Resilience of Gig Economy during COVID-19 Pandemic:
Insights from Location Big Data

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Abstract

The COVID-19 pandemic has led to an unprecedented unemployment crisis. Despite the economic significance of the gig economy ($300+ billion, 36% labor participation), the literature on individual gig worker behavior remains blank largely due to lack of granular data. Leveraging newly available, population-scale smartphone location data and the COVID-19 pandemic as a natural shock, this research presents initial yet powerful evidence of various aspects of resilience of the gig economy during a public health and economic crisis, hence advising policy-making. Analyses of 1 billion location records over a span of eight months reveal that (1) in-person gig jobs remain resilient throughout the crisis, suffering fewer job losses than the traditional labor market; (2) the gig sector enhances resilience of the overall labor market by absorbing the non-gig labor during the crisis; (3) the gig economy boosts resilience of the disadvantaged, curbing job losses more in Black neighborhoods; and (4) gig workers exhibit remarkable resilience during the crisis, for instance shifting work hours to suit the populations' changing circadian rhythm during the lockdown period. These findings coherently highlight resilience of the gig economy, hence advocating policy-making to support the sector, particularly at times of crises.

1 Introduction

The unprecedented COVID-19 pandemic and mitigation measures, such as state-issued lockdown orders, have led to a grave level of unemployment in the U.S., similar to that of the Great Depression[1]. While recent studies have shown wide spread employment losses across sectors (Mongey et al., 2020), none have looked at the gig economy, defined by the Oxford dictionary as "a labor market characterized by the prevalence of short-term contracts or freelance work as opposed to permanent jobs". Importantly, despite the economic significance of the gig economy, with $348 billion globally by 2021 (*Statista*), astounding growth rate[2], and 36% labor participation (*U.S. Bureau of Labor Statistics*), the literature on individual gig worker behavior remains blank, largely due to lack of granular data. Leveraging newly available, population-scale smartphone location data and the COVID-19 pandemic as a natural shock, this research hence examines how the gig economy performed and how individuals in the gig workforce reacted during the public health and economic crisis.

The emergence of digital platforms has enabled firms to create a flexible work environment (Burtch et al., 2018) and hire a large number of workers without facing significant hiring costs (Friedman, 2014). Similarly, workers are drawn towards the gig economy due to its flexibility, freedom of job choice[3], and opportunities to earn extra or primary income, often at above the minimum wage[4]. Propelled by both the demand- and supply-side forces, gig economy has grown to be an integral part of the U.S. labor market, employing more than a third of the U.S. workforce [5]. Nonetheless, given the non-contractual, temporary nature of gig work, and lack of a clear definition of what gig work really means[6], the gig economy remains largely unobserved and gig workers remain "invisible" or "intractable" to governments, businesses, policy-makers, and labor market researchers. Even the "government data sources have difficulty counting how many gig workers there are", as the only available data on gig workers are at least a decade old[7]. Moreover, household survey data, such as the Current Population Survey (CPS) do not have refined definitions of gig workers; and administrative data sources, such as tax return filings, are available annually instead of in real-time. All these contribute to the dire dearth of research on the gig economy and individual gig workers, making sound policy-making infeasible.

The newly available, population-scale, granular smartphone location data offer an unparalleled opportunity to examine the performance of the gig economy and behaviors of individual gig workers, particularly during an economic crisis entailed by the COVID-19 pandemic, thus advising policy-making of immense economic and societal significance. We are specifically interested in the following four research questions:

[1] https://www.cnbc.com/2020/07/21/some-big-cities-are-hitting-great-depression-unemployment-levels.html
[2] https://www.cnbc.com/2020/02/04/gig-economy-grows-15percent-over-past-decade-adp-report.html
[3] https://www.theatlantic.com/business/archive/2011/09/the-freelance-surge-is-the-industrial-revolution-of-our-time/244229/
[4] https://venturebeat.com/2014/08/17/inside-the-sharing-economy-workers-find-flexibility-and-19-hour-days/
[5] https://www.forbes.com/sites/tjmccue/2018/08/31/57-million-u-s-workers-are-part-of-the-gig-economy/?sh=13b600af7118
[6] https://www.gigeconomydata.org/basics/how-many-gig-workers-are-there
[7] https://www.bls.gov/careeroutlook/2016/article/what-is-the-gig-economy.htm

RQ1: How did the gig economy perform during the crisis, compared to the traditional labor market?

RQ2: Did individual workers transition between the gig economy and traditional labor market during the unemployment crisis?

RQ3: Did gig workers across socioeconomic groups react differently do the crisis?

RQ4: How did individual gig workers behave differently during the crisis, for instance, did they adapt their gig work categories and work styles?

To accomplish the research objectives, we develop a novel spatial-temporal analytic methodology to identify the individual gig and non-gig workers from the location big data. Specifically, we focus on three primary and fastest growing work categories in the gig economy - food delivery ($470 billion market[8]), grocery delivery ($130 billion[9]), and ridesharing ($218 billion[10]). They are also all in-person categories, making it easier to identify the individuals performing these jobs from the location data. Analyses of 1 billion location records from Boston, MA over a span of eight months reveal that, corresponding to the four research questions raised earlier: (RQ1) in-person gig jobs remain resilient throughout the crisis, suffering fewer job losses than the traditional labor market; (RQ2) the gig sector enhances resilience of the overall labor market by absorbing the non-gig labor during the crisis; (RQ3) the gig economy boosts resilience of the disadvantaged, curbing job losses more in Black neighborhoods; and (RQ4) gig workers exhibit remarkable resilience during the crisis, for instance shifting work hours to suit the populations' changing circadian rhythm during the lockdown period. These findings coherently highlight resilience of the gig economy, hence advocating policy-making to support the sector, particularly at times of crises.

