Resilience of the U.S. Gig Economy during the COVID-19 Pandemic: Insights from Location Big Data

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The COVID-19 pandemic has led to sharp increase in job losses leading to an unprecedented unemployment crisis. Albeit the abyss of loss in traditional labor market, new opportunities emerge in gig economy to support a more flexible form of labor participation. In our research, we study the role of gig economy during the COVID-19 pandemic and its response to various pandemic mitigation policies. Leveraging the novel, population-scale, longitudinal, and high-frequency smartphone location data, we build a longitudinal panel data of approximately 10000 individuals in the city of Boston spanned across 8 months and present our evidence on the impact of COVID-19 policies on the gig economy. We find that, even though the COVID-19 policies led to job losses across categories, gig sector suffered fewer job losses. Furthermore, there were significant differences in this impact based on racial composition of the neighborhoods with a lower number of job losses in neighborhoods with higher proportions of Black populations. While there was some increase in employment numbers after the eventual relaxing of the social distancing restrictions, it was not enough to offset the job losses. Additionally, we find that the probability of working also decreased more for non-gig work types compared to gig work types. More interestingly, we find significant increase in non-gig workers opting for gig work and gig workers opting for non-gig work upon the emergency declaration and these transitions remained significant even after the re-opening. Our findings highlight the resilience of the gig economy in terms of job losses in the face of an unprecedented public health crisis and the importance of gig jobs to the vulnerable populations.

Key words: gig economy, covid-19, location data
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1. Introduction

To curb the spread of the virus from social contact and to mitigate the effects of COVID-19 pandemic, many states issued lockdown orders severely restricting human mobility and closing down venues that enable gathering of people - including workplaces. For instance, Massachusetts declared state emergency on March 15, 2020 [1] and lockdown on March 31, 2020 closing all non-essential businesses [2]. As a consequence, many employers laid off their workforce indefinitely which resulted in severe job losses across industries and unemployment levels similar to those during the Great Depression [3]. Since such a large scale measure has rarely been taken which impacted millions of livelihoods, it is important for policymakers to understand the unemployment impact of these policies.

Although many studies have found that the lockdown resulted in employment losses across sectors (Glover et al. (2020), Mongey et al. (2020)), none have looked at the differential impact on non-gig versus the gig sectors. The differential impact is interesting because the gig economy is found to act as a cushion for people who face financial distress due to unforeseen external shocks (Koustas (2018)). Moreover, the gig sector has been one of the fastest growing sectors in the last decade with an addition 6 million more jobs since 2010 [4].

In our study, we look at the impact of these policies on three major gig work types - food delivery, grocery delivery, and ridesharing. Of the many jobs that comprise the gig economy, ride-hailing and delivery - both food and grocery, comprise the fastest growing categories. Driven by the emergence of digital platforms, these categories have added 1.6 million jobs just in the last decade [5]. This impressive growth is poised to increase still with the ride sharing sector projected to be a 218 billion market [6], the food delivery sector to a 470 billion market [7], and the grocery delivery sector to a 130 billion market [8] employing even more gig workers by 2025. But the COVID-19 pandemic has disrupted the growth of these gig sectors with people concerned by the spread of the coronavirus, have increased the usage of food and grocery delivery services [9]. To cater to this increased demand, firms have started hiring more gig workers [10] and these gig workers have been at the forefront delivering essential supplies [11]. On the flip side, demand for ride-hailing services had dropped sharply and ride-hailing firms are having to cut down on their workforce [12] and the

[1] https://www.mass.gov/news/baker-polito-administration-announces-emergency-actions-to-address-covid-19

[2] https://www.boston.gov/departments/public-health-commission/coronavirus-timeline

[3] https://www.cnbc.com/2020/07/21/some-big-cities-are-hitting-great-depression-unemployment-levels.html

[4] https://www.cnbc.com/2020/02/04/gig-economy-grows-15percent-over-past-decade-adp-report.html

[5] https://www.reuters.com/article/us-biggerpicture-health-coronavirus-gigw/waiting-for-work-pandemic-leaves-u-s-gig-workers-clamoring-for-jobs-idUSKBN2741DM

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

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

[8] 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

[9] https://news.uchicago.edu/story/how-covid-19-pandemic-has-disrupted-demand-gig-economy

[10] https://www.cnn.com/2020/03/23/tech/instacart-hiring/index.html

[11] https://www.wsj.com/articles/unexpected-heroes-on-the-frontlines-of-americas-coronavirus-lockdown-11585058205

[12] https://www.wsj.com/articles/uber-cuts-3-000-more-jobs-shuts-45-offices-in-coronavirus-crunch-11589814608

gig workers having to work to avoid losing their homes [13]. Given the importance of delivery and ride-hailing services to the gig economy, it is crucial to understand the impact of large scale policies implemented during the COVID-19 pandemic on these work types.

"Gig economy" is defined as "a labor market characterized by the prevalence of short-term contracts or freelance work as opposed to permanent jobs." The emergence of new business models driven digital platforms has enabled firms create a flexible work environment (Burtch et al. (2018)) and to hire a large number of workers without facing significant hiring costs (Friedman (2014)). Similarly workers are drawn towards the gig economy driven by the flexibility of time, the freedom to choose the jobs they do [14], and even the opportunity to earn much above the minimum wage [15]. Driven by both these demand and supply side factors,gig economy has grown to be an integral part of the US labor market with more than one third of the US workers engaging in gig work [16].

The advent of platform economy driven by digital technologies has helped the rise of the gig economy. Just in the past decade, the gig economy has added 6 million workers. Given the flexibility of work hours and the independence of choosing work types, workers are attracted to the independence offered by the gig economy with many of them doing gig work to earn additional income over their traditional job or even completely substitute traditional job with gig work to earn their living wage.

Given the non-contractual, temporary nature of gig work, and the lack of clear definitions of what gig work really means [17], the gig economy remains largely unobserved by labor market researchers (Kässi and Lehdonvirta (2018)). Even the US "government data sources have difficulty counting how many gig workers there are" and only had data that on gig workers that is at least a decade old [18]. Therefore, it becomes essential to use non-traditional data while measuring the gig economy and policy implications on gig workers.

In this study, we use population-scale, high-frequency, smartphone location data to address these questions. We develop a novel methodology to identify home and work locations using the location data and further classify the work locations into non-gig and gig work types. We use this classification to understand the job losses across different jobs. We track these work activities on a

[13] https://www.reuters.com/article/us-health-coronavirus-uber-lyft/risk-coronavirus-or-default-ride-hail-drivers-face-tough-choices-as-u-s-aid-expires-idUSKCN2521M6

[14] https://www.theatlantic.com/business/archive/2011/09/the-freelance-surge-is-the-industrial-revolution-of-our-time/244229/

[15] https://venturebeat.com/2014/08/17/inside-the-sharing-economy-workers-find-flexibility-and-19-hour-days/

[16] https://www.forbes.com/sites/tjmccue/2018/08/31/57-million-u-s-workers-are-part-of-the-gig-economy/?sh=13b600af7118

[17] https://www.gigeconomydata.org/basics/how-many-gig-workers-are-there

[18] https://www.bls.gov/careeroutlook/2016/article/what-is-the-gig-economy.htm

weekly basis to understand any shifts in work. Any positive shift from non-gig to gig work activities due to the COVID-19 policies indicate that the gig sector was able to provide some respite to individuals who lost their jobs as a result of these policies.

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 [19]. 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.

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), Hannák 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)). 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) analyse 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

[19] https://www.boston.gov/news/temporary-guidance-construction-city-boston

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 Huang et al. (2020) study 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 behaviour 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 shared their location data to help with contact tracing during the COVID crisis. We build on this nascent literature to identify labor market impacts of COVID-19 policies.

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. For the sake of uniformity and to construct a meaningful longitudinal panel, 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.

We cluster these raw GPS locations by location and time to identify daily stay-points for all the individuals. To consistently identify these stay-points across multiple days, we assign a GeoHash to each stay-points.

Home Location Identification

To compare the raw GPS traces across multiple time periods, we assign a GeoHash (a 150 meter x 150 meter grid) to each latitude-longitude pair. Using the DBSCAN algorithm (Ester et al. 1996), we cluster the raw data by location and time to identify stay-points for all the individuals. The clusters are created such that there are at least 10 consecutive location records within a cluster and the maximum distance of a record from the cluster's centroid is 200 meters. The modal GeoHash for a cluster is assigned as stay-point identifier for the cluster. For records that cannot be assigned to any cluster, the actual GeoHash is retained as the stay-point identifier. For each day and each individual, we calculate the time spent at each stay-point and the total Haversine distance traveled. We also assign a *Night-GeoHash* to each individual, which is the modal GeoHash where the individual spends the weekday nights 1 AM - 5 AM. If there are no data between 1 AM - 5 AM, we assign the GeoHash where the individual spends > 12 hours in a day as the *Night-GeoHash*. For each individual, we identify a pre-COVID (1/15-3/15/2020) and a post-COVID (3/16-8/27/2020) home location to account for potential changes of home locations as a result of COVID.

Work Location and Work Type Identification

We identify each individual's work location and work type from the location data via carefully designed algorithms (Table 1.) For example, a full- (part-) time non-gig work location is the GeoHash where an individual spends 6 - 10 (1 - 6) hours a day and at least 3 days in a week other than home. Furthermore, we identify the Point of Interest (POI) that is closest, on average, to all the GPS traces within a work location as the workplace of the individual and the 6-digit NAICS code of this POI is assigned as the work-industry of the individual. Based on these work locations, we can determine different work types conducted by each individual daily (Table 2).

Table 1 WORK LOCATION IDENTIFICATION

Location Type	Definition
Home location	Modal GeoHash where an individual spends weekdays 1 - 5 AM
Non-Gig work location	Non-home GeoHash where an individual spends 1-6 hours (part-time) or 6-10 hours (full-time) per day
Food delivery location	Top half restaurant GeoHashes where an individual spends < 10 minutes per day
Grocery delivery location	Top half grocery GeoHashes where an individual spends 10-60 minutes per day
Driving location	Unique GeoHashes where an individual spends < 2 minutes per day

In summary, non-gig work includes both full-time and part-time non-gig work. Gig work includes full-time and part-time food delivery, grocery delivery, and driving work. The final panel data consists of 1.2 million location records from 9,310 individuals in Boston over 234 days.

Table 2 Work Type Identification

Work Type	Definition
Full-time Non-Gig (FTNG)	An individual spends > 4 hours in a day at a full-time work location, > 3 days in a week
Part-time Non-Gig (PTNG)	An individual is at a part-time work location in a day, > 3 days in a week
Full-time Food delivery (FTFD)	An individual visits > 6 food delivery locations and travels > 5 km in a day, > 3 days in a week
Part-time Food delivery (PTFD)	An individual visits 3 - 6 food delivery locations and travels > 5 km in a day, > 3 days in a week
Full-time Grocery delivery (FTGD)	An individual visits > 1 grocery delivery locations and traveled > 5 km in a day, > 3 days in a week
Part-time Grocery delivery (PTGD)	An individual visits 1 grocery delivery location and travels > 5 km in a day, > 3 days in a week
Full-time Driving (FTDR)	An individual visits > 25 driving locations and travels > 50 km in a day, > 3 days in a week
Part-time Driving (PTDR)	An individual visits > 25 driving locations and travels 25 - 50 km in a day, > 3 days in a week
Stay-at-home (STHM)	An individual spends entire day at home location or travels < 5 km in a day

3.1. Summary Statistics

We first present the summary statistics and model free evidence.

