the Middle East. The authors use data from one provider of information technology services (aggregated up to the metropolitan area) and apply an event study methodology of eight weeks around the start of the lock-down phase. DeFilippis et al. (2020) find that the number of daily meetings per person as well as the average number of attendees per meeting increased during the lock-down period (both by about 13%). On the other hand, meetings became 20% shorter. An interesting finding is that employees reduced the total number of time in meetings by 11.5%, or 18.6 minutes per person per day.[8]

Our results are consistent with the findings reported by DeFilippis et al. (2020), although the magnitudes we quantify are larger. Our paper complements and extends these earlier findings in two ways. First, we provide a measure of (connection) quality; this is an important dimension given that remote communications are now occurring over employees' residential connections rather than through the more robust enterprise networks. Second, the disaggregate nature of our data allows to study how the effect varied by industry sector; this dimension is also important as certain types of activities may not find remote connectivity to be a viable substitute for on-site operations (e.g. retail operations that can only be done in person).

Our work is also related to the literature on the economics of firms' internal organization, in particular as it pertains to the measurement of internal communication as new technologies emerge (e.g.Polzer et al. (2018), Impink et al. (2020)), as well as the effects of remote working

[6]The resulting metrics are used to help businesses focus resources based on the quality and the actual level of usage of the technology.

[7]In Section 4 we discuss the potential drawbacks and upsides of our sample and our focus on the video conferencing aspect of remote working.

[8]The authors also find that internal emails increased by 5.2% per person per day.

on firms' performance (e.g.Bloom and Van Reenen (2010), Bloom et al. (2015)) and other factors such as traveling/commuting (Bento et al. (2005)) and land prices Rossi-Hansberg et al. (2009).

We divide the remainder of the paper in a Data, Identification and Model section, a Results section and a Discussion section.

2 Data, Identification and Model

2.1 Data

As stated earlier, our focus is on the usage of UC by companies (and its employees) rather than on the intensity of usage of a particular software platform by individual users (e.g. personal Zoom or Skype accounts). Thus, the structure of our data is a daily panel of firms (Vyopta's clients). For a given firm, the data have detailed daily records of video conference usage covering the first semester of 2019 and the first semester of 2020.[9] For each firm-day record, the data contains information on the total number of meetings ($T\#M$), the total number of meeting minutes across all meetings ($T\#m$), the total number of participants across all meetings ($T\#P$), and a measure of the video and audio quality of the meeting connection (Q).[10]. The variable Q is defined by the ratio of meeting minutes deemed to have a good quality connection over the meeting minutes deemed to have a bad quality connection.[11] Using these variables we compute average meeting duration ($Length = T\#m/T\#M$) and average number of meeting participants ($Participants = T\#P/T\#M$).

The means of the variables, reported separately for each of the two years, are shown in Table I. The number of observations across years is similar (37,196 in 2019 and 34,865 in 2020) as is the number of firms (224 in 2019 and 225 in 2020).[12] One limitation is that the quality variable (Q) is only available for approximately 40% of the data (15,274 observations in 2019 and 13,938 in 2020).[13] The reason for this is that quality measurements depend on the availability of software (and in some cases hardware) used by the customer.

[9]The available data spans 180 days in 2019 and 172 days in 2020. For consistency in the analysis, we discard observations beyond day 172 in 2019.

[10]We removed outliers (using an interquantile range, IQR, method), as well as inconsistent (i.e. negative usage) data points; the resulting dataset comprises 98% of the original data.

[11]The parameters that determine a good vs a bad connection are set by the data provider

[12]Further, the identity of firms remains largely stable across years.

[13]There are 155 observations for which the quality variable is equal to zero (0.34% of all quality observations. Regressions below exclude these instances from the estimation. We have carried out regressions in which we use these observations by shifting the dependent variable by +1 and results remain essentially unchanged.

While Table I does not adequately segment the data in the before and after periods, the effects of the pandemic that we measure more precisely later in the paper are already evident: means for the total number of meetings, meeting minutes, total participants and participants per meeting are larger in 2020 than they are in 2019. Similarly, the means for quality and meeting duration are lower in 2020 with respect to 2019.