This research contributes to the literature by offering the initial, yet powerful, evidence of resilience of the gig economy and its important value to the overall job market and workforce well-being during an economic crisis. Our findings illuminate the economic and societal debates over the pandemic's differential impacts across sectors of the labor market and across socioeconomic groups; and advise policy-making to support the gig economy, particularly over economic downturns. Our novel spatial-temporal analytic methods applied to the massive, unstructured location data also enrich big data analytics in the information technology and marketing literatures. Also contributing to the CIST 2021's theme of "digital transformation", our research demonstrates the immense value of non-traditional data and methods in accelerating digital transformation in government and labor market analytics of immense business and societal value.

[8]https://www.morganstanley.com/ideas/food-delivery-app-profits

[9]https://www.prnewswire.com/in/news-releases/online-grocery-market-size-is-projected-to-reach-usd-129-540-billion-by-2025-valuates-reports-895082817.html

[10]https://www.marketsandmarkets.com/Market-Reports/mobility-on-demand-market-198699113.html

2 Literature

The primary contribution of our study is to the burgeoning literature on the gig economy and particularly the gig workers. Extant literature on gig economy has significantly studied the platform side of the gig economy including the employer shift towards contractual labor, bias and discrimination in gig platforms (Edelman et al., 2017, Ge et al., 2016, Hannak et al., 2017),the reputation driven business models of most gig platforms (Ert et al., 2016), and the social welfare generated by these platforms (Greenwood and Wattal, 2015). The research on economic impacts of the gig economy has largely been limited to macroeconomic impacts with Zervas et al. (2017) showing that the entry of Airbnb reduced hotel revenues in Texas. Research on the labor market composition of gig economy has shown that workers prefer gig jobs because of their flexibility (Cramer and Krueger, 2016, Chen et al., 2019) and mostly enter the gig economy to earn more to supplement their income from other jobs (Hall and Krueger, 2018). But the research on the supply side of the gig economy - the gig workers, is still nascent which mostly includes industry surveys (Manyika et al., 2016) and descriptive statistics (Hall and Krueger, 2018). Related to our research, gig economy is found to act as a cushion for people who face financial distress due to unforeseen external shocks (Koustas, 2018). Perhaps the most detailed analyses of gig workers is provided by Burtch et al. (2018) who show that gig economy provides employment opportunities to individuals who otherwise would have chosen low quality entrepreneurial enterprise.

Although there is an employer driven growth in gig jobs during periods of high unemployment where firms would rather hire low cost contractual workers rather than invest in costly long-term employment contracts (Friedman, 2014), the empirical evidence is lacking. More recently, Huang et al., 2020, analyze the impact of unemployment on the growth of online labor markets and find that there is a substitution from traditional forms of employment to employment in online gig platforms. They also find that the eventual recovery from the global financial crisis in 2008 was associated with a shrinkage in the online labor market size suggesting that the shift from traditional employment to gig work types reverts back once the effects of the unemployment shocks disappear.

The dearth of research on gig labor markets can be explained by the fact that there has been the lack of benchmark data on gig workers. Given that the gig economy is still largely unregulated, there are no official data sources documenting the employment patterns of gig workers. Even the study by Huang et al. (2020) touches upon only the online gig labor markets and ignore the larger part of gig economy sectors like delivery and ridesharing that involves significant offline presence. In our study, we overcome this challenge by using population-scale location data to identify individual gig workers. Since our panel extends for almost 8 months, by identifying and observing these workers over the entire period, we can make meaningful inferences on their work behavior and assess how the COVID-19 pandemic impacted their work patterns.

Our study also contributes to the growing literature on the impact of COVID-19 pandemic on unemployment. The economic impact of the COVID-19 policies has been well documented. Chetty et al. (2020) report that, following the closure of non-essential businesses, there were severe job losses - particularly among low-wage workers. Brynjolfsson et al. (2020) show that jobs that could be done from home saw fewer job losses than the jobs that require traveling for work. Dingel and Neiman (2020) go further and construct a work from home index to identify an occupation's exposure to COVID-19 policies Using this index, they find that, typically, low paying jobs cannot be done from home. Mongey et al. (2020) use a variant of this measure and find that the COVID-19 policies disproportionately affect less educated, lower-income workers. Furthermore, studies have shown that the gig jobs are preferred by specific demographics (Katz and Krueger, 2019) which is interesting to explore in the context of a public-health crisis like the COVID-19 situation. By studying the heterogeneous effects, our study aims to highlight the importance of the gig sector to these demographic populations.

Since the turn of the 21st century, there has been an increased interest in using location data to understand urban mobility. Increasingly, location based data is being used by policy researchers to understand commuting patterns (Ratti et al., 2006), identify tourists in a city (Girardin et al., 2008), identify home and work locations (Ahas et al., 2010), and even model social contact during the COVID-19 period (Chevalier et al., 2021). Since individuals carry their smartphones with them everywhere, by tracking their location trajectories we can essentially identify their mobility patterns which include work and stay-at-home behaviors. Additionally, since each individual carries a separate personal smartphone, it is easier to track these mobility patterns on an individual basis giving us an individual-level picture of the worker activities. By following these location trajectories over several months, we can essentially identify the shifts in employment patterns.

Although location data has not been used widely in economics research, its usage has exploded since the onset of the COVID-19 pandemic. Coven and Gupta (2020) use individual level GPS location data to identify demographic disparities in mobility patterns in New York city. Engle et al. (2020) show that the social distancing measures helped curb the spread of Coronavirus significantly. Chiou and Tucker (2020) show that there are severe income disparities in adherence to stay-at-home policies and neighborhoods with high-speed Internet have higher proportion of individuals staying at home. Gupta et al. (2020) measure the unemployment impact of COVID-19 policies using aggregate level data from SafeGraph. Ghose et al. (2020) show that individuals suspended their privacy concerns and traded their privacy for the greater social good to help with contact tracing during the COVID-19 crisis. We build on this nascent literature to identify labor market impacts of COVID-19 policies.