Table 3 Summary Statistics of CBG-level weekly Labor Counts

	Week < 12				Week >= 12 & <= 21				Week > 21			
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 3 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 **Weekly Labor Counts**

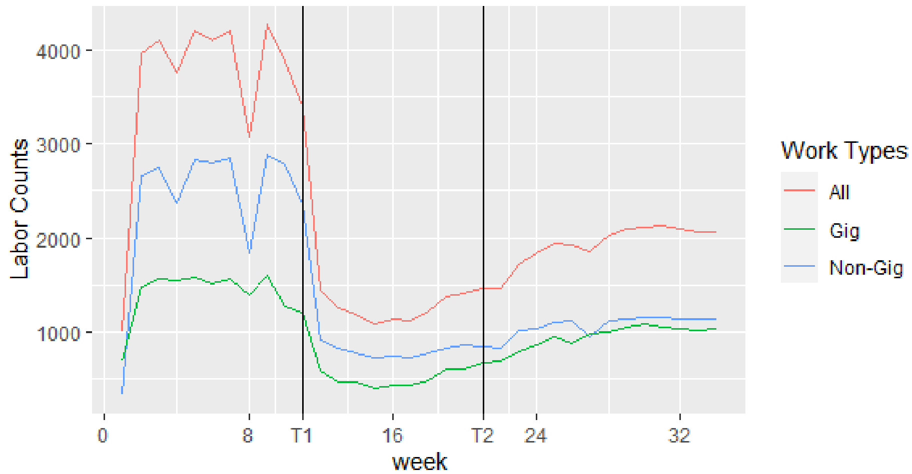


Figure 1 displays the weekly labor counts in Boston by work type over time. We can see a sharp drop in the labor count post T1 across all work types. An uptick emerged across most work types after T2, but the labor counts remained much lower than before T1, highlighting the persistent impact of COVID on the job market even as late as late August, 2020.

Table 4 Summary Statistics of Work Hours

Variable:	Definition	Mean	SD	Min	Max
FTWH (Hours)	Time spent at full-time non-gig work	36	8.83	18.18	118.85
PTWH (Hours)	Time spent at part-time non-gig work	17.42	8.59	2.57	150.08
FTFG (Locations)	Locations visited during full-time food-delivery work	19.54	18.90	7	169
PTFG (Locations)	Locations visited during part-time food-delivery work	12.4	4.69	3	36
FTGG (Locations)	Locations visited during full-time grocery-delivery work	3.07	1.81	2	18
PTGG (Locations)	Locations visited during part-time grocery-delivery work	2.86	0.88	1	7
FTDD (Distance in Kms)	Distance traveled during full-time driving work	231.92	195.20	50.01	1839.78
PTDD (Distance in Kms)	Distance traveled during part-time driving work	87.58	48.64	25	313.42

Table 4 presents the summary statistics of the weekly work hours across the CBGs for all work types. Recall the work hours for delivery is proxied by the number of delivery locations visited and those for driving by the daily distance traveled.

Figure 2 gives the graphical representation of our results. Each subplot gives the average weekly labor counts for all work types in CBGs across Boston for different time periods. We can see that the labor counts decreased across all CBGs during the second time period (between week 12 and week 21) compared to the first time period (week before 12) but there is some increase in the last time period (after week 21) compared to the second time period.

Figure 2 Weekly average Labor Counts across all CBGs

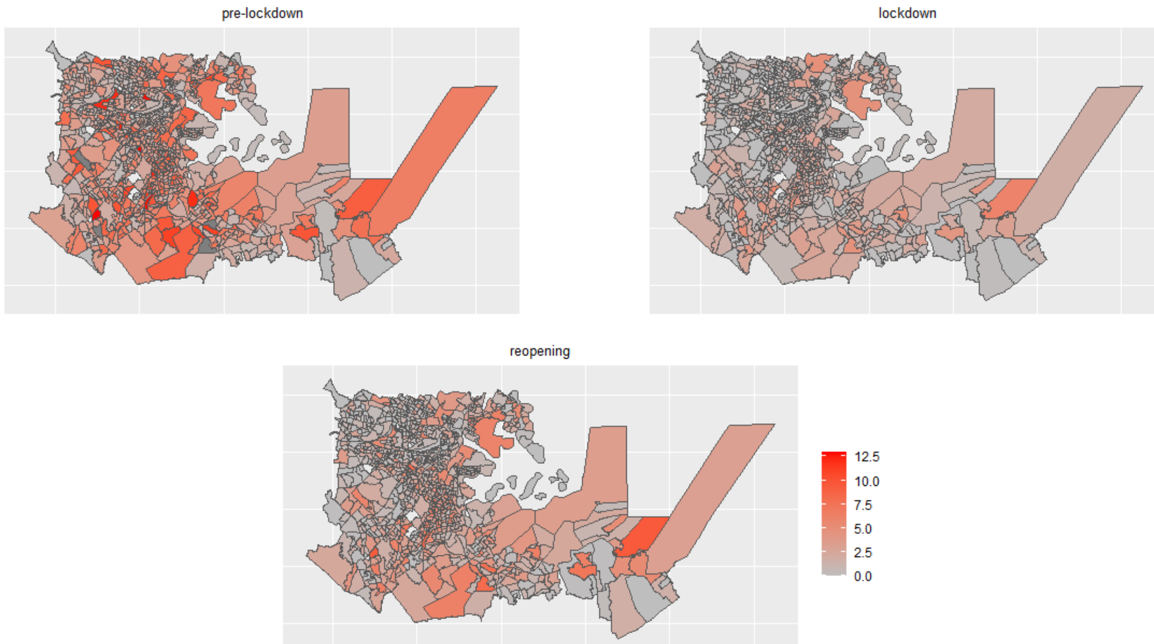


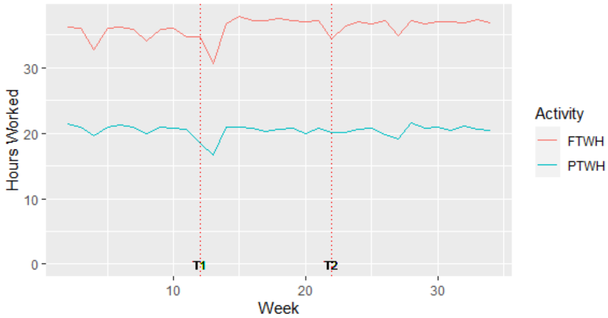
Figure 3 displays the weekly average work hours for each work type. We see a decline (increase) in the total locations visited per week by the food (grocery) delivery workers after the national emergency declaration. Interestingly, in contrast to the decline in the labor counts, the total work hours (or locations visited, distance traveled) across work types do not see major decline indicating that, conditional on working, the hours that individuals worked did not change much as a result of COVID-19 policies.

Next, we will discuss the model estimation results from the analyses on the labor counts, work hours, and work transitions. We also perform a series of more granular analysis and robustness checks (available upon request).

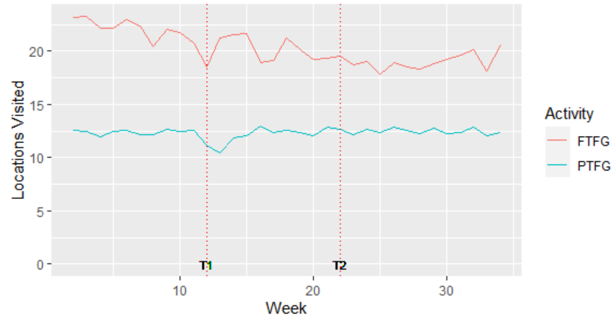
4. Modeling

We conduct three levels of analyses to examine the impact of the COVID mitigation policies on the total labor counts across non-gig and gig work types (Brynjolfsson et al. (2020), Chetty et al. (2020)), total work counts, total work hours, and transitions between non-gig and gig work types, while accounting for the heterogeneous effects of key worker demographics (income, race, and gender).

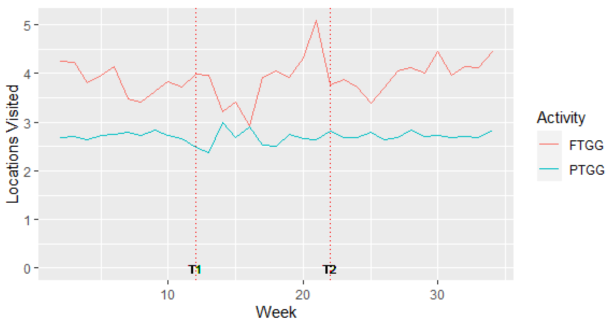
Figure 3 Weekly average measures of time spent during work activity



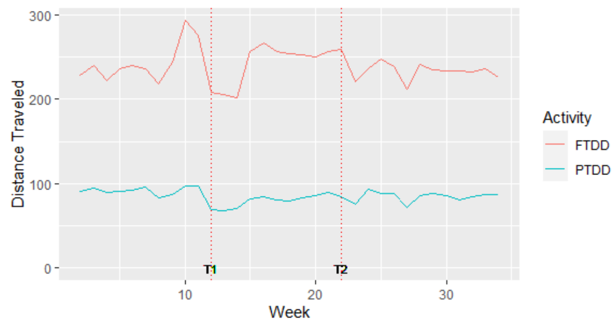
(a) non-gig work



(b) Food Delivery



(c) Grocery Delivery



(d) Driving

4.1. CBG-Level Labor Counts

We use a Poisson Count Model to study the impact of the COVID policies on the weekly labor counts for non-gig and gig work types at a Census Block Group (CBG) level:

$$\begin{aligned}
E[LaborCount_{jt}] = exp(&\alpha_j + \beta_1 T_1 + \beta_2 T_2 + \beta_3 WorkType_{jt} \\
&+ \beta_4 T_1 \times WorkType_{jt} + \beta_5 T_2 \times WorkType_{jt} \\
&+ \beta_6 T_1 \times Demographics_j + \beta_7 T_2 \times Demographics_j \\
&+ \beta_8 LagLaborCount_{jt} + \beta_9 COVIDControls_{jt} \\
&+ \beta_{10} NumUsers_{jt} + \beta_{11} t + \epsilon_{jt})
\end{aligned} \tag{1}$$

where $LaborCount_{jt}$ refers to the total labor count in the CBG j for the week t. T_1 is a dummy variable that 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 that takes a value 1 if the week is after May 18, 2020. $WorkType_{jt}$ is a dummy variable which indicates whether the labor count for the CBG j for the week t is of non-gig type or gig type. The interaction terms $T_1 \times WorkType_{jt}$ and $T_2 \times WorkType_{jt}$ capture the effect of COVID-19 policies on non-gig labor counts relative to the gig labor counts. $Demographics_j$ 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 heterogeneous effects of the COVID policies on various demographic groups. $LagLaborCount_{jt}$ 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 further verify our model assumptions, we also conduct our analyses using a Negative Binomial Count model.

4.2. Individual-level Work Probabilities

We employ a binary choice Logit model at an individual level to analyse the impact of COVID-19 policies on probability of working in a week. The probability of an individual i working in a week t is modeled as

$$Pr(Work_{it}) = \frac{exp(U_{it})}{1 + exp(U_{it})} \tag{2}$$

where

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

where $WorkType_{it}$ is a dummy variable which indicates whether the work is non-gig type or gig type. $LagWorkCount_{it}$ refers to the total number of work type activities performed by individual i in week $t-1$. The interaction terms $T_1 \times WorkType_{it}$ and $T_2 \times WorkType_{it}$ capture the effect of COVID-19 policies on non-gig work type relative to the gig work type. We include the individual level fixed effects (α_i) for robustness. Since nonlinear models with fixed time periods are also subject to the incidental parameter problem Neyman and Scott (1948), we correct for the incidental parameter bias Fernández-Val (2009) when reporting our results. Moreover, since the interaction terms in logit models do not necessarily equal the marginal effects Ai and Norton (2003), to further verify our results and the robustness of interaction variables, we also conduct our analyses using a Linear Probability model.