Table I: Means (Standard Deviation) [10th pctile; 90th pctile] of Dependent Variables

	2019	**2020**
Total Number of Meetings, $T\#M$	246 (526)	297 (590)
	[2; 798]	[2; 898]
Total Number of Meeting minutes, $T\#m$	12055 (25580)	14844 (29178)
	[62; 37830]	[66; 48778]
Total Number of Participants, $T\#P$	919 (2091)	1310 (2731)
	[6; 3004]	[6; 3910]
Quality (Good/Bad), Q	27.44 (43.35)	27.13 (51.24)
	[2.50; 65.34]	[2.33; 67.21]
Average Meeting Duration (in minutes), $Length$	28.20 (174)	29.49 (786)
	[4.51; 38.63]	[4.01; 36.57]
Average Number of Participants Per Meeting, $Participants$	3.50 (4.54)	4.16 (4.29)
	[1.67; 5.07]	[1.72; 6.41]

Figure 1 shows the distribution of firms per sector and year in our data. Most of Vyopta's customers are concentrated in the Services, Finance and Manufacturing sectors. The number of firms remains relatively stable across years, a desirable feature from an identification standpoint.

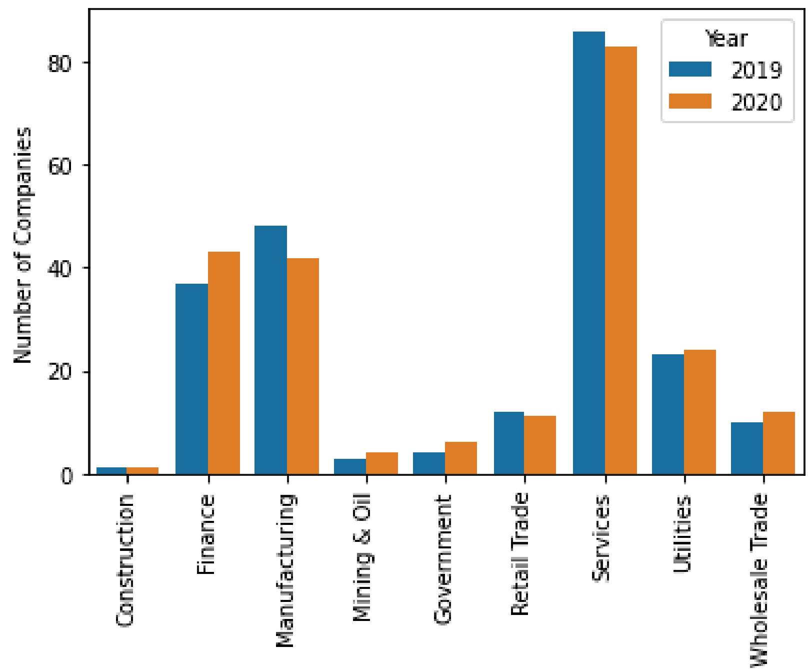
2.2 Identification and Model

We employ a difference-in-difference (DID) approach. The before data consists of the days leading up to the day prior to States declaring an emergency and the after data encompasses the period afterwards up until the end of June.[14] Our control group is the January-June 2019 period. Using the total number of daily participants as an example, Figure 2 provides visual support for key identification assumption required by the DID approach: parallel trends in the before period (up to March 8th).[15] As it can be seen, 2019 and 2020 series move in a

[14] Since different States declared an emergency in different (but nearby) days, we use the average day, March 8th

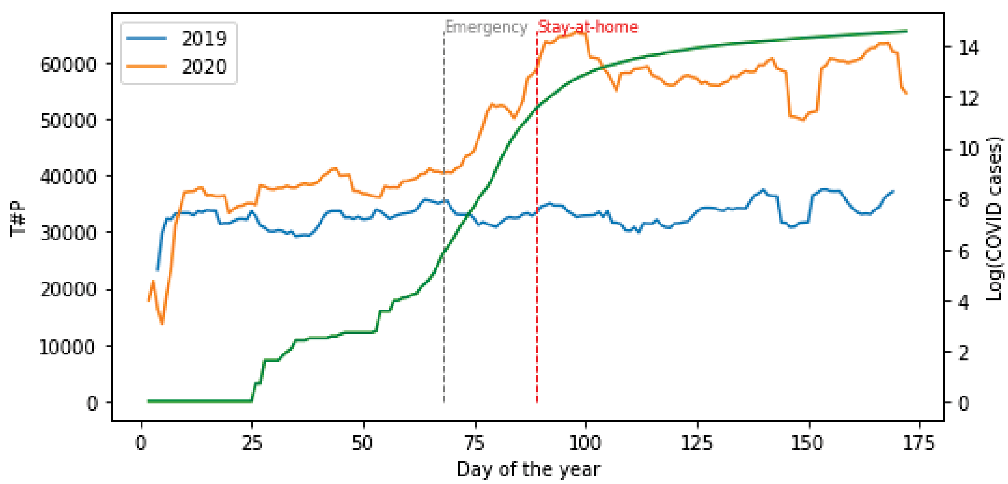
[15] The figures are produced by aggregating firm data up to the daily level. Similar support can be seen in figures (available upon request) that plot other measures of usage