In summary, this study contributes to three important streams of literature. We create a novel methodology to identify worker mobility patterns and classify them based on the type of work they do. Secondly, we contribute to the growing literature on the impact on COVID-19 policies on unemployment and labor markets. Thirdly, we add to the literature on the importance of gig jobs and the resilience of the gig economy in the face of a public-health crisis.

3 Data

We integrate three data sources: individual-level smartphone location data to identify worker mobility patterns, the 2016 American Community Survey data for demographics, and the New York Times COVID tracking data to measure the COVID severity. The location data are collected using GPS technology from more than 300 commonly used mobile applications from both Android and iOS devices in a GDPR and CCPA privacy compliant manner. Depending on the application that collects the data, the GPS location traces are recorded either in 5-20 minute intervals or when the mobile device moves more than a 100 meters. The data cover a quarter of the U.S. population and each location record contains a unique device ID, timestamp, speed, longitude, and latitude of the location.

For this study, we limit our analysis to the city of Boston and within the time period ranging from 1st January 2020 to 26th August 2020. Massachusetts declared state emergency on March 15, 2020 [11] and lockdown on March 31, 2020 closing all non-essential businesses [12]. Although the emergency was declared on all non-essential services, the decision to roll back these restrictions and allow the economic activities to resume was done in a phased manner. For the city of Boston, phase one of reopening which allowed some businesses to open was announced on May 18, 2020 [13]. Since the primary purpose of these reopening decisions was to resume economic activity and mitigate job losses created by the COVID-19 policies, it is worthwhile to verify if this move indeed helped mitigate the job losses even at the risk of increased Coronavirus infections. Also interesting is the shift in non-gig versus gig work type transitions - to verify if the transitions that occurred during the lockdown period persisted or reverted back to the pre-lockdown levels.

For the sake of uniformity and to identify accurate mobility patterns across the specified time period, our study only includes individuals with at least 25 GPS traces a day and who appear in our data for least 10 days a month for each of the 8 months which leaves us with over 1 Billion GPS traces from 9,310 unique individuals. We also complement the location data with Point of Interest (POI) data from SafeGraph and Google Maps.

3.1 Identifying Mobility Patterns

We identify mobility patterns of each individual based on their daily stay-points. We cluster the raw GPS traces by space and time such that no two traces within a cluster are more than 100 meters apart and that there are at least 10 traces in a cluster and use these clusters as stay-points. A home location for an individual is defined as the modal stay-point where the individual spends between 1 AM - 5 AM on weekdays. If there are no data between 1 AM - 5 AM, we assign the modal stay-point where the individual spends > 12 hours in a day as the home location. We identify the Census Block Group (CBG) that contains each individual's home location and assign it as the home CBG of the

[11]https://www.mass.gov/news/baker-polito-administration-announces-emergency-actions-to-address-covid-19
[12]https://www.boston.gov/departments/public-health-commission/coronavirus-timeline
[13]https://www.boston.gov/news/temporary-guidance-construction-city-boston

individual

We define an individual's work location as the non-home stay-point where the individual spends 1-10 hours a day. If the individual spends 6 - 10 (1 - 6) hours a day at the stay-point, we define it as a full- (part-) time non-gig work location. Furthermore, we identify the POI that is closest, on average, to all the GPS traces within a work location as the workplace of the individual and the North American Industry Classification System (NAICS) code of this POI is assigned as the work-industry of the individual.

To identify the gig work types, we identify stay-points that define different gig work behavior. If an individual spends less than 10 minutes at a restaurant location, we consider it as a restaurant visit. An individual who visits more than 6 (3 - 6) restaurant locations in a day and travels more than 5 Kms is classified as a full- (part-) time food delivery worker. Similarly, we consider daily visits for grocery stores and supermarkets that last between 10 - 60 minutes as grocery store visits and an individual who visits more than 1 (= 1) in a day and travels more than 5 Kms is classified as a full- (part-) time grocery delivery worker. To identify drivers, we count the total unique locations visited by an individual and the total distance traveled in a day. If the individual travels more than 50 Kms (25 Kms) and visits at least 50 unique locations, we classify them as a full- (part-) time driving worker. To ensure that these mobility patterns are not one-off behaviors, for all the work types mentioned above, we include only those individuals who repeat the work behavior at least three days in a week. We define a non-gig worker as an individual who did either full-time or part-time non-gig work in a week. Similarly, a gig worker is an individual who did either full-time or part-time gig work types - food delivery, grocery delivery, driving in a week. We aggregate non-gig workers and gig workers using their home location at the CBG level to define weekly non-gig and gig labor counts.

3.2 Summary Statistics

We first present the summary statistics and model free evidence. Table 1 provides the summary statistics of the labor counts performing different work types across the 979 CBGs in Boston during the sample period. T1 (week = 12) is the week immediately after the declaration of the national COVID emergency and T2 (week = 22) is the week immediately after the first phase of reopening in Boston.

Figure 1 gives the graphical representation of our results. Each subplot represents the average weekly labor counts in CBGs across Boston for different treatment periods. We can see that the labor counts decreased across all CBGs during the lockdown period (between week 12 and week 21) compared to the pre-lockdown period (week before 12). We also see a significant increase in the weekly labor counts in the reopening period (after week 21). However, the increase does not seem to offset the drop in labor counts when we compare to the pre-lockdown period suggesting that the labor count recovery after reopening was not sufficient to offset the job losses that occurred as a result of the lockdown. The same pattern can be observed when we look at either only non-gig labor counts or only gig labor counts as well.