4.3. Individual-level Work Type Transitions

In addition to the impact on work probabilities, we are also interested in understanding the effect of COVID-19 policies on the transitions between non-gig and gig work types. To study these transitions, we use an individual-level binary choice logit model. Again, we model the probability of an individual i choosing a specific work type in a week t as

$$Pr(WorkType_{wit}) = \frac{exp(U_{it})}{1 + exp(U_{it})} \tag{4}$$

where

$$\begin{aligned} U_{it} = {} & \alpha_i + \beta_1 T_1 + \beta_2 T_2 + \beta_3 LagWorkType_{wit} \\ & + \beta_4 T_1 \times LagWorkType_{wit} + \beta_5 T_2 \times LagWorkType_{wit} \\ & + \beta_6 LagWorkCount_{it} + \beta_7 COVIDControls_{it} + \beta_8 t + \epsilon_{it} \end{aligned} \tag{5}$$

where $WorkType_{wit}$ is a binary variable which takes a value of 1 if individual i performed the work type w in week t. For example $WorkType_{NGit}$ takes a value 1 if the individual i did a non-gig work in week t and 0 otherwise. $LagWorkType_{wit}$ is a binary variables equal to 1 if individual i performed a the work type w in week $t-1$ and 0 otherwise. The interaction terms $T_1 \times LagWorkType_{wit}$ and $T_2 \times LagWorkType_{wit}$ capture the effect of COVID-19 policies on week-on-week work transitions. For example, the interaction term $T_1 \times LagWorkType_{NGit}$ with $WorkType_{Git}$ as the dependent variable captures the change in transition from non-gig to gig work types during the lockdown period. Similar to the work probability model, we include the individual fixed effects (α_i) for robustness and correct for the indicental parameter bias. We also verify the interaction coefficients using a Linear Probability model.

5. Results

In this section, we present the main results from estimating the models we discussed.

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 5. Column (1) shows the results for all labor counts. We see that the coefficients for both T1 and T2 are negative and significant suggesting that, consistent with prior studies (Brynjolfsson et al. (2020), Chetty et al. (2020)), significant job losses occurred since the onset of the COVID-19 pandemic.

Interestingly, the magnitude of T2 is less than that of T1, indicating some job growth after the reopening, yet the growth is insufficient to offset the initial job losses. On average, we find that the total 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 dropped more than the gig labor counts - particularly in the T2 time period (23% more) suggesting that the

Table 5 Effect of COVID-19 Policies on Labor Counts

	Labor Counts by CBG			
	(1)	(2)	(3)	(4)
T1	-1.002^{***}	-0.996^{***}	-0.976^{***}	-0.908^{***}
	(0.028)	(0.035)	(0.027)	(0.036)
T2	-0.791^{***}	-0.654^{***}	-0.778^{***}	-0.603^{***}
	(0.029)	(0.029)	(0.029)	(0.030)
week	0.000	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
numUsers	0.043^{***}	0.044^{***}	0.040^{***}	0.042^{***}
	(0.010)	(0.010)	(0.010)	(0.010)
labCount_lag	0.171^{***}	0.164^{***}	0.222^{***}	0.214^{***}
	(0.009)	(0.009)	(0.009)	(0.010)
wTypeNG	0.223^{***}	0.325^{***}		
	(0.022)	(0.020)		
wTypeFTNG			0.068^{***}	0.210^{***}
			(0.020)	(0.019)
wTypePTNG			-0.944^{***}	-0.857^{***}
			(0.033)	(0.035)
wTypeNG x T1		-0.027		
		(0.037)		
wTypeNG x T2		-0.257^{***}		
		(0.024)		
wTypeFTNG x T1				-0.146^{***}
				(0.042)
wTypeFTNG x T2				-0.334^{***}
				(0.029)
wTypePTNG x T1				-0.058
				(0.053)
wTypePTNG x T2				-0.234^{***}
				(0.040)
COVID controls	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes
Log-Likelihood	-63912.964	-63800.588	-76647.501	-76483.178
Observations	61612	61612	92418	92418

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

gig sector suffered relatively lower job losses than the non-gig sector. In columns (3) and (4) we further split the non-gig work types into full-time non-gig and part-time non-gig work types. Here again we observe that both the non-gig work types has higher job losses than the gig work type and within the non-gig sector, full-time non-gig work types had lower labor counts compared to gig sector in both T1 and T2 suggesting that the COVID-19 policies had a disproportionately larger negative impact on the full-time non-gig workers compares to the gig sector workers.

We also see significant heterogeneous impact of the COVID-19 policies in terms on demographic composition of the CBGs for both non-gig and gig labor counts. Table 6 shows the impact of COVID-19 policies by income groups (Columns 1 and 4), race (Columns 2 and 5), and gen-

Table 6 EFFECT OF COVID-19 POLICIES AND DEMOGRAPHICS ON LABOR COUNTS

	Non-Gig			Gig		
	(1)	(2)	(3)	(4)	(5)	(6)
T1	-1.065^{***}	-1.313^{***}	-0.926^{***}	-0.969^{***}	-1.102^{***}	-1.371^{***}
	(0.043)	(0.042)	(0.212)	(0.050)	(0.050)	(0.220)
T2	-0.889^{***}	-1.057^{***}	-0.823^{***}	-0.688^{***}	-0.772^{***}	-0.846^{***}
	(0.045)	(0.044)	(0.153)	(0.050)	(0.048)	(0.131)
NG_lag	0.067^{***}	0.068^{***}	0.067^{***}			
	(0.006)	(0.006)	(0.006)			
G_lag				0.152^{***}	0.147^{***}	0.145^{***}
				(0.009)	(0.009)	(0.009)
week	0.002	0.002	0.002	0.001	0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
numUsers	0.064^{***}	0.056^{***}	0.057^{***}	0.046^{***}	0.047^{***}	0.048^{***}
	(0.013)	(0.014)	(0.014)	(0.014)	(0.012)	(0.012)
Income_med x T1	-0.145^{*}			-0.057		
	(0.059)			(0.064)		
Income_high x T1	-0.351^{***}			-0.225^{*}		
	(0.085)			(0.105)		
Income_vhigh x T1	-0.459^{**}			$-0.297^{\cdot}$		
	(0.176)			(0.172)		
Income_med x T2	$-0.084^{\cdot}$			-0.102^{**}		
	(0.049)			(0.040)		
Income_high x T2	-0.224^{***}			-0.081		
	(0.068)			(0.063)		
Income_vhigh x T2	-0.363^{**}			-0.073		
	(0.123)			(0.105)		
% Black x T1		0.470^{***}			0.254^{**}	
		(0.081)			(0.087)	
% Black x T2		0.278^{***}			0.150^{*}	
		(0.069)			(0.060)	
% Women x T1			-0.539			0.650
			(0.405)			(0.409)
% Women x T2			-0.342			0.220
			(0.287)			(0.237)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-31144.093	-33115.376	-33159.749	-24178.658	-26013.012	-26019.792
Observations	27970	29918	29918	26355	28147	28147

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

der(Columns 3 and 6). The interaction variables for high-income groups (60k-100k, 100k-150k, >150k) for non-gig work types are negative and significant for both T1 and T2 but are not significant for gig work types. These results suggest that high income groups saw a larger drop in labor counts only for non-gig work types but not for gig work types.

Generally speaking, across work types (both non-gig and gig), the CBGs with a high share of the Black population saw a lower extent of job losses, particularly after the reopening in Boston. However, we do not see any differential impact by gender for either non-gig or gig work types.

Table 7 EFFECT OF COVID-19 POLICIES AND WORK TYPE CHOICES ON WEEKLY WORK PROBABILITIES

	Work probability			
	(1)	(2)	(3)	(4)
	(Logit)	(Logit)	(LPM)	(LPM)
T1	-1.523^{***}	-1.241^{***}	-0.159^{***}	-0.094^{***}
	(0.016)	(0.019)	(0.001)	(0.002)
T2	-1.227^{***}	-0.734^{***}	-0.137^{***}	-0.062^{***}
	(0.027)	(0.029)	(0.003)	(0.003)
# Jobs_lag	0.192^{***}	0.157^{***}	0.028^{***}	0.028^{***}
	(0.002)	(0.002)	(0.000)	(0.000)
week	0.001	0.001	$0.000^{\cdot}$	$0.000^{\cdot}$
	(0.001)	(0.001)	(0.000)	(0.000)
wTypeNG	0.562^{***}	1.019^{***}	0.058^{***}	0.160^{***}
	(0.007)	(0.011)	(0.001)	(0.001)
work_lag	0.752^{***}	0.172^{***}	0.021^{***}	0.021^{***}
	(0.015)	(0.009)	(0.001)	(0.001)
wTypeNG x T1		-0.554^{***}		-0.129^{***}
		(0.019)		(0.002)
wTypeNG x T2		-0.928^{***}		-0.151^{***}
		(0.015)		(0.002)
COVID controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Log Likelihood/Adj. R^2	−281624.920	−280705.588	0.085	0.094
Observations	847348	847348	847348	847348

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

We also analyse the impact of COVID-19 policies on stay-at-home count in Table A8. Our results concur with other studies (Alexander and Karger (2020)) showing 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 cushioned the unemployment shock better than the non-gig sector. Furthermore, the job losses are less severe in the black neighborhoods, revealing the benefit of gig economy to such potentially more economically vulnerable neighborhoods.

5.2. Individual-level Work Probabilities

We now look at the impact of COVID-19 policies on the probability of doing work in a given week at an individual level. The dependent variable is a binary outcome variable which indicates if an individual performed any work activity in a given week. Table 7 shows the results of our analyses.

Column (1) shows the aggregate impact of T1 and T2. We see that there is a significant negative impact on probability of working in both the time periods, indicating that after COVID-19 the probability of an individual doing either a non-gig or a gig work reduces significantly. We again observe that this impact reduced after the reopening but did not completely disappear. On an average, the probability of working decreased by 35% and 25% during T1 and T2 respectively. On average, upon the emergency declaration, the probability of an individual doing work in a week decreased by 41% points compared to the pre-lockdown levels. Even after the first phase of reopening, there was a 38% points and 29% points decrease in the probability of an individual doing work, compared to the pre-lockdown levels. In column (2) we further split this impact by non-gig and gig work types. The dummy $workTypeNG$ captures the impact on non-gig work types relative to gig work types. Consistent with our results on labor counts, we again find that there was a disproportionately larger impact on non-gig work types. Columns (3) and (4) present the results using a linear probability model and show estimates consistent with the logit model.

5.3. Individual-level Work Type Transitions

In Table 8, we look at weekly transitions from non-gig to gig and gig to non-gig work types. The coefficients of NG_lag and G_lag Columns (1) and (4) suggest that a person who did non-gig work in a week is more likely to continue doing non-gig work and less likely doing gig work next week, suggesting no week-on-week transition between non-gig and gig work types. However, as can be seem in the interaction terms in columns (2) and (5), there is a positive and significant job transitions between non-gig and gig work associated with T1. Even for T2, the interaction coefficients indicate a transition between non-gig and gig work although the magnitude is smaller than the T1 coefficients. The findings suggest the stickiness of the job transitions even after reopening.

In Table A14, we separate the non-gig transitions by full-time and part-time non-gig work types. Our results further reveal interesting patterns of job transition between non-gig and gig work types. We see that the non-gig work type to gig work type transitions are mostly driven by full-time non-gig work - there is no significant transition from part-time work to gig work.