Figure 1: Firms per industry



similar fashion up to March 8th; after this date, the 2020 series clearly picks up.[16].

Figure 2: Comparison of Total Number of Participants across Years



Formally, our modeling approach allows for a flexible DID specification that captures the weekly effect of the pandemic. Further, we decompose both the before and after periods into weeks which allows for a more precise identification of the week in which the effect takes place (this also serves as a formal test for the parallel trends assumption). Our baseline

[16]The stay-at-home order line is March 27th, the average date across all States

specification is:

$$log(Y_{igt}) = \alpha \cdot year_g + \sum_{t=-8}^{12} \beta_t \cdot I_t \cdot year_g + \gamma_S + \delta_{DW} + \lambda_{DY} + \epsilon_{igt} \quad (1)$$

The subscript i denotes a firm, g represents the group (i.e. 2019 or 2020) and t indexes time (in weeks). For the dependent variable Y_{igt}, we consider the six variables listed in Table I; using the logarithm of the variable allows us to interpret the DID coefficient as a (reasonable approximation of the) percentage change. $year_g$ is a variable that takes a value of one in 2020 and I_t is a weekly indicator variable (equal to one for the corresponding subscript t). γ_S, δ_{DW} and λ_{DY} are industry sector, day of the week and day of the year fixed effects; ϵ_{git} is the usual idiosyncratic error term.[17] To capture the effect by industry, we also consider a version of (1) in which the term $I_t \cdot year_g$ is interacted with industry sector fixed effects. We estimate both the baseline model and the industry-specific variant with OLS and cluster standard errors at the industry sector level.[18]

2.3 Sample Discussion

Table II reports a comparison of the distribution of the number of firms per industry in our sample with that reported by the Census. Based on these figures, Vyopta's sample provides a reasonable representation of some industries (Government, Wholesale Trade and to a lesser degree Mining and Oil), over represents others (Finance, Manufacturing, Utilities and to a lesser extent Services) and under represents Construction and Retail. This relative mismatch is not surprising given Vyopta's focus on clients for who decided to adopt video conferencing and remote teamwork technologies prior to the pandemic.

Our data is likely most informative for the Services sector as a largest fraction of firms in our data (and in the economy) belong to this sector. The industry regression results that we discuss below highlight this element. One final note is in place. Not having a representative sample for all industries in the economy can be a limitation. However, as we argue in the 4 section, our study has methodological advantages that render it useful.

[17]For robustness, we also considered a specification with firm fixed effects (in lieu of industry firm effects). Results (available upon request) and conclusions remain consistent.

[18]The duration of a meeting can depend on the type of meeting (e.g. weekly "check in" meeting v. "new project" meeting). We cannot account for this aspect in the estimation as our data does not contain meeting specific information.

Table II: Distribution of Firms by Industry Vyopta v. Census

Industry	**Vyopta (%)**	**Census (%)**
Construction	0.36%	8.66%
Finance	19.20%	4.47%
Manufacturing	20.29%	3.66%
Mining & Oil	1.45%	0.18%
Government	2.54%	1.45%
Retail	5.07%	10.35%
Services	36.23%	27.63%
Utilities	9.78%	0.27%
Wholesale Trade	5.07%	3.98%