When we further compare the impact on non-gig and gig labor counts separately as shown in Figure 2, even though both types of labor counts dropped sharply after the lockdown, the gig labor counts picked up relatively quicker in the reopening period compared to the non-gig labor counts. Our model free evidence suggests that there was a sharp decline in weekly labor counts across all the CBGs in Boston during the lockdown period. Although we see significant recovery post-reopening, the weekly labor counts were still below the pre-lockdown levels. We also find that after the reopening, the gig labor counts saw a relatively sharper uptick compared to the non-gig labor counts suggesting that the gig jobs were relatively resilient to the COVID-19 policies compared to the non-gig jobs.

4 Empirical Modeling

We conduct multiple levels of analyses to examine the impact of the COVID-19 policies on non-gig versus gig labor counts, the heterogeneous impact on various socioeconomic groups, and to understand the potential underlying mechanisms that drive the differences between the impact of COVID-19 policies on non-gig versus gig labor counts.

4.1 CBG-Level Labor Counts

We start our analyses by estimating the impact of the policies on overall non-gig versus gig labor counts at a Census Block Group level. We use a Poisson Count Model to model the differential impact of the policies on non-gig and gig work types. Specifically, we estimate:

$$E[LaborCount_{jt}] = exp(\alpha_j + \beta_1 T_1 + \beta_2 T_2 + \beta_3 WorkTypeNG_{jt} + \beta_4 T_1 \times WorkTypeNG_{jt} + \beta_5 T_2 \times WorkTypeNG_{jt} + \beta_6 LagLaborCount_{jt} + \beta_7 COVIDControls_{jt} + \beta_8 NumUsers_{jt} + \beta_9 t + \epsilon_{jt}) \quad (1)$$

where $LaborCount_{jt}$ refers to the labor count in the CBG j for the week t. T_1 is a dummy variable indicating the lockdown period and takes a value 1 if week t is between March 15,2020 when the national COVID emergency was declared and May 18, 2020 when the first round of reopening was announced for the city of Boston. T_2 is a dummy variable indicating the reopening period that takes a value 1 if the week is after May 18, 2020. $WorkTypeNG_{jt}$ is a dummy variable which indicates whether the weekly labor count refers to non-gig work type or gig work type. The interaction terms $T_1 \times WorkTypeNG_{jt}$ and $T_2 \times WorkTypeNG_{jt}$ capture the effect of COVID-19 policies on non-gig labor counts relative to the gig labor counts. $LagLaborCount_{jt}$ refers to the total number of individuals in CBG j in week $t-1$. $COVIDControls_{jt}$ refers to COVID infection rate and mortality rate for CBG j in week t. $NumUsers_{jt}$ refers to the total number of individuals with homes in CBG j in week t. The variable t captures the weekly trends. The standard errors are clustered at CBG level. We also use CBG level fixed effects (α_j) for robustness.

To understand the heterogeneous importance of the gig work types for various socioeconomic groups, we interact the treatment variables with the demographic characteristics of the home CBGs. We again use a Poisson Count model such that:

$$
\begin{aligned}
E[GigLaborCount_{jt}] = exp(&\alpha_j + \beta_1 T_1 + \beta_2 T_2 + \beta_3 T_1 \times Demographics_j + \beta_4 T_2 \times Demographics_j \\
&+ \beta_5 LagLaborCount_{jt} + \beta_6 COVIDControls_{jt} + \beta_7 NumUsers_{jt} + \beta_8 t + \epsilon_{jt})
\end{aligned} \tag{2}
$$

where $GigLaborCount_{jt}$ is gig labor counts in the CBG j for the week t. $Demographics_j$ refers to the demographic controls of the CBG j: 4 buckets of median household income, percentage of female population, and percentage of black population. The interaction terms $T_1 \times Demographics_j$ and $T_2 \times Demographics_j$ thus respectively capture the relative importance of the gig work types on various demographic groups during the lockdown period and after the reopening.

4.2 Mechanisms of Gig Resilience

To understand the mechanisms that drive the differences between how non-gig jobs and gig jobs responded to the COVID-19 policies, we look at the potential transition from non-gig to gig jobs during the treatment periods. To study these transitions, we use an individual-level Binary Choice Logit model where we model an individual's utility in choosing to perform a gig work type given that they did a non-gig job in the previous week.

Again, we model the probability of an individual i choosing a specific work type in a week t as

$$Pr(GigWorkChoice_{it}) = \frac{exp(U_{it})}{1 + exp(U_{it})}$$

where

$$
\begin{aligned}
U_{it} = {}&\alpha_i + \beta_1 T_1 + \beta_2 T_2 + \beta_3 LagNonGigWorkChoice_{it} \\
&+ \beta_4 T_1 \times LagNonGigWorkChoice_{wit} + \beta_5 T_2 \times LagNonGigWorkChoice_{wit} \\
&+ \beta_6 LagWorkCount_{it} + \beta_7 COVIDControls_{it} + \beta_8 t + \epsilon_{it}
\end{aligned} \tag{3}
$$

where $GigWorkChoice_{it}$ is a binary variable which takes a value of 1 if individual i performed any gig work type in week t. $LagNonGigWorkChoice_{it}$ is a binary variables equal to 1 if individual i performed a non-gig work type in week $t-1$ and 0 otherwise. The interaction terms $T_1 \times LagNonGigWorkChoice_{it}$ and $T_2 \times LagNonGigWorkChoice_{it}$ capture the effect of COVID-19 policies on week-on-week non-gig to gig work type transitions. We include individual level fixed effects (α_i) for robustness and also correct for the incidental parameter bias. We also verify the interaction coefficients using a Linear Probability model.