In Table A15, we look at the transitions between each work type and non-gig and gig work types. We see several interesting patterns. Among the gig work types, the gig to non-gig transitions are driven by driving work type whereas the non-gig to gig transitions are driven by food delivery and driving.

In summary, there is a significant transition from non-gig to gig work - particularly full-time non-gig work type to gig work types, suggesting that the gig sector offered some protection against the job losses arising from the emergency declaration. 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.

Table 8 Effect of COVID-19 Policies and work type choices on Non-gig and Gig Work Transitions

	Non-Gig		Gig	
	(1)	(2)	(3)	(4)
T1	-2.712^{***}	-2.303^{***}	-1.965^{***}	-2.186^{***}
	(0.041)	(0.035)	(0.044)	(0.050)
T2	-2.390^{***}	-1.954^{***}	-1.462^{***}	-1.655^{***}
	(0.064)	(0.060)	(0.073)	(0.076)
NG_lag	0.672^{***}	1.112^{***}	-0.704^{***}	-0.582^{***}
	(0.040)	(0.036)	(0.049)	(0.043)
G_lag	0.007	-0.315^{***}	1.002^{***}	0.645^{***}
	(0.043)	(0.050)	(0.034)	(0.042)
# Jobs_lag	0.017^{*}	0.027^{***}	0.161^{***}	0.165^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
week	0.000	0.002	−0.001	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
NG_lag x T1	1.071^{***}		0.579^{***}	
	(0.045)		(0.073)	
NG_lag x T2	0.920^{***}		0.319^{***}	
	(0.040)		(0.057)	
G_lag x T1		0.906^{***}		0.776^{***}
		(0.070)		(0.056)
G_lag x T2		0.569^{***}		0.516^{***}
		(0.053)		(0.046)
COVID controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Log Likelihood	−56058.807	−56356.219	−40162.711	−40086.660
Num. obs.	164944	164944	127560	127560

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

6. Heterogeneous Impacts by Work Types

In this section, we separate the impact of COVID-19 policies on gig work types into the individual work type components that constitute the gig category. Specifically, we look at the impact of these policies on full-time/part-time delivery and driving work types.

6.1. CBG-Level Labor Counts

We further investigate this by looking at the differential impact on the work types that constitute the gig work categories in Table 9.

Table 9 Effect of COVID-19 Policies on Gig Labor Counts

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-1.918^{***}	-1.665^{***}	-1.190^{***}	-1.170^{***}	-0.813^{***}	-0.849^{***}
	(0.100)	(0.067)	(0.091)	(0.065)	(0.053)	(0.053)
T2	-1.519^{***}	-1.294^{***}	-1.085^{***}	-1.060^{***}	-0.487^{***}	-0.432^{***}
	(0.123)	(0.078)	(0.138)	(0.095)	(0.062)	(0.064)
week	0.004	0.002	0.013^{*}	0.015^{***}	-0.007^{**}	-0.008^{*}
	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)	(0.003)
numUsers	$0.054^{\cdot}$	0.054^{*}	$0.088^{\cdot}$	0.067^{*}	0.068^{***}	0.038
	(0.032)	(0.027)	(0.046)	(0.030)	(0.020)	(0.024)
Lag Counts	Yes	Yes	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	−9144.788	−15487.057	−7036.300	−13062.430	−14010.421	−14400.863
Observations	17247	23291	17694	24149	18335	18783

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

Similar to our main results, we see a decrease in CBG level labor counts across all gig work types in the T1 period and some recovery in the T2 period. Among the gig categories, food delivery had the largest drop and driving had the smallest percentage drop in job counts.

6.2. Individual-Level Work Hours

Table 10 tabulates the impact of COVID-19 policies on gig work type work hours and work hour proxies. We see that the full-time (part-time) food delivery workers saw a 49% (8%) decrease in the number of delivery locations visited; and full-time (part-time) drivers saw a 33% (25%) decrease in the driving distance. These declines persisted even after the first phase of reopening.

Table 10 Effect of COVID-19 Policies on mean weekly Gig Work Hour Proxies

	Average weekly Gig work hour proxies					
	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.666^{***}	-0.081^{***}	−0.068	-0.045^{*}	-0.397^{***}	-0.287^{***}
	(0.061)	(0.022)	(0.055)	(0.022)	(0.037)	(0.028)
T2	-0.566^{***}	-0.098^{**}	−0.056	−0.046	-0.417^{***}	-0.376^{***}
	(0.083)	(0.033)	(0.088)	(0.035)	(0.050)	(0.045)
week	−0.002	0.000	−0.002	−0.000	0.003	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	−25119.467	−36447.456	−5321.874	−11491.529	−336546.339	−148228.467
Observations	6325	12874	3233	7432	12427	12402

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

Interestingly, even though there are job losses across work types, conditional on an individual working, there is limited impact on the number of hours worked. During T_1, most restaurants were

Table 11 Effect of COVID-19 Policies Gig Work Transitions

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-2.879^{***}	-2.603^{***}	-1.426^{***}	-1.475^{***}	-1.214^{***}	-1.109^{***}
	(0.101)	(0.067)	(0.099)	(0.066)	(0.073)	(0.068)
T2	-2.345^{***}	-2.078^{***}	-1.326^{***}	-1.356^{***}	-0.703^{***}	-0.575^{***}
	(0.160)	(0.106)	(0.165)	(0.111)	(0.122)	(0.112)
NG_lag	-0.568^{***}	-0.539^{***}	-0.583^{***}	-0.577^{***}	-0.439^{***}	-0.106
	(0.076)	(0.056)	(0.099)	(0.067)	(0.075)	(0.069)
G_lag	0.455^{***}	0.507^{***}	0.323^{***}	0.207^{***}	1.872^{***}	2.201^{***}
	(0.058)	(0.042)	(0.068)	(0.049)	(0.047)	(0.042)
# Jobs_lag	0.108^{***}	0.077^{***}	0.054^{***}	0.058^{***}	0.208^{***}	0.120^{***}
	(0.008)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)
week	0.004	0.002	0.016^{*}	0.019^{***}	-0.035^{***}	-0.035^{***}
	(0.006)	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)
NG_lag x T1	0.811^{***}	0.831^{***}	0.753^{***}	0.614^{***}	0.182	0.259^{*}
	(0.146)	(0.099)	(0.163)	(0.113)	(0.126)	(0.114)
NG_lag x T2	0.341^{**}	0.500^{***}	0.128	$0.160^{\cdot}$	0.225^{*}	0.144
	(0.107)	(0.075)	(0.141)	(0.095)	(0.098)	(0.091)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−11000.969	−22169.370	−8761.823	−18639.070	−14132.497	−16622.214
Observations	42171	75022	37374	72499	47425	51939

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

closed whereas grocery outlets were mostly open, potentially explaining the reduction in working hours for food delivery and driving but not for grocery delivery work.

6.3. Individual-Level Work Transitions

When we further split the gig work types by its constituent work types in Table 11, we see that the non-gig to gig work type transitions are primarily driven by food and grocery delivery jobs.

Since the concerns about Coronavirus infections dissuaded people from doing their own grocery shopping thereby boosting demand for online grocery deliveries, there was a significant hiring spree from major online grocers. 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 restaurants, the demand for food delivery also increased which was fulfilled to some extent by non-gig workers.

We present the marginal effects of emergency declaration and the reopening for each work type in Table 12. Again we observe that, except for food delivery, gig work types are more resilient compared to non-gig work.

Table 12 MARGINAL EFFECTS OF COVID-19 POLICY MEASURES ON THE PROBABILITY OF DOING A WORK TYPE

	T1	T2
FTFD	-0.418	-0.391
PTFD	-0.399	-0.361
FTGD	-0.294	-0.296
PTGD	-0.303	-0.301
FTDR	-0.290	-0.127
PTDR	-0.265	-0.107

7. Robustness Checks

To verify the validity of our results, we perform various robustness tests.

7.1. Non-Gig Work vs Stay-at-Home

After the introduction of the national lockdown, most firms enabled their employees to work from home without having to travel to their employer location. So one of the uncertainties of our identification method is that we cannot distinguish between individuals working from home and individuals who were laid off. To test the hypothesis that our results are not driven by potential non-gig employees working from home, we repeat our analyses using a subset of the individuals whose jobs cannot 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. We exploit this difference to identify only those non-gig workers who work in either Accommodation and Food Services or Retail Trade sector and analyse the impact of the COVID-19 policies on their jobs. Therefore, if 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 robustness of our identification methodology, we use non-gig work counts only from Accommodation and Food Services and Retail Trade sectors and we repeat our analyses from Table 5 and report the results in Table 13.

Table 13 EFFECT OF COVID-19 POLICIES ON LABOR COUNTS - SELECT INDUSTRIES

	Labor Counts by CBG			
	(1)	(2)	(3)	(4)
T1	-0.931^{***}	-0.797^{***}	-0.931^{***}	-0.797^{***}
	(0.031)	(0.033)	(0.031)	(0.033)
T2	-0.726^{***}	-0.566^{***}	-0.726^{***}	-0.566^{***}
	(0.035)	(0.034)	(0.035)	(0.034)
week	-0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
numUsers	0.046^{***}	0.047^{***}	0.046^{***}	0.047^{***}
	(0.011)	(0.012)	(0.011)	(0.012)
labCount_lag	0.273^{***}	0.278^{***}	0.273^{***}	0.278^{***}
	(0.012)	(0.011)	(0.012)	(0.011)
wTypeNG	-0.417^{***}	-0.185^{***}	-0.417^{***}	-0.185^{***}
	(0.030)	(0.026)	(0.030)	(0.026)
wTypeNG x T1		-0.355^{***}		-0.355^{***}
		(0.047)		(0.047)
wTypeNG x T2		-0.456^{***}		-0.456^{***}
		(0.035)		(0.035)
COVID controls	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes
Log-Likelihood	-48525.636	-48319.246	-48525.636	-48319.246
Observations	60162	60162	60162	60162

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

As we can see, our main results are consistent with the new definition of labor counts.

7.2. Different Treatment Weeks

First, we change the treatment weeks for both T1 and check the average impact of COVID-19 policies for the T1 period. We select alternate weeks - two weeks before the declaration of national emergency and two weeks after the declaration of national emergency, for T1 - instead of T1 = 1 after week 11 when the national emergency was actually declared. Thus, we have two robustness checks for T1 - one with T1 = 1 after week 9 and another with T1 = 1 after week 13.

Table 14 EFFECT OF COVID-19 POLICIES ON LABOR COUNTS WITH DIFFERENT TREATMENT WEEKS FOR T1

	Labor Counts by CBG			
	T1 = 1 for week > 9		T1 = 1 for week > 13	
T1	-1.002^{***}	-0.996^{***}	-1.002^{***}	-0.996^{***}
	(0.028)	(0.035)	(0.028)	(0.035)
T2	-0.791^{***}	-0.654^{***}	-0.791^{***}	-0.654^{***}
	(0.029)	(0.029)	(0.029)	(0.029)
week	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
numUsers	0.043^{***}	0.044^{***}	0.043^{***}	0.044^{***}
	(0.010)	(0.010)	(0.010)	(0.010)
labCount_lag	0.171^{***}	0.164^{***}	0.171^{***}	0.164^{***}
	(0.009)	(0.009)	(0.009)	(0.009)
wTypeNG	0.223^{***}	0.325^{***}	0.223^{***}	0.325^{***}
	(0.022)	(0.020)	(0.022)	(0.020)
wTypeNG x T1		-0.027		-0.027
		(0.037)		(0.037)
wTypeNG x T2		-0.257^{***}		-0.257^{***}
		(0.024)		(0.024)
COVID controls	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes
Log-Likelihood	-63912.964	-63800.588	-63912.964	-63800.588
Observations	61612	61612	61612	61612

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

As we can see from Table 14 columns 1-3, the coefficients for both T1 and T2 have a lower magnitude compared to the actual results in Table **??** 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 Table 14 columns 4-6.