Source: https://www.naics.com/business-lists/counts-by-naics-code/

3 Results

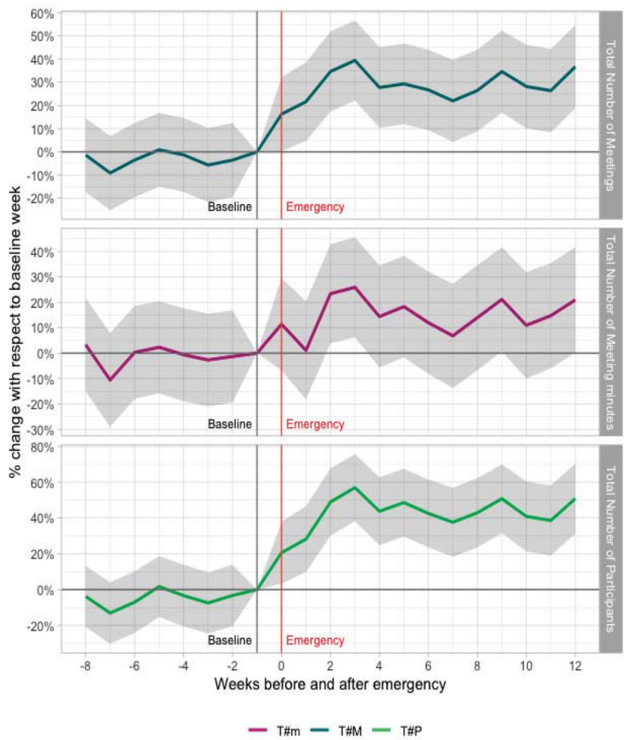
We run a separate regression for each of the variables in Table I. Figure 3 reports the coefficients of interest (β_t in Equation 1) and the corresponding 95% confidence intervals (CI) for the baseline specification. After close inspection (and as it can be seen in the Figure), we determined that the most sensible baseline week is February 26 to March 3 (one week prior to the average date in which States declared an emergency, March 8).

Effects are significant both economically and statistically. The largest average weekly increase is seen in the overall number of daily participants ($T\#P$, 48%), followed by daily meetings ($T\#M$, 33%), total number of minutes ($T\#m$; 19%), and participants per meeting ($Participants$; 15%, or about half an attendee). On the other hand, the average meeting duration ($Length$) is shorter by a weekly average of 30% (about 10 minutes) and meeting quality (Q) decreases by a weekly average of 60%. [19] Effects were quick to fully materialize, in all cases stabilizing around week 5 ($Length$ only took 2 weeks to reach its full effect).

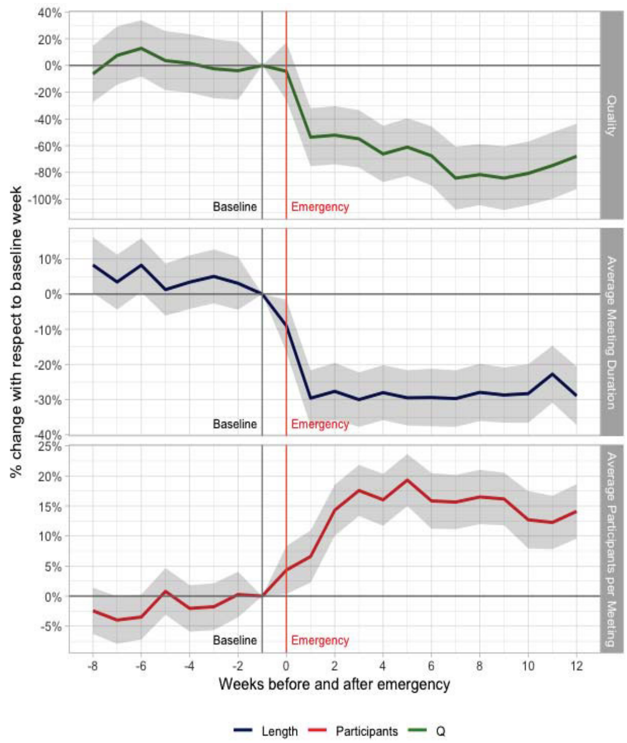
Results that break down the DID effect by industry sector are reported in the next three Figures. The results indicate that the only sector with a significant increase in the three main measures of overall usage ($T\#M$, $T\#m$, and $T\#P$) is Services, with other industries having either a weakly significant increase (Government and, to a lesser extent, Finance), no detectable effect (Manufacturing, Mining & Oil, Utilities and Wholesale Trade) and in one case (Retail) a (weakly significant) decrease. Conversely, the effects on meeting quality