4.3 Changes in Gig Worker Behavior

In addition to the overall impact on gig work types, we also look into the work behavior changes induced by the COVID-19 policies in gig workers. The introduction of national emergency measures led to drastic drop in road traffic and thereby reducing the travel times for those vehicles on the road. Along with this, many restaurants and grocery outlets also changes their hours of operations to adapt to the lockdown guidelines and changing consumer shopping patterns. Moreover, since people stopped going out of their home in accordance with the social distancing measures, their daily work and sleep cycles changes as well inducing a shift in their circadian rhythms. Considering these changes in travel times, operating hours, and consumer circadian rhythms, we are interested whether these changes induced any changes to gig worker behaviors. Specifically, we are interested in changes in daily work hours and within day work timings of gig workers. Given the daily high frequency nature of location data, we can answer these questions easily which is not possible using either household survey data or administrative data sources.

Firstly, we use a Poisson Count model at individual-day level to model the impact on daily work hours as:

$$E[WorkHours_{wit}] = exp(\alpha_i + \beta_1 T_1 + \beta_2 T_2 + \beta_3 COVIDControls_{it} + \beta_4 t + \beta_5 DOW_t + \epsilon_{it}) \tag{4}$$

where $WorkHours_{wit}$ is the daily work hours for an individual i doing a gig work type w on day t. For food delivery workers, we calculate daily work hours as the time difference between the first restaurant visit and the last restaurant visit within a day. Similarly for grocery delivery workers, we calculate daily work hours as the time difference between the first grocery store visit and the last restaurant visit within a day. Since we cannot identify the starting and ending work time for ridesharing drivers, we limit our analysis to only the delivery workers as discussed above. $T1$ and $T2$ refer to the lockdown period and reopening period and t is the weekly time trend variable. We include individual level fixed effects (α_i) and day of week fixed effects (DOW_t) for robustness.

Secondly, we use a Binary Choice Logit model at individual-day level to model the impact on within day work timings as:

$$Pr(WorkingTime_{wpit}) = \frac{exp(U_{it})}{1 + exp(U_{it})}$$

where

$$U_{it} = \alpha_i + \beta_1 T_1 + \beta_2 T_2 + \beta_3 COVIDControls_{it} + \beta_4 t + \beta_5 DOW_t + \epsilon_{it} \tag{5}$$

where $WorkingTime_{wpit}$ is a binary variable which takes a value of 1 if and individual i started performing work type w in time period p on day t. For food delivery workers, we split the day into three time periods - morning hours (between 7 AM and 12 PM), noon hours (between 12 PM and 6 PM), and evening hours (after 6 PM). For grocery delivery workers, we split the day into four time periods - early morning hours (between 6 AM and 10 PM), noon hours (between 10 AM and 2 PM), late noon hours (between 2 PM and 6 PM), and evening hours (after 6 PM). We include individual level fixed effects (α_i) and day of week fixed effects (DOW_t) for robustness and also correct for the incidental parameter bias.

5 Results

In this section, we present the empirical results from estimating the models we discussed. Additional tables and results can be found in the Online Appendix.

5.1 CBG-level Labor Counts

We present the results for the impact of COVID-19 policies on weekly labor counts at a CBG level in Table 2. We see that the coefficients for both T1 and T2 are negative and significant suggesting that there was a drop in weekly labor counts as a result of the COVID-19 policies. Interestingly, the magnitude of T2 is less than that of T1, indicating an increase in weekly labor counts after the reopening most likely as a result of relaxed social distancing norms. However, as we observed in the model free evidence, this increase is insufficient to offset the initial drop in labor counts resulted due to the lockdown. On average, we find that the weekly job counts fell by 63% in the lockdown period and 55% in the reopening period relative to the pre-lockdown period. In column (2) we check for the differential impact on non-gig versus gig labor counts. The interaction term coefficient suggests that non-gig labor counts decreased more than the gig labor counts - particularly in the T2 time period (23% more) suggesting that in-person gig jobs were resilient relative to traditional non-gig jobs - particularly after the reopening.

We also see significant heterogeneity in the impact of the COVID-19 policies on weekly gig labor counts in terms on demographic composition of home CBGs. Table 3 shows the impact of COVID-19 policies by income groups (Column 1), race (Column 2), and gender(Column 3). We see that CBGs with a higher share of black populations saw a significant lower drop in weekly gig labor counts during both the lockdown as well as the reopening period. Our results suggest that not only gig jobs were resilience to the COVID-19 pandemic, they also boosted the resilience of neighborhoods with a larger share of black populations by curbing job losses.

Although not significant, the interaction variables for high-income groups (60k-100k, 100k-150k, >150k) are negative for both T1 and T2 suggesting that high income groups saw a larger drop in labor counts for gig work types. Finally, we do not see any differential impact on gig labor counts by gender during either of the treatment periods.

We also analyze the impact of COVID-19 policies on stay-at-home count (Online Appendix Table 1) and our results concur with the general consensus that individuals adhered to social distancing measures following the onset of COVID-19 and continued to do so even after reopening.

In summary, we find that the COVID-19 policies led to significant job losses for both non-gig and gig work types. Interestingly, gig work types suffered a lower impact than non-gig work types, suggesting that the gig sector was resilient to the unemployment shock compared to the non-gig sector. Furthermore, the gig job losses are less severe in black neighborhoods, revealing the importance of gig jobs to such marginalized neighborhoods.