We further repeat the same exercise for T2. Boston announced the second stage of reopening on 8th June 2020 [20] with the additional easing of restrictions on economic activities like allowing restaurants to open, compared to the first phase of reopening. We verify how much did the easing of the restrictions impact the weekly labor counts by changing T2 = 1 after week 24 instead of week 21. As we can see in Table 15, the impact of these easing measures was very minimal Add supporting literature references.

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

Table 15 EFFECT OF COVID-19 POLICIES ON LABOR COUNTS WITH DIFFERENT TREATMENT WEEK FOR T2

	Labor Counts by CBG	
T1	-1.002^{***}	-0.996^{***}
	(0.028)	(0.035)
T2	-0.791^{***}	-0.654^{***}
	(0.029)	(0.029)
week	0.000	0.000
	(0.001)	(0.001)
numUsers	0.043^{***}	0.044^{***}
	(0.010)	(0.010)
labCount_lag	0.171^{***}	0.164^{***}
	(0.009)	(0.009)
wTypeNG	0.223^{***}	0.325^{***}
	(0.022)	(0.020)
wTypeNG x T1		-0.027
		(0.037)
wTypeNG x T2		-0.257^{***}
		(0.024)
COVID controls	Yes	Yes
CBG FE	Yes	Yes
Log-Likelihood	-63912.964	-63800.588
Observations	61612	61612

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

7.3. Alternate Dependent Variable

We also verify the robustness of our results by using alternate definitions of the dependent variables. Firstly, we use weekly percentage change in the labor counts in a CBG with respect to the labor counts in the previous week as the dependent variable. We run a linear regression model with CBG level fixed effects and report the results in Table 16. We confirm that our results are consistent with our main model results presented in Table 5 .

Secondly, we modify the CBG level labor counts to accommodate the daily total counts of work done by individuals. Specifically, the dependent variable is the sum of all the work types performed in a week by all the individuals in a CBG, i.e., $DV_{cw} = \Sigma_{individuals\ in\ CBG\ c}\Sigma_{days\ in\ week\ w}WorkTypeCount$. We present our results in Table 17. Consistent with our main results, we find a significant decrease associated with the COVID-19 policies. Moreover, the decline is smaller for the individuals residing in lower-income CBGs or CBGs with a higher fraction of Black population.

8. Limitations

The primary limitation in our study is that we cannot objectively verify the complete validity of our work type identification strategies. Even though we cannot verify the work types, we have tested our results by changing several parameters that define different work types and found our results

Table 16 EFFECT OF COVID-19 POLICIES ON LABOR COUNTS

	% weekly change in Labor Counts by CBG			
	(1)	(2)	(3)	(4)
T1	-34.592^{***}	-28.701^{***}	-28.052^{***}	-27.266^{***}
	(0.657)	(0.777)	(0.511)	(0.684)
T2	-29.199^{***}	-21.832^{***}	-23.579^{***}	-18.434^{***}
	(1.178)	(1.239)	(0.916)	(1.008)
week	0.157^{*}	0.157^{*}	0.117^{*}	0.117^{*}
	(0.063)	(0.063)	(0.049)	(0.049)
numUsers	2.969^{***}	2.969^{***}	2.342^{***}	2.342^{***}
	(0.466)	(0.465)	(0.363)	(0.361)
wTypeNG	9.664^{***}	19.337^{***}		
	(0.322)	(0.606)		
wTypeFTNG			3.206^{***}	14.143^{***}
			(0.307)	(0.575)
wTypePTNG			-17.858^{***}	-21.784^{***}
			(0.307)	(0.575)
wTypeNG x T1		-11.783^{***}		
		(0.835)		
wTypeNG x T2		-14.735^{***}		
		(0.788)		
wTypeFTNG x T1				-12.711^{***}
				(0.793)
wTypeFTNG x T2				-17.132^{***}
				(0.748)
wTypePTNG x T1				10.352^{***}
				(0.793)
wTypePTNG x T2				1.697^{*}
				(0.748)
COVID controls	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes
Adj. R^2	0.078	0.084	0.102	0.113
Num. obs.	62548	62548	93822	93822

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

robust to all the changes in parameters. Secondly, as mentioned already, we cannot distinguish individuals working from home from individuals who are just staying at home. Although, we verified the robustness of our results under this scenario, we acknowledge the necessity of an objective measure of work type - most likely a survey, which is outside the scope of this study. Our study also limits the study of gig economy to three major sectors - food delivery, grocery delivery, and ridesharing, while not covering other salient gig sectors like hotel services, cleaning services, freelancing, etc. Moreover, the findings in our study are limited to the city of Boston and since the COVID-19 policies were enforced nationwide, we believe similar impacts can be found in different cities although some level of idiosyncrasies might exist.

Table 17 EFFECT OF COVID RESTRICTIONS ON WEEKLY WORK TYPE COUNTS BY CBG

	All (Poisson)	Non-Gig (Poisson)	Gig (Poisson)	All (Negative Binomial)	Non-Gig (Negative Binomial)	Gig (Negative Binomial)
T1	-1.266^{***}	-1.248^{***}	-1.253^{***}	-1.470^{***}	-1.540^{***}	-1.539^{***}
	(0.030)	(0.036)	(0.044)	(0.039)	(0.049)	(0.052)
T2	-1.054^{***}	-1.092^{***}	-0.993^{***}	-1.276^{***}	-1.379^{***}	-1.263^{***}
	(0.031)	(0.040)	(0.048)	(0.040)	(0.054)	(0.061)
# Jobs_lag	0.010^{***}			0.016^{***}		
	(0.001)			(0.001)		
# Non-Gig Jobs_lag		0.015^{***}			0.026^{***}	
		(0.001)			(0.002)	
# Gig Jobs_lag			0.026^{***}			0.043^{***}
			(0.002)			(0.003)
week	0.002	$0.003^{\cdot}$	-0.001	0.007^{***}	0.011^{***}	0.006^{*}
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-96047.199	-83459.864	-65694.319	-83823.824	-71085.704	-56238.741
Observations	30806	30108	28243	30806	30108	28243

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

9. Conclusion

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 non-gig and gig type jobs and analyse the impact of COVID-19 policies on these work types. We find that there was a significant decrease in labor counts and the probability of working following the implementation of these policies. We also find that this impact varied by the income and race composition of individuals' home locations. Generally speaking, the impact was higher for richer neighborhoods and lower for neighborhoods with high proportion of black populations. Finally, we find that there is a significant transition from non-gig to gig work types and gig to non-gig work types associated with the induction of COVID-19 policies and this shift remained significant even after the reopening, revealing the stickiness of this transition.

The most significant contribution of our study is in highlighting the impact of COVID-19 policies on the gig economy. Since traditional data sources like the Bureau of Labor Statistics' Current Employment Statistics do not contain detailed information about workers in the gig economy, studying large scale policy impacts on gig economy is not possible from these data. Our study provides a unique method for policy makers to gain important insights into the gig sector. From a data analyst perspective, our study highlights the importance of large scale location data in identifying work types and classifying workers.

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10. Appendix

Figure A1 Weekly average non-gig work type Labor Counts across all CBGs

Figure A2 Weekly average gig work type Labor Counts across all CBGs

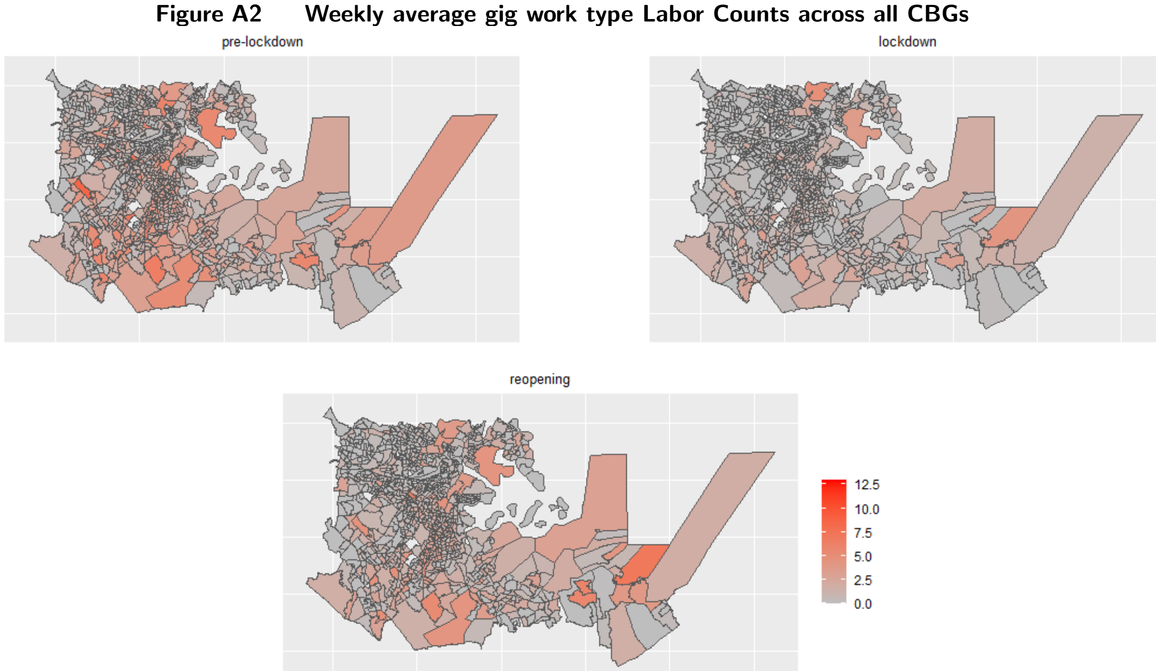

Table A1 EFFECTS OF COVID-19 POLICIES AND DEMOGRAPHICS ON LABOR COUNTS - PERCENTAGE CHANGE FROM PREVIOUS WEEK

	% weekly change in Labor Counts by CBG					
		Non-Gig			Gig	
	(1)	(2)	(3)	(4)	(5)	(6)
T1	-36.445^{***}	-43.243^{***}	-39.744^{***}	-36.224^{***}	-36.372^{***}	-46.875^{***}
	(1.305)	(1.051)	(4.401)	(1.816)	(1.466)	(6.132)
T2	-33.223^{***}	-38.559^{***}	-33.472^{***}	-25.675^{***}	-30.339^{***}	-36.468^{***}
	(1.961)	(1.762)	(4.403)	(2.730)	(2.457)	(6.134)
% Cases	2.145^{**}	1.980^{**}	2.704^{***}	5.551^{***}	5.882^{***}	6.593^{***}
	(0.663)	(0.640)	(0.618)	(0.923)	(0.892)	(0.862)
% Deaths	-0.018	0.019	-0.163	0.921^{***}	0.852^{***}	0.684^{**}
	(0.175)	(0.170)	(0.166)	(0.243)	(0.237)	(0.231)
week	0.282^{**}	0.317^{***}	0.296^{**}	-0.049	-0.081	-0.103
	(0.094)	(0.091)	(0.091)	(0.131)	(0.128)	(0.127)
numUsers	3.145^{***}	2.840^{***}	2.883^{***}	3.734^{***}	3.702^{***}	3.735^{***}
	(0.704)	(0.677)	(0.677)	(0.980)	(0.943)	(0.943)
Income_med x T1	-5.935^{***}			-0.689		
	(1.496)			(2.083)		
Income_high x T1	-5.679^{***}			-1.163		
	(1.703)			(2.370)		
Income_vhigh x T1	-6.227^{*}			-2.460		
	(2.872)			(3.998)		
Income_med x T2	-3.391^{*}			-6.261^{**}		
	(1.454)			(2.023)		
Income_high x T2	-4.569^{**}			-5.031^{*}		
	(1.653)			(2.301)		
Income_vhigh x T2	-4.212			-7.518		
	(2.770)			(3.856)		
% Black x T1		15.117^{***}			-0.995	
		(2.432)			(3.390)	
% Black x T2		12.608^{***}			8.698^{**}	
		(2.398)			(3.343)	
% Women x T1			-1.356			20.323
			(8.300)			(11.564)
% Women x T2			-5.538			14.770
			(7.836)			(10.918)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.112	0.113	0.112	0.045	0.044	0.044
Adj. R^2	0.083	0.084	0.083	0.014	0.013	0.013
Num. obs.	29042	31054	31054	29042	31054	31054