[19] These values, not reported in the figures, are obtained from a specification that pools all post-baseline weeks into a "post" period and all other weeks into a "pre" period. All estimates are statistically significant at the 95% level. As a robustness check, we carried out this pooled DID estimation using firm fixed effects in lieu of industry fixed effects; results remain almost identical: $T\#P$, 50%; $T\#M$, 36%; $T\#m$, 20%; $Participants$, 15%; $Length$, -30%; Q, -66%

Figure 3: DID Results in Baseline Specification, by Week



(a) Panel A



(b) Panel B

(Q), duration ($Length$) and size ($Participants$) are significant in (and consistent across) all sectors with the exception of Retail (and Government for the $Participants$ variable).

4 Discussion

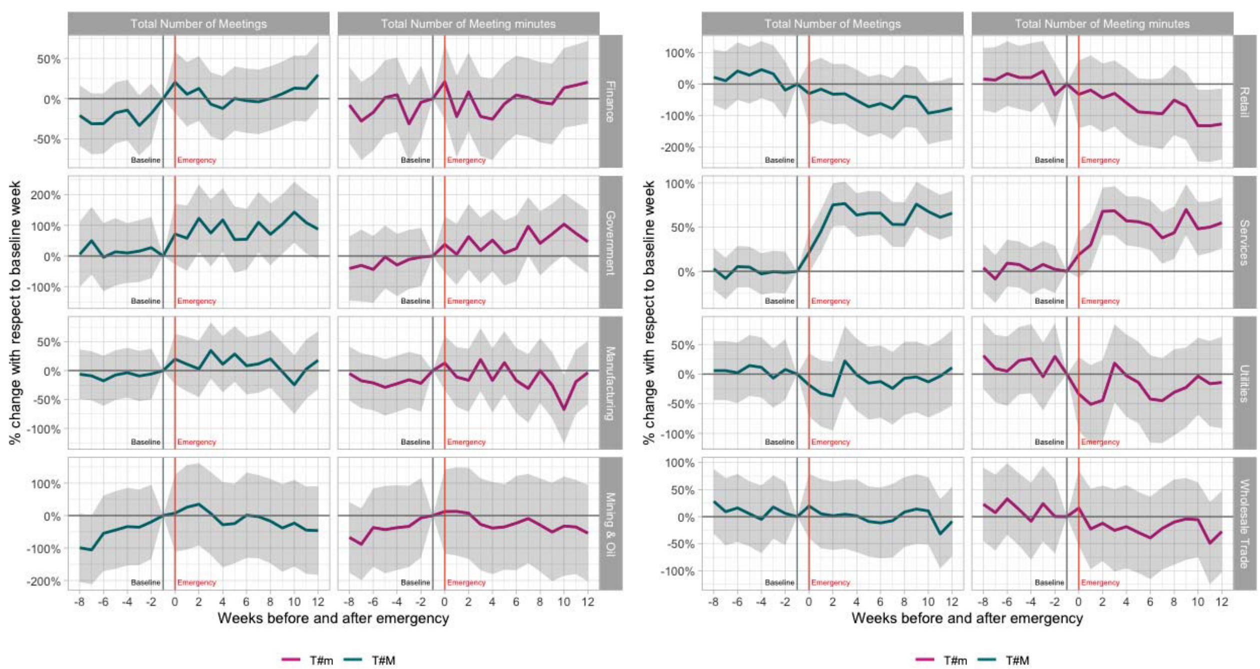
Our analysis finds, unsurprisingly, that the pandemic significantly increased the overall usage of remote meetings, a sign that the negative effects of not being to go to work were mitigated by this technology.[20] However, this effect seems to have only been important in one Sector (Services), which suggests that remote working is a viable substitute for on-site work only for a limited set of firms in the economy. For instance, firms in the Retail sector seem to have decreased their usage of video meetings, which suggests that many of these firms reduced their operations significantly as on-site operations were the only viable alternative. These results are consistent with analysis provided by Nicola et al. (2020) who show that industries

[20]We acknowledge the possibility that a portion of the volume increase that we measure could have been propelled by coordination issues generated by the pandemic rather than by a substitution from on-site meetings to online meetings. Our data does not allow us to disentangle this effect.

like construction or retail were particularly impacted by the pandemic as the nature of their activity prevented them to shift to a remote mode.