5.2 Mechanisms of Gig Resilience

We now look at the potential mechanisms that are driving the resilience of gig jobs compared to non-gig jobs during the COVID-19 pandemic. In Table 4, we look at weekly transitions from non-gig to gig work types. The coefficients of $LagNonGig$ in both columns (1) and (2) suggest that an individual who did non-gig work in a week is less likely to transition to a gig work type in the next week before the pandemic, suggesting no week-on-week transition from non-gig to gig work types. However, as can be seem in the interaction terms in columns (2), there is a positive and significant job transition from non-gig to gig work types during both the lockdown and the reopening periods. Moreover the magnitude of this interaction variable is smaller in the reopening period suggesting that the non-gig to gig work type transitions decreased after the relaxation of COVID-19 policies.

In summary, there is a significant transition from non-gig to gig work types, suggesting that some of the job losses in the non-gig sector were absorbed by the gig sector. Extant literature suggests that once the reopening was announced, firms rehired the employees they had fired during the emergency period (Cheng et al., 2020). But we find that there is also some stickiness to the job transitions, suggesting that these transitions may be longer-lasting - individuals who shifted to gig work types because of job losses remained in the gig sector and did not return to their previous employers even after the reopening.

5.3 Changes in Gig Worker Behavior

In Table 5, we present the results of daily work hour analysis. As expected, both food and grocery delivery workers worked shorter daily hours during the lockdown period. However, this behavior is different between food and grocery delivery workers and as well as during lockdown and reopening periods. The work hours reduced to a higher extent in both the treatment periods for food delivery workers compared to the grocery delivery workers. Similarly, the reduction in work hours is smaller in the reopening period and even insignificant for grocery delivery workers indicating there was no significant change in working hours compared to the pre-lockdown period. Three possible explanations for this difference in behaviors exist - 1) with increased adherence to social distancing measures driving down road traffic, the gig workers had to spend less time traveling to fulfil their orders and therefore were able to get the same amount of work done in a shorter time period 2) it is possible that people staying at home started cooking more and reduced ordering whereas there was no significant reduction in ordering groceries and 3) since groceries are essential goods whereas takeout meals are not, people somewhat continued with reduced food ordering but resumed grocery ordering after reopening.

Table 6 and Table 7 show how the working times for the gig workers changed as a result of COVID-19 policies. The likelihood of gig workers starting their work in the morning hours decreases (column 1) whereas the likelihood of starting work in the evening hours increases (column 3) during the lockdown period indicating that there is a shift from morning work routine to an evening work routine. Reduced travel time uncertainty as a result of lockdown measures as well as a shift in consumers' circadian rhythms could potentially explain this interesting behavioral change. Moreover, these changes disappear after the reopening suggesting that these behavioral modifications were temporary in nature and reverted back once the lockdown was eased.

6 Heterogeneous Impacts by Work Types

In this section, we look at how different in-person gig work types included in our study responded to the COVID-19 policies. Specifically, we look at the impact of lockdown and the reopening on weekly labor counts and the transition from non-gig work types to each of the six different gig work types - full-time food delivery (FTFD), part-time food delivery (PTFD), full-time grocery delivery (FTGD), part-time grocery delivery (PTGD), full-time driving (FTDR), and part-time driving (PTDR).

6.1 CBG-Level Labor Counts

The impact of COVID-19 policies on weekly labor counts for each gig work type is presented in Online Appendix Table 2. Similar to our main results, we see a decrease in weekly labor counts across all gig work types in the lockdown period and some recovery in the reopening period. However, the impact differs across the gig work types - food delivery had the largest drop and driving had the smallest drop in weekly labor counts.

6.2 Mechanisms of Gig Resilience

When we further split the gig work types by its constituent work types in Online Appendix Table 3, we see interesting patterns in the substitutions from traditional jobs to the in-person gig jobs. We see that food and grocery delivery jobs absorbed the highest share of transition from non-gig jobs. Since the concerns about COVID-19 infections dissuaded people from doing their own grocery shopping thereby boosting demand for home deliveries, there was a significant hiring spree from major leading delivery firms. Our results seem to suggest that some of these positions were filled by the non-gig workers. Similarly, since most restaurants resorted to delivery only setting to stop large gatherings inside the restaurant premises, the demand for food delivery also increased which was fulfilled to some extent by non-gig workers.

7 Robustness Checks

Impact of Remote Work. After the introduction of the national lockdown, most firms enabled their employees to work from home without having to travel to their employer location. Therefore, one of the natural uncertainties in our identification method is that we cannot distinguish between individuals who moved to a remote setup and started working from home and individuals who were laid-off. To test the hypothesis that our results are not driven by non-gig employees potentially working from home, we repeat our analyses using a subset of the individuals who have jobs that are less likely to be done from home. Dingel and Neiman (2020) build an occupation level metric using the Occupational Employment Statistics to identify the feasibility of working from home. Even though they find that 37% of the jobs in the U.S. can be done from home, this share differs across occupations. For example, only 4% of the jobs in the Accommodation and Food Services sector and 14% of the jobs in the Retail Trade sector can be done from home whereas 83% of the jobs in the Educational Services sector can be done from home. Therefore, if an employee working in the Accommodation and Food Services sector is not traveling to work, they are more likely to have lost their job than to have been working from home. To verify the validity of our results, we identify only those non-gig workers who work in either Accommodation and Food Services or Retail Trade sector. We then aggregate only these non-gig labor counts at CBG level and identify this count as the total weekly non-gig labor count and repeat the analysis from Table 2. As we can see from the results in Table 8, our main results are consistent with the new definition of labor counts.