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A2 EFFECT OF COVID-19 POLICIES AND LAGGED COUNTS ON GIG LABOR COUNTS

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-1.776^{***}	-1.615^{***}	-1.137^{***}	-1.136^{***}	-0.738^{***}	-0.793^{***}
	(0.100)	(0.068)	(0.097)	(0.067)	(0.054)	(0.052)
T2	-1.426^{***}	-1.262^{***}	-1.048^{***}	-1.037^{***}	-0.425^{***}	-0.402^{***}
	(0.123)	(0.079)	(0.140)	(0.095)	(0.063)	(0.064)
week	0.002	0.001	0.012	0.014^{***}	-0.008^{**}	-0.010^{**}
	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)	(0.003)
numUsers	0.053	0.054^{*}	0.083	0.066^{*}	0.059^{**}	0.046
	(0.033)	(0.026)	(0.046)	(0.029)	(0.019)	(0.024)
FTFD_lag	0.036	-0.002	0.010	0.016	0.007	-0.014
	(0.023)	(0.013)	(0.028)	(0.020)	(0.018)	(0.019)
PTFD_lag	0.112^{***}	0.065^{***}	0.032	0.016	0.021	0.008
	(0.016)	(0.015)	(0.021)	(0.016)	(0.014)	(0.015)
FTGD_lag	0.023	0.020	0.070	0.105^{***}	0.061^{**}	0.048^{*}
	(0.026)	(0.018)	(0.037)	(0.024)	(0.022)	(0.024)
PTGD_lag	0.004	0.027	0.064^{*}	0.005	-0.009	-0.017
	(0.020)	(0.014)	(0.031)	(0.020)	(0.017)	(0.018)
FTDR_lag	0.099^{***}	0.060^{***}	-0.022	-0.006	0.262^{***}	0.147^{***}
	(0.024)	(0.016)	(0.038)	(0.022)	(0.026)	(0.019)
PTDR_lag	0.001	0.017	0.007	0.015	0.113^{***}	0.225^{***}
	(0.020)	(0.015)	(0.030)	(0.017)	(0.014)	(0.023)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-9104.344	-15467.874	-7032.191	-13053.257	-13961.957	-14334.159
Observations	17247	23291	17694	24149	18335	18783

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

10.1. Additional summaries for Labor counts

Table A3 EFFECT OF COVID-19 POLICIES ON NON-GIG LABOR COUNTS

	FTNG	PTNG
T1	-1.255^{***}	-0.913^{***}
	(0.041)	(0.063)
T2	-1.035^{***}	-0.777^{***}
	(0.045)	(0.084)
week	0.002	0.003
	(0.002)	(0.004)
numUsers	0.055^{***}	0.069^{*}
	(0.014)	(0.028)
FTNG_lag	0.089^{***}	
	(0.008)	
PTNG_lag		0.264^{***}
		(0.018)
COVID controls	Yes	Yes
CBG FE	Yes	Yes
Log-Likelihood	-29253.310	-14317.564
Observations	29343	25817

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A4 Effect of COVID-19 Policies and Demographics on Non-Gig Labor Counts

	FTNG	FTNG	FTNG	PTNG	PTNG	PTNG
T1	-1.116^{***}	-1.381^{***}	-1.004^{***}	-0.776^{***}	-0.970^{***}	-0.659^{*}
	(0.052)	(0.049)	(0.250)	(0.083)	(0.074)	(0.331)
T2	-0.912^{***}	-1.106^{***}	-0.796^{***}	-0.712^{***}	-0.794^{***}	-0.887^{***}
	(0.054)	(0.050)	(0.186)	(0.095)	(0.090)	(0.258)
week	0.002	0.002	0.002	0.004	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
numUsers	0.058^{***}	0.053^{***}	0.054^{***}	0.088^{**}	0.069^{*}	0.069^{*}
	(0.014)	(0.014)	(0.014)	(0.028)	(0.028)	(0.028)
FTNG_lag	0.090^{***}	0.090^{***}	0.089^{***}			
	(0.008)	(0.008)	(0.008)			
PTNG_lag				0.258^{***}	0.264^{***}	0.264^{***}
				(0.019)	(0.019)	(0.018)
Income_med x T1	-0.118			-0.182		
	(0.069)			(0.110)		
Income_high x T1	-0.427^{***}			-0.190		
	(0.107)			(0.128)		
Income_vhigh x T1	-0.384^{*}			-0.733^{*}		
	(0.189)			(0.323)		
Income_med x T2	-0.093			0.005		
	(0.059)			(0.087)		
Income_high x T2	-0.255^{**}			-0.160		
	(0.080)			(0.107)		
Income_vhigh x T2	-0.410^{*}			-0.206		
	(0.165)			(0.216)		
% Black x T1		0.537^{***}			0.253	
		(0.095)			(0.169)	
% Black x T2		0.346^{***}			0.075	
		(0.081)			(0.138)	
% Women x T1			-0.484			-0.497
			(0.479)			(0.632)
% Women x T2			-0.459			0.212
			(0.354)			(0.477)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-27549.278	-29125.483	-29174.818	-13261.106	-14252.225	-14253.556
Observations	27397	29249	29249	23931	25657	25657

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A5 Effect of COVID-19 Policies and Income on Gig Labor Counts

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-2.124^{***}	-1.758^{***}	-1.130^{***}	-1.053^{***}	-0.648^{***}	-0.664^{***}
	(0.126)	(0.084)	(0.124)	(0.080)	(0.087)	(0.085)
T2	-1.642^{***}	-1.351^{***}	-1.038^{***}	-1.012^{***}	-0.367^{***}	-0.329^{***}
	(0.144)	(0.093)	(0.165)	(0.106)	(0.084)	(0.080)
NG_lag	-0.000	-0.004	0.013			
	(0.012)	(0.008)	(0.016)			
G_lag				0.022^{***}	0.107^{***}	0.104^{***}
				(0.005)	(0.007)	(0.008)
week	0.009^{*}	0.005	0.015^{*}	0.014^{**}	-0.009^{**}	-0.009^{**}
	(0.004)	(0.003)	(0.007)	(0.004)	(0.003)	(0.003)
numUsers	0.055	0.080^{***}	0.116^{*}	0.066^{*}	0.042^{*}	0.016
	(0.034)	(0.024)	(0.049)	(0.031)	(0.020)	(0.025)
Income_med x T1	0.081	-0.039	-0.016	-0.024	-0.145	-0.234^{*}
	(0.175)	(0.113)	(0.153)	(0.097)	(0.104)	(0.110)
Income_high x T1	0.146	-0.134	-0.533^{*}	-0.377^{*}	-0.214	-0.310^{*}
	(0.259)	(0.176)	(0.254)	(0.158)	(0.140)	(0.147)
Income_vhigh x T1	-1.289^{*}	-0.939^{*}	0.077	-0.163	-0.471^{*}	-0.490^{*}
	(0.594)	(0.449)	(0.368)	(0.265)	(0.226)	(0.246)
Income_med x T2	-0.021	-0.055	-0.108	-0.004	-0.142^{*}	-0.194^{**}
	(0.104)	(0.072)	(0.128)	(0.079)	(0.071)	(0.073)
Income_high x T2	-0.033	-0.114	-0.181	-0.134	-0.040	-0.122
	(0.160)	(0.103)	(0.166)	(0.104)	(0.093)	(0.094)
Income_vhigh x T2	-1.358^{***}	-0.787^{**}	-0.041	-0.046	-0.051	-0.169
	(0.302)	(0.260)	(0.311)	(0.213)	(0.149)	(0.132)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-8465.412	-14263.038	-6470.872	-12066.818	-13230.585	-13576.711
Observations	15807	21595	16446	22485	17151	17535

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A6 Effect of COVID-19 Policies and Race on Gig Labor Counts

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-2.092^{***}	-1.927^{***}	-1.429^{***}	-1.325^{***}	-0.768^{***}	-0.883^{***}
	(0.144)	(0.095)	(0.133)	(0.085)	(0.070)	(0.069)
T2	-1.737^{***}	-1.480^{***}	-1.284^{***}	-1.150^{***}	-0.426^{***}	-0.440^{***}
	(0.142)	(0.090)	(0.161)	(0.103)	(0.072)	(0.071)
NG_lag	0.004	-0.003	0.010			
	(0.012)	(0.008)	(0.015)			
G_lag				0.025^{***}	0.104^{***}	0.102^{***}
				(0.005)	(0.006)	(0.007)
week	0.008	0.005	0.015^{*}	0.015^{***}	-0.008^{**}	-0.010^{**}
	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)	(0.003)
numUsers	0.057	0.054	0.084	0.060^{*}	0.045^{*}	0.036
	(0.032)	(0.029)	(0.046)	(0.029)	(0.018)	(0.021)
% Black x T1	0.069	0.364^{*}	0.611^{**}	0.693^{***}	0.056	0.200
	(0.248)	(0.156)	(0.213)	(0.132)	(0.149)	(0.159)
% Black x T2	0.313^{*}	0.284^{**}	0.542^{**}	0.449^{***}	0.025	0.034
	(0.145)	(0.101)	(0.186)	(0.105)	(0.112)	(0.114)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-9163.459	-15476.999	-7020.998	-13002.999	-14160.270	-14579.341
Observations	17183	23195	17662	24053	18303	18783

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A7 Effect of COVID-19 Policies and Gender on Gig Labor Counts

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-2.160^{***}	-2.059^{***}	-0.777	-1.274^{***}	-0.668	-1.292^{***}
	(0.528)	(0.359)	(0.590)	(0.383)	(0.373)	(0.342)
T2	-2.099^{***}	-1.492^{***}	-1.266^{**}	-1.179^{***}	-0.604^{*}	-0.466^{*}
	(0.353)	(0.239)	(0.404)	(0.240)	(0.258)	(0.228)
NG_lag	0.003	-0.004	0.009			
	(0.012)	(0.008)	(0.015)			
G_lag				0.020^{***}	0.104^{***}	0.101^{***}
				(0.005)	(0.006)	(0.007)
week	0.007	0.004	0.014^{*}	0.014^{***}	-0.008^{**}	-0.010^{**}
	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)	(0.003)
numUsers	0.060	0.057	0.088	0.065^{*}	0.046^{*}	0.036
	(0.033)	(0.029)	(0.046)	(0.029)	(0.018)	(0.020)
% Women x T1	0.199	0.516	-0.803	0.315	-0.168	0.861
	(0.959)	(0.654)	(1.099)	(0.709)	(0.704)	(0.641)
% Women x T2	0.916	0.215	0.335	0.308	0.352	0.064
	(0.584)	(0.410)	(0.727)	(0.422)	(0.476)	(0.423)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-9166.011	-15488.228	-7029.758	-13024.987	-14159.286	-14578.959
Observations	17183	23195	17662	24053	18303	18783