Another way in which the mitigating effect of technology might have been less than ubiquitous is a degradation in quality. Millions of users working from home produced stress over the residential network infrastructure which is not designed for this volume of traffic. Further, UC service providers seem to have had less than adequate processing and network capacity to support the level of UC video and voice demand that the pandemic generated.[21] These two factors significantly affected video and audio quality of meetings. The pandemic also generated more crowded meetings, which are arguably of lesser quality as attendees' attention and participation decay with meeting size. The reduction in meeting quality during the pandemic may reduce the productivity gains from remote working that have been reported in non-pandemic settings (e.g. Bloom et al. (2015)).

Figure 4: DID by Industry, $T\#M$ and $T\#m$



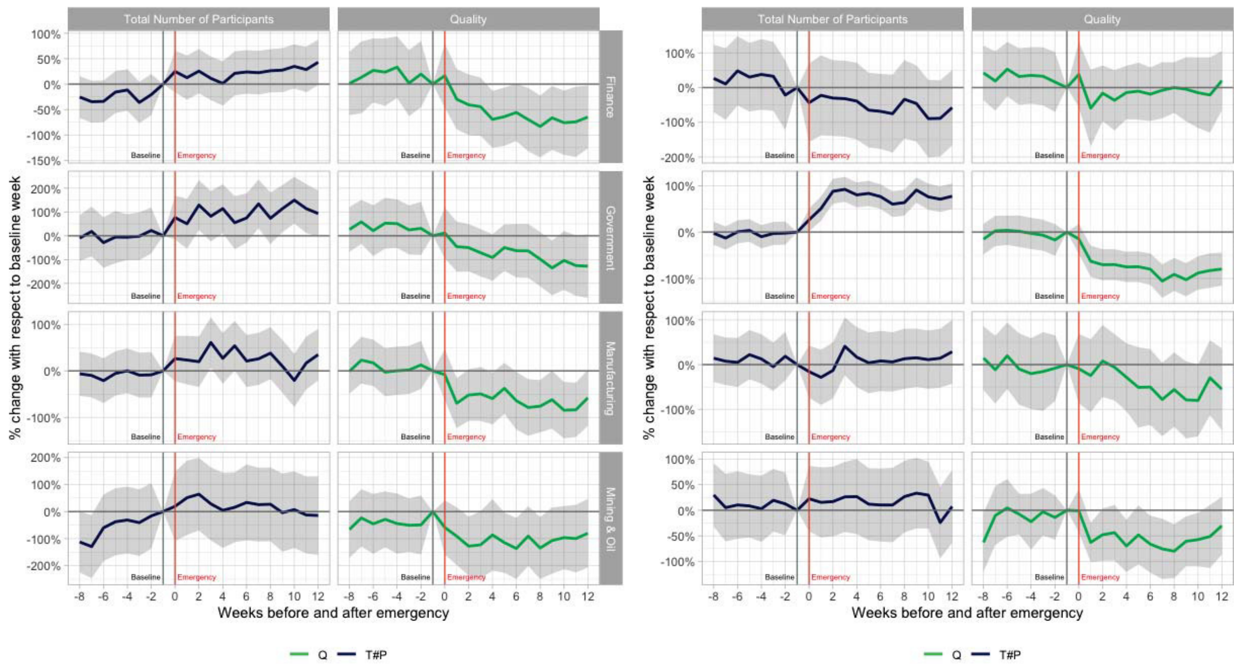
(a) Panel A

(b) Panel B

An open question for future research is whether (and to what extent) the massive exogenous shock generated by the pandemic will create a permanent shift towards remote working. Our results suggests that, to the extent that this permanent shift occurs, it will likely manifest itself primarily in the Service sector. This conclusion is consistent with the observation

[21] We thank Vyopta for providing this insight. Some of these limitations, however, were relaxed with the ability that firms had to transition their UC services on-site to a cloud-based format.

Figure 5: DID by Industry, $T\#P$ and Q



(a) Panel A

(b) Panel B

that some industries substitution of daily activities to a remote version is unfeasible or impractical (e.g. preparation of meals by restaurants and the construction of buildings can only be done onsite).