Alternate Treatment Dates. To validate that the drop in labor counts is indeed a result of the COVID-19 policies and not because of pre-existing trends, we use hypothetical treatment dates and verify our results. First, we change the treatment date for the lockdown policy change and check the average impact of COVID-19 policies for the lockdown period. We select two alternate weeks - two weeks before the declaration of national emergency and two weeks after the declaration of national emergency. Thus, we have two robustness checks for T1 - one with T1 = 1 after week 9 and another with T1 = 1 after week 13. As we can see from Online Appendix Table 4 columns 1-3, the coefficients for both T1 and T2 have a lower magnitude compared to the actual results in Table 2 indicating a lower impact on weekly labor counts with the alternate treatment week. Since most people were still traveling to work during weeks 10 and 11 i.e., before declaration of national emergency, the average effect for T1 becomes less negative as explained by our results. We also observe a reduction in the impact when T1 is two weeks after the actual treatment week in Online Appendix Table 4 columns 4-6. We further repeat the same exercise for the reopening policy change. Boston announced the second stage of reopening on 8th June 2020 [14] with further easing of restrictions on economic activities compared to the first phase of reopening. We verify how much did the additional easing of the restrictions impact the weekly labor counts by moving the reopening treatment three weeks later than the first phase of reopening. As we can see in Online Appendix Table 5, the impact of these easing measures was very minimal suggesting that the impact of second round of easing restrictions was limited.

8 Conclusion

The emergence of high accuracy location data and the unfortunate COVID-19 pandemic give us an opportunity to overcome the limitations of traditional benchmark data and study the impact of convoluted public health and economic crises on gig workers. In this study, we use the newly available, population-scale, longitudinal, and high-frequency smartphone location data to examine the impact of the unprecedented COVID-19 pandemic on the U.S. gig sector. We develop a novel methodology to identify individuals working in in-person non-gig and gig type jobs and analyze the impact of COVID-19 policies on these work types. We find that in-person gig jobs remained resilient to the COVID-19 pandemic relative to traditional non-gig jobs - the gig sector suffered fewer job losses compared to the non-gig sector following the onset of the pandemic. The gig sector enhances labor market resilience by absorbing job losses from the non-gig sector and the transition from non-gig to gig jobs remained significant even after the reopening suggesting long term nature of the resilience. Moreover, the gig economy also provided additional resilience to marginalized populations whereby neighborhoods with a higher share of black populations saw a lower drop in weekly gig labor counts. Finally, we observe that, at the onset of the pandemic, gig workers showed remarkable resilience by adapting their working behavior to suit the populations' changing circadian rhythm by working shorter hours and showing an increased preference to working later hours in the day.

Our study highlights the shortcomings of benchmark data sources in understanding the response of gig economy during public health and economic crises. By leveraging non-traditional data sources and devising a novel, unique methodology to identify gig worker mobility patterns, our study sheds light on the importance of these data sources as a policy-making tool. More importantly, we provide evidence on the resilience of gig economy to the labor market and the importance of in-person gig jobs to marginalized populations. Our results advocate support from policy-makers to the under-studied gig labor market.

[14] https://www.boston.com/news/coronavirus/2020/06/06/what-can-open-in-phase-2-massachusetts