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A8 EFFECT OF COVID-19 POLICIES AND DEMOGRAPHICS ON STAY-AT-HOME COUNTS

	STHM	STHM	STHM	STHM
T1	0.265^{***}	0.259^{***}	0.254^{***}	0.252^{***}
	(0.006)	(0.009)	(0.007)	(0.037)
T2	0.215^{***}	0.199^{***}	0.213^{***}	0.225^{***}
	(0.007)	(0.009)	(0.007)	(0.031)
	(0.001)	(0.001)	(0.001)	(0.001)
week	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
numUsers	0.069^{***}	0.071^{***}	0.069^{***}	0.069^{***}
	(0.004)	(0.003)	(0.004)	(0.004)
STHM_lag	0.018^{***}	0.019^{***}	0.018^{***}	0.018^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Income_med x T1		0.008		
		(0.012)		
Income_high x T1		−0.000		
		(0.013)		
Income_vhigh x T1		0.017		
		(0.023)		
Income_med x T2		0.024^{*}		
		(0.010)		
Income_high x T2		0.021		
		(0.012)		
Income_vhigh x T2		0.016		
		(0.019)		
% Black x T1			0.062^{***}	
			(0.017)	
% Black x T2			0.013	
			(0.016)	
% Women x T1				0.025
				(0.070)
% Women x T2				−0.019
				(0.059)
COVID controls	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes
Log-Likelihood	−57913.912	−54093.427	−57617.353	−57622.099
Observations	31210	28978	30990	30990

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

10.2. Additional summaries for Work Types Counts

Table A9 Effect of COVID restrictions and Demographics on Individual Weekly Work Type Counts

	Total Work Type Count					
		(Poisson)			(Negative Binomial)	
T1	-1.102^{***}	-1.307^{***}	-1.127^{***}	-1.816^{***}	-2.144^{***}	-1.862^{***}
	(0.030)	(0.029)	(0.140)	(0.042)	(0.038)	(0.174)
T2	-0.946^{***}	-1.073^{***}	-1.068^{***}	-1.556^{***}	-1.765^{***}	-1.573^{***}
	(0.030)	(0.029)	(0.096)	(0.046)	(0.042)	(0.152)
# Jobs_lag	0.110^{***}	0.109^{***}	0.108^{***}	0.158^{***}	0.157^{***}	0.157^{***}
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
week	0.001	0.001	0.000	0.011^{***}	0.012^{***}	0.011^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Income_med x T1	-0.106^{*}			-0.198^{***}		
	(0.042)			(0.054)		
Income_high x T1	-0.284^{***}			-0.500^{***}		
	(0.064)			(0.073)		
Income_vhigh x T1	-0.443^{***}			-0.597^{***}		
	(0.123)			(0.130)		
Income_med x T2	-0.082^{**}			-0.161^{**}		
	(0.030)			(0.049)		
Income_high x T2	-0.132^{**}			-0.250^{***}		
	(0.042)			(0.062)		
Income_vhigh x T2	-0.198^{**}			-0.244^{*}		
	(0.076)			(0.102)		
% Black x T1		0.396^{***}			0.629^{***}	
		(0.060)			(0.079)	
% Black x T2		0.261^{***}			0.410^{***}	
		(0.043)			(0.072)	
% Women x T1			-0.143			-0.257
			(0.266)			(0.330)
% Women x T2			0.114			-0.197
			(0.177)			(0.284)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-297879.326	-317409.128	-317698.659	-248753.848	-264936.346	-265044.513
Observations	198544	211188	211188	198544	211188	211188

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A10 EFFECT OF COVID RESTRICTIONS AND DEMOGRAPHICS ON INDIVIDUAL WEEKLY NON-GIG AND GIG WORK TYPE COUNTS

		Non-Gig			Gig	
T1	-1.040^{***}	-1.250^{***}	-0.867^{***}	-1.194^{***}	-1.319^{***}	-1.370^{***}
	(0.036)	(0.034)	(0.169)	(0.050)	(0.048)	(0.221)
T2	-0.930^{***}	-1.048^{***}	-0.860^{***}	-0.990^{***}	-1.030^{***}	-1.079^{***}
	(0.039)	(0.036)	(0.128)	(0.050)	(0.046)	(0.126)
# Non-Gig Jobs_lag	0.166^{***}	0.166^{***}	0.166^{***}			
	(0.003)	(0.003)	(0.003)			
# Gig Jobs_lag				0.117^{***}	0.117^{***}	0.116^{***}
				(0.003)	(0.003)	(0.003)
week	0.001	0.001	0.001	−0.000	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Income_med x T1	-0.119^{*}			−0.038		
	(0.050)			(0.066)		
Income_high x T1	-0.309^{***}			-0.224^{*}		
	(0.073)			(0.101)		
Income_vhigh x T1	-0.443^{**}			-0.415^{*}		
	(0.151)			(0.166)		
Income_med x T2	−0.052			−0.055		
	(0.040)			(0.041)		
Income_high x T2	-0.157^{**}			−0.057		
	(0.054)			(0.055)		
Income_vhigh x T2	-0.314^{**}			−0.060		
	(0.105)			(0.099)		
% Black x T1		0.388^{***}			0.253^{**}	
		(0.073)			(0.092)	
% Black x T2		0.184^{**}			0.115^{*}	
		(0.060)			(0.058)	
% Women x T1			−0.564			0.249
			(0.324)			(0.413)
% Women x T2			−0.289			0.163
			(0.239)			(0.229)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	−209320.123	−221414.625	−221532.795	−141930.093	−152908.705	−152949.685
Observations	155526	164828	164828	119725	127949	127949

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A11 Effect of COVID restrictions and Demographics on Individual Weekly Non-Gig and Gig Work Type Counts - Negative Binomial model

	Non-Gig			Gig		
T1	-2.006^{***}	-2.382^{***}	-2.006^{***}	-1.921^{***}	-2.130^{***}	-2.175^{***}
	(0.057)	(0.051)	(0.246)	(0.061)	(0.057)	(0.240)
T2	-1.765^{***}	-1.979^{***}	-1.773^{***}	-1.546^{***}	-1.646^{***}	-1.584^{***}
	(0.066)	(0.059)	(0.228)	(0.073)	(0.067)	(0.203)
# Non-Gig Jobs_lag	0.185^{***}	0.185^{***}	0.186^{***}			
	(0.004)	(0.003)	(0.003)			
# Gig Jobs_lag				0.187^{***}	0.184^{***}	0.184^{***}
				(0.005)	(0.005)	(0.005)
week	0.013^{***}	0.014^{***}	0.013^{***}	0.014^{***}	0.014^{***}	0.013^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income_med x T1	-0.217^{**}			-0.090		
	(0.074)			(0.076)		
Income_high x T1	-0.571^{***}			-0.445^{***}		
	(0.098)			(0.103)		
Income_vhigh x T1	-0.720^{***}			-0.411^{*}		
	(0.177)			(0.178)		
Income_med x T2	-0.101			-0.143^{*}		
	(0.071)			(0.067)		
Income_high x T2	-0.293^{**}			-0.163		
	(0.090)			(0.087)		
Income_vhigh x T2	-0.387^{*}			-0.071		
	(0.152)			(0.143)		
% Black x T1		0.686^{***}			0.406^{***}	
		(0.115)			(0.107)	
% Black x T2		0.351^{**}			0.194^{*}	
		(0.112)			(0.097)	
% Women x T1			-0.431			0.301
			(0.465)			(0.453)
% Women x T2			-0.255			-0.019
			(0.427)			(0.375)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-166537.748	-175745.669	-175802.479	-112868.536	-121983.255	-122000.290
Observations	155526	164828	164828	119725	127949	127949

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

10.3. Additional summaries for Work Type Transitions

Table A12 Effect of COVID-19 Policies and work type choices on Non-gig and Gig Work Transitions - LPM

	Non-Gig	Gig
T1	-0.273^{***}	-0.166^{***}
	(0.003)	(0.004)
T2	-0.253^{***}	-0.127^{***}
	(0.006)	(0.007)
NG_lag	0.243^{***}	-0.109^{***}
	(0.005)	(0.004)
G_lag	-0.016^{**}	0.217^{***}
	(0.005)	(0.004)
# Jobs_lag	0.005^{***}	0.028^{***}
	(0.001)	(0.001)
week	0.000	0.000
	(0.000)	(0.000)
Adj. R^2	0.181	0.151
Num. obs.	164944	127560

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A13 Effect of COVID-19 Policies and Non-Gig work types on Non-gig and Gig Work Transitions - LPM

	Non-Gig			Gig		
T1	-0.257^{***}	-0.275^{***}	-0.269^{***}	-0.177^{***}	-0.165^{***}	-0.177^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
T2	-0.245^{***}	-0.256^{***}	-0.258^{***}	-0.138^{***}	-0.128^{***}	-0.139^{***}
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
FTNG_lag	0.272^{***}	0.267^{***}	0.261^{***}	-0.135^{***}	-0.107^{***}	-0.136^{***}
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
PTNG_lag	0.108^{***}	0.029^{***}	0.027^{***}	-0.115^{***}	-0.122^{***}	-0.128^{***}
	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)
G_lag	-0.009	-0.010^{*}	-0.010	0.216^{***}	0.217^{***}	0.216^{***}
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
# Jobs_lag	0.007^{***}	0.007^{***}	0.007^{***}	0.028^{***}	0.028^{***}	0.028^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FTNG_lag x T1	-0.052^{***}		-0.039^{***}	0.074^{***}		0.075^{***}
	(0.006)		(0.006)	(0.008)		(0.008)
FTNG_lag x T2	0.036^{***}		0.050^{***}	0.050^{***}		0.052^{***}
	(0.005)		(0.005)	(0.007)		(0.007)
PTNG_lag x T1		0.151^{***}	0.149^{***}		-0.001	0.010
		(0.011)	(0.011)		(0.012)	(0.012)
PTNG_lag x T2		0.129^{***}	0.138^{***}		0.020	0.029^{**}
		(0.009)	(0.009)		(0.011)	(0.011)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.188	0.188	0.189	0.152	0.151	0.152
Num. obs.	164944	164944	164944	127560	127560	127560

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A14 Effect of COVID-19 Policies and Non-gig work type choices on Non-gig and Gig Work Transitions