Our work has limitations. First, we have data from a sample of firms in the U.S. that is not representative of the entire U.S. (see subsection 2.3). Second, our work can shed light on one aspect of remote working (video conferencing), which makes up a portion of a typical day in remote working. As we explain below, however, these two aspects do not negate the usefulness of our results.

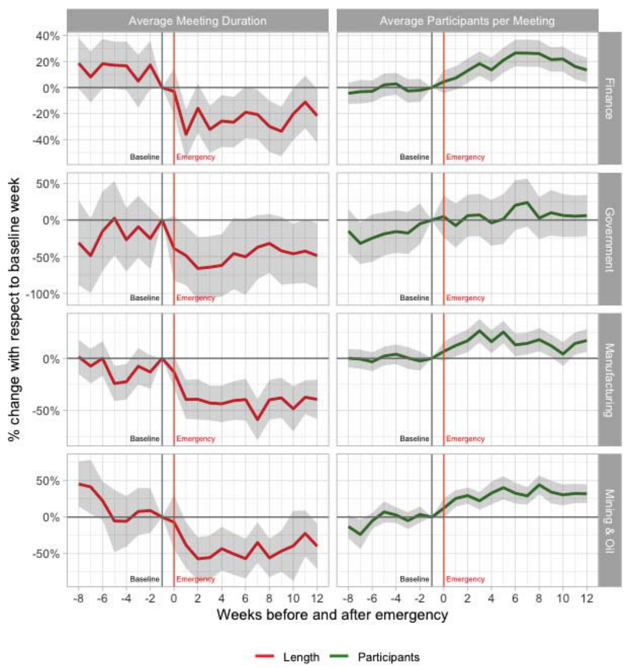
The main issue with sample selection has to do with the fact that we use a sample of firms that were more technologically prepared to transition to remote working. This selection, however, has two advantages.[22] First, since unprepared firms (not captured by our data) are likely to have struggled more in their transition to remote work, the effects we measure (on prepared firms) are likely a lower bound for the effects in the entire economy. Second, focusing on technologically prepared firms results in a methodological advantage as we are

[22]Another possible source of sample selection is the fact that we are studying data from a single data provider in the UC software industry. The possibility of selection issue on this dimension is less likely as Vyopta is a leader in the UC software market (market share of approximately 35%). Further, Vyopta executives assert that the profile of their client base is similar to that of the entire UC software market.

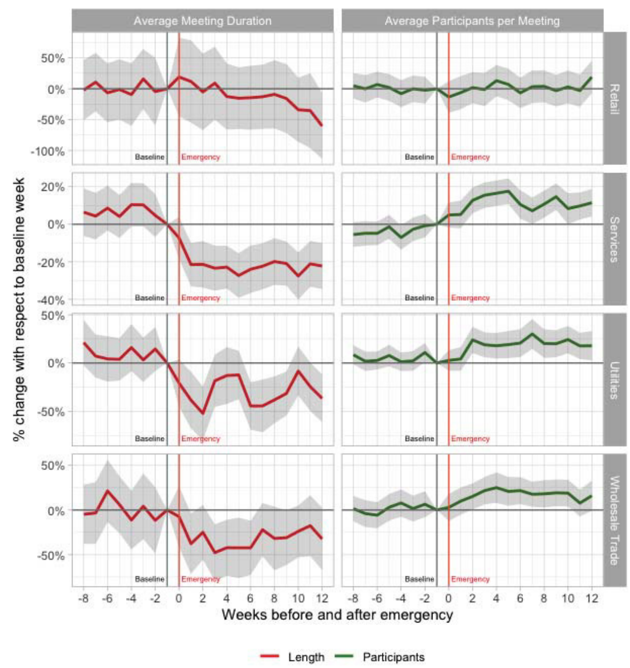
able to have a control group (the same set of firms over time) that differs from the treatment on one dimension only (the pandemic).

Regarding our focus on video conferencing, we note that While meetings only make up a fraction of a day's work, video conferencing has arguably been the central technological element of the sudden transition to remote work caused by the pandemic. Virtual meetings now permeate all aspects life in and outside the office. It is not surprising that much of the recent research on remote working has video conferencing as its primary focus (e.g. Bloom et al. (2020); Fauville et al. (2021)).

Figure 6: DID by Industry, *Length* and *Participants*



(a) Panel A



(b) Panel B

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