Figure 1: Weekly average Labor Counts

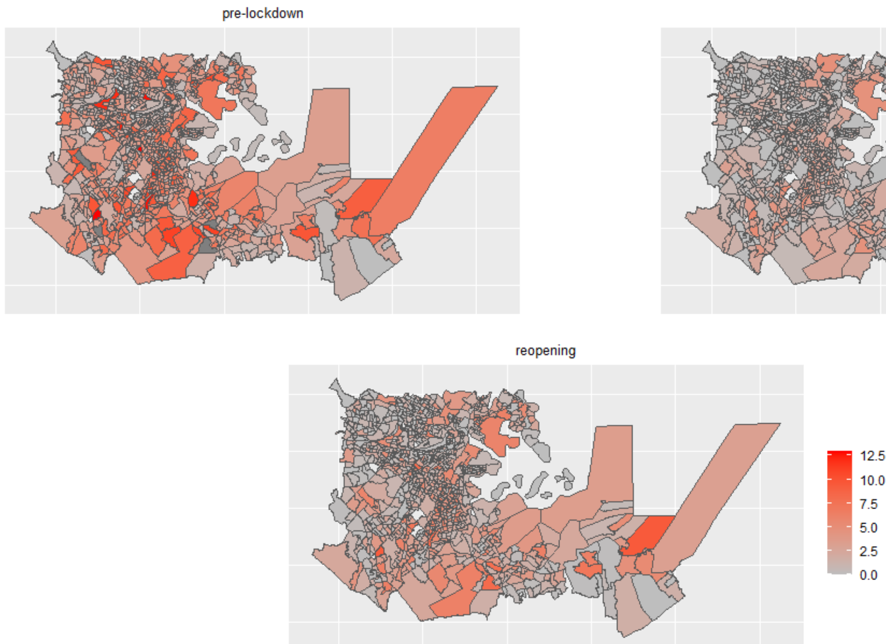

Figure 2: Weekly Labor Counts

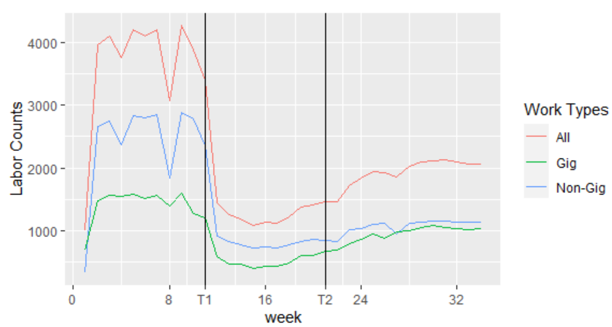

Table 1: Summary Statistics for CBG-level weekly Labor Counts

	Pre-Lockdown				During-Lockdown				After-Reopening			
Variable:	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
All	3.674	3.125	0	22	1.082	1.336	0	9	1.739	1.901	0	13
Non-Gig only	2.470	2.275	0	20	0.664	0.951	0	7	0.941	1.190	0	10
Gig only	1.384	1.660	0	13	0.458	0.821	0	7	0.883	1.253	0	10
Full-time non-gig	2.086	2.016	0	16	0.504	0.815	0	6	0.715	1.005	0	7
Part-time non-gig	0.384	0.674	0	5	0.159	0.420	0	4	0.226	0.506	0	4
Full-time food delivery	0.372	0.737	0	7	0.066	0.275	0	4	0.161	0.449	0	5
Part-time food delivery	0.696	1.116	0	11	0.157	0.455	0	6	0.358	0.727	0	6
Full-time grocery delivery	0.152	0.416	0	4	0.058	0.249	0	2	0.093	0.321	0	4
Part-time grocery delivery	0.349	0.661	0	5	0.136	0.396	0	5	0.214	0.505	0	5
Full-time driving	0.544	0.940	0	8	0.196	0.511	0	5	0.406	0.810	0	9
Part-time driving	0.571	1.053	0	11	0.183	0.492	0	5	0.392	0.803	0	8
Stay-at-home	5.977	4.544	0	38	7.936	5.790	0	51	7.133	5.251	0	41

Table 2: Impact of COVID-19 Policies on Labor Counts

	Labor Counts by CBG	
	(1)	(2)
T1	-1.002^{***}	-0.996^{***}
	(0.028)	(0.035)
T2	-0.791^{***}	-0.654^{***}
	(0.029)	(0.029)
WorkTypeNG	0.223^{***}	0.325^{***}
	(0.022)	(0.020)
WorkTypeNG x T1		-0.027
		(0.037)
WorkTypeNG x T2		-0.257^{***}
		(0.024)
COVID controls	Yes	Yes
Other controls	Yes	Yes
CBG FE	Yes	Yes
Log-Likelihood	-63912.964	-63800.588
Observations	61612	61612

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 3: Effect of COVID-19 Policies and Demographics on Gig Labor Counts

	Gig Labor Counts by CBG		
	(1)	(2)	(3)
Income_med x T1	-0.057		
	(0.064)		
Income_high x T1	-0.225^{*}		
	(0.105)		
Income_vhigh x T1	$-0.297^{\cdot}$		
	(0.172)		
Income_med x T2	-0.102^{**}		
	(0.040)		
Income_high x T2	-0.081		
	(0.063)		
Income_vhigh x T2	-0.073		
	(0.105)		
% Black x T1		0.254^{**}	
		(0.087)	
% Black x T2		0.150^{*}	
		(0.060)	
% Women x T1			0.650
			(0.409)
% Women x T2			0.220
			(0.237)
COVID controls	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes
Log-Likelihood	-24178.658	-26013.012	-26019.792
Observations	26355	28147	28147

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Note: Only variables of interest are shown

Table 4: Impact of COVID-19 Policies on Non-Gig to Gig Work Transitions

	Gig work choice	
	(1)	(2)
T1	-1.903^{***}	-2.016^{***}
	(0.042)	(0.044)
T2	-1.398^{***}	-1.489^{***}
	(0.072)	(0.073)
LagNonGigWorkChoice	-1.404^{***}	-1.587^{***}
	(0.033)	(0.041)
LagNonGigWorkChoice x T1		0.621^{***}
		(0.073)
LagNonGigWorkChoice x T2		0.347^{***}
		(0.057)
COVID controls	Yes	Yes
Other controls	Yes	Yes
Individual FE	Yes	Yes
Log Likelihood	−40660.774	−40616.455
Observations	127560	127560

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 5: Impact of COVID-19 Policies on Hours Worked

	Hours Worked	
	Food Delivery	Grocery Delivery
T2	-1.807^{***}	-0.300^{***}
	(0.109)	(0.065)
T1	-1.021^{***}	$-0.201^{\cdot}$
	(0.190)	(0.115)
COVID controls	Yes	Yes
Other controls	Yes	Yes
Individual FE	Yes	Yes
Day of Week FE	Yes	Yes
R^2	0.023	0.004
Observations	52406	26069

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 6: Impact of COVID-19 Policies on time of work

	Choice of Food Delivery working time		
	<= 12 PM	12 PM - 6 PM	>= 6 PM
T1	-0.309^{***}	0.132^{*}	0.214^{**}
	(0.065)	(0.060)	(0.077)
T2	-0.112	-0.001	0.143
	(0.113)	(0.103)	(0.135)
COVID controls	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes
Log Likelihood	-25070.152	-28900.797	-18931.705
Observations	48595	50072	46922

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 7: Impact of COVID-19 Policies on time of work

	Choice of Grocery Delivery working time			
	<= 10 AM	10 AM - 2 PM	2 PM - 6 PM	>= 6 PM
T1	-0.858^{***}	0.098	0.258^{***}	-0.036
	(0.135)	(0.086)	(0.075)	(0.080)
T2	-0.552^{*}	0.034	$0.257^{\cdot}$	-0.081
	(0.245)	(0.153)	(0.133)	(0.143)
COVID controls	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Log Likelihood	-5216.791	-10160.883	-13718.429	-12822.885
Observations	14720	20203	23913	23510

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 8: Impact of COVID-19 Policies on Labor Counts - Select Occupations

	Labor Counts by CBG	
	(1)	(2)
T2	-0.931^{***}	-0.797^{***}
	(0.031)	(0.033)
T2	-0.726^{***}	-0.566^{***}
	(0.035)	(0.034)
wTypeNG	-0.417^{***}	-0.185^{***}
	(0.030)	(0.026)
wTypeNG x T1		-0.355^{***}
		(0.047)
wTypeNG x T2		-0.456^{***}
		(0.035)
COVID controls	Yes	Yes
Other controls	Yes	Yes
CBG FE	Yes	Yes
Log-Likelihood	-48525.636	-48319.246
Observations	60162	60162

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$