	Non-Gig			Gig		
T1	-2.416^{***}	-2.308^{***}	-2.665^{***}	-1.939^{***}	-1.871^{***}	-1.963^{***}
	(0.039)	(0.035)	(0.041)	(0.044)	(0.043)	(0.044)
T2	-2.143^{***}	-1.964^{***}	-2.348^{***}	-1.442^{***}	-1.388^{***}	-1.462^{***}
	(0.063)	(0.061)	(0.064)	(0.073)	(0.073)	(0.073)
FTNG_lag	0.944^{***}	1.230^{***}	0.818^{***}	-0.679^{***}	-0.496^{***}	-0.688^{***}
	(0.041)	(0.036)	(0.041)	(0.052)	(0.046)	(0.052)
PTNG_lag	0.632^{***}	-0.048	-0.195^{***}	-0.606^{***}	-0.719^{***}	-0.752^{***}
	(0.048)	(0.058)	(0.058)	(0.060)	(0.076)	(0.076)
G_lag	0.062	0.073	0.053	1.006^{***}	1.012^{***}	1.005^{***}
	(0.043)	(0.042)	(0.042)	(0.034)	(0.034)	(0.034)
# Jobs_lag	0.031^{***}	0.034^{***}	0.031^{***}	0.163^{***}	0.163^{***}	0.163^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
week	0.000	0.003	0.000	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
FTNG_lag x T1	0.635^{***}		0.879^{***}	0.686^{***}		0.710^{***}
	(0.047)		(0.048)	(0.085)		(0.086)
FTNG_lag x T2	0.657^{***}		0.840^{***}	0.347^{***}		0.363^{***}
	(0.043)		(0.044)	(0.066)		(0.067)
PTNG_lag x T1		1.493^{***}	1.815^{***}		0.281^{*}	0.366^{**}
		(0.075)	(0.077)		(0.119)	(0.119)
PTNG_lag x T2		1.073^{***}	1.356^{***}		0.185	0.240^{*}
		(0.066)	(0.067)		(0.098)	(0.098)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-56144.004	-56044.848	-55790.247	-40161.085	-40195.828	-40155.203
Num. obs.	164944	164944	164944	127560	127560	127560

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A15 EFFECT OF COVID-19 POLICIES ON WORK TRANSITIONS

	Individual Work Choice			
	Non-Gig (Logit)	Gig (Logit)	Non-Gig (LPM)	Gig (LPM)
T1	-2.128^{***}	-2.078^{***}	-0.176^{***}	-0.150^{***}
	(0.071)	(0.056)	(0.006)	(0.004)
T2	-1.588^{***}	-1.424^{***}	-0.147^{***}	-0.103^{***}
	(0.115)	(0.088)	(0.010)	(0.008)
NG_lag	0.429^{***}	-0.473^{***}	0.197^{***}	-0.079^{***}
	(0.045)	(0.063)	(0.006)	(0.007)
G_lag	-0.434^{***}	0.966^{***}	-0.059^{***}	0.262^{***}
	(0.062)	(0.032)	(0.007)	(0.004)
totJobCount_lag	0.099^{***}	0.099^{***}	0.011^{***}	0.017^{***}
	(0.008)	(0.006)	(0.001)	(0.001)
fracCases	0.122^{***}	0.345^{***}	0.008^{*}	0.025^{***}
	(0.035)	(0.027)	(0.003)	(0.002)
fracDeaths	0.012	0.046^{***}	0.001	0.002^{**}
	(0.010)	(0.008)	(0.001)	(0.001)
week	-0.005	-0.019^{***}	-0.000	-0.002^{***}
	(0.005)	(0.004)	(0.000)	(0.000)
T1:FTNG_lag	1.237^{***}	0.851^{***}	0.030^{**}	0.066^{***}
	(0.085)	(0.159)	(0.010)	(0.014)
T2:FTNG_lag	0.811^{***}	0.484^{***}	0.045^{***}	0.057^{***}
	(0.068)	(0.105)	(0.008)	(0.011)
T1:PTNG_lag	0.937^{***}	0.377	-0.041^{*}	0.033
	(0.135)	(0.213)	(0.017)	(0.021)
T2:PTNG_lag	0.296^{**}	0.263	-0.079^{***}	0.031
	(0.105)	(0.151)	(0.014)	(0.016)
T1:FTFD_lag	-0.438	0.590^{***}	-0.039	0.107^{***}
	(0.339)	(0.160)	(0.031)	(0.019)
T2:FTFD_lag	0.089	0.359^{***}	0.007	0.067^{***}
	(0.172)	(0.087)	(0.017)	(0.010)
T1:PTFD_lag	0.271	-0.355^{***}	0.019	-0.157^{***}
	(0.231)	(0.102)	(0.021)	(0.012)
T2:PTFD_lag	0.139	-0.480^{***}	0.017	-0.126^{***}
	(0.128)	(0.061)	(0.013)	(0.007)
T1:FTGD_lag	-0.512	0.301	-0.037	0.071^{***}
	(0.374)	(0.161)	(0.033)	(0.019)
T2:FTGD_lag	-0.244	0.159	-0.021	0.049^{***}
	(0.255)	(0.107)	(0.024)	(0.013)
T1:PTGD_lag	0.617^{*}	-0.406^{***}	0.050^{*}	-0.214^{***}
	(0.257)	(0.114)	(0.023)	(0.013)
T2:PTGD_lag	-0.019	-0.728^{***}	0.003	-0.189^{***}
	(0.174)	(0.077)	(0.017)	(0.009)
T1:FTDR_lag	0.639^{**}	1.445^{***}	0.047^{*}	0.190^{***}
	(0.245)	(0.094)	(0.022)	(0.011)
T2:FTDR_lag	0.149	1.022^{***}	0.016	0.152^{***}
	(0.152)	(0.065)	(0.015)	(0.008)
T1:PTDR_lag	0.566^{*}	1.141^{***}	0.059^{**}	0.100^{***}
	(0.250)	(0.091)	(0.022)	(0.011)
T2:PTDR_lag	0.366^{*}	1.133^{***}	0.038^{*}	0.158^{***}
	(0.154)	(0.063)	(0.015)	(0.007)
Individual FE	Yes	Yes	Yes	Yes
Log Likelihood	-22290.126	-37228.713		
Deviance	44580.251	74457.425		
Num. obs.	70880	118872	70880	118872
R^2			0.137	0.203
Adj. R^2			0.107	0.175

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A16 EFFECT OF COVID-19 POLICIES AND GIG WORK TYPE CHOICES ON NON-GIG AND GIG WORK TRANSITIONS - LPM

	Non-Gig	Gig
T1	-2.283^{***}	-2.074^{***}
	(0.034)	(0.050)
T2	-1.935^{***}	-1.553^{***}
	(0.060)	(0.078)
NG_lag	1.211^{***}	-0.590^{***}
	(0.036)	(0.045)
G_lag	-0.116^{**}	0.749^{***}
	(0.044)	(0.038)
# Jobs_lag	0.006	0.165^{***}
	(0.007)	(0.008)
week	0.002	-0.009^{*}
	(0.003)	(0.003)
FTFD_lag x T1	-0.029	0.370^{**}
	(0.174)	(0.130)
FTFD_lag x T2	0.142	0.283^{***}
	(0.110)	(0.085)
PTFD_lag x T1	0.476^{***}	-0.640^{***}
	(0.124)	(0.093)
PTFD_lag x T2	0.193^{*}	-0.557^{***}
	(0.079)	(0.060)
FTGD_lag x T1	-0.271	0.263
	(0.204)	(0.142)
FTGD_lag x T2	-0.073	0.133
	(0.155)	(0.105)
PTGD_lag x T1	0.543^{***}	-0.503^{***}
	(0.142)	(0.105)
PTGD_lag x T2	0.094	-0.834^{***}
	(0.105)	(0.075)
FTDR_lag x T1	0.569^{***}	1.470^{***}
	(0.132)	(0.088)
FTDR_lag x T2	0.303^{***}	0.985^{***}
	(0.086)	(0.064)
PTDR_lag x T1	0.444^{***}	1.220^{***}
	(0.133)	(0.086)
PTDR_lag x T2	0.336^{***}	1.138^{***}
	(0.084)	(0.062)
COVID controls	Yes	Yes
Individual FE	Yes	Yes
Log Likelihood	-56362.989	-38915.754
Num. obs.	164944	127560

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A17 Effect of COVID-19 Policies and Gig work type choices on Non-gig and Gig Work Transitions - LPM

	Non-Gig	Gig
T1	-0.282^{***}	-0.154^{***}
	(0.004)	(0.004)
T2	-0.260^{***}	-0.119^{***}
	(0.006)	(0.006)
NG_lag	0.250^{***}	-0.117^{***}
	(0.005)	(0.004)
G_lag	-0.040^{***}	0.213^{***}
	(0.005)	(0.004)
# Jobs_lag	0.003^{**}	0.030^{***}
	(0.001)	(0.001)
week	0.000	-0.001^{*}
	(0.000)	(0.000)
FTFD_lag x T1	-0.007	0.053^{***}
	(0.019)	(0.015)
FTFD_lag x T2	0.014	0.049^{***}
	(0.013)	(0.010)
PTFD_lag x T1	0.056^{***}	-0.212^{***}
	(0.014)	(0.010)
PTFD_lag x T2	0.031^{***}	-0.136^{***}
	(0.009)	(0.007)
FTGD_lag x T1	-0.027	0.056^{***}
	(0.022)	(0.016)
FTGD_lag x T2	-0.005	0.039^{**}
	(0.017)	(0.013)
PTGD_lag x T1	0.061^{***}	-0.223^{***}
	(0.015)	(0.011)
PTGD_lag x T2	0.017	-0.202^{***}
	(0.012)	(0.009)
FTDR_lag x T1	0.062^{***}	0.204^{***}
	(0.015)	(0.010)
FTDR_lag x T2	0.039^{***}	0.146^{***}
	(0.010)	(0.007)
PTDR_lag x T1	0.055^{***}	0.116^{***}
	(0.014)	(0.010)
PTDR_lag x T2	0.046^{***}	0.161^{***}
	(0.010)	(0.007)
COVID controls	Yes	Yes
Individual FE	Yes	Yes
Adj. R^2	0.182	0.185
Num. obs.	164944	127560

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A18 Effect of COVID-19 Policies on Non-Gig to Non-Gig and Non-Gig to Gig Work Transitions - LPM

	Individual Work Choice					
		Non-Gig			Gig	
T1	-0.041^{***}	-0.039^{***}	-0.073^{***}	-0.072^{***}	-0.050^{***}	-0.056^{***}
	(0.002)	(0.002)	(0.007)	(0.003)	(0.002)	(0.009)
NG_lag	0.319^{***}	0.322^{***}	0.360^{***}	-0.046^{***}	-0.043^{***}	-0.115^{***}
	(0.004)	(0.003)	(0.017)	(0.005)	(0.004)	(0.023)
T2	-0.033^{***}	-0.032^{***}	-0.060^{***}	-0.043^{***}	-0.033^{***}	-0.033^{***}
	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)	(0.009)
G_lag	-0.019^{***}	-0.018^{***}	-0.018^{***}	0.317^{***}	0.314^{***}	0.315^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
totJobCount_lag	0.005^{***}	0.004^{***}	0.005^{***}	0.012^{***}	0.012^{***}	0.012^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
fracCases	-0.001	-0.001	-0.000	0.006^{***}	0.007^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
fracDeaths	0.001^{***}	0.001^{***}	0.001^{***}	0.002^{***}	0.001^{***}	0.002^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
week	0.000	0.000	0.000	-0.000^{*}	-0.000^{**}	-0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T1:NG_lag	-0.140^{***}	-0.115^{***}	-0.138^{***}	0.033^{***}	0.006	0.006
	(0.007)	(0.006)	(0.034)	(0.009)	(0.008)	(0.044)
T1:Income_med	0.002			0.012^{***}		
	(0.002)			(0.003)		
T1:Income_high	0.008^{**}			0.018^{***}		
	(0.003)			(0.003)		
T1:Income_vhigh	0.012^{**}			0.011^{*}		
	(0.004)			(0.005)		
NG_lag:Income_med	0.008			-0.010		
	(0.005)			(0.007)		
NG_lag:Income_high	-0.020^{**}			0.009		
	(0.007)			(0.009)		
NG_lag:Income_vhigh	-0.062^{***}			0.006		
	(0.013)			(0.017)		
NG_lag:T2	-0.090^{***}	-0.105^{***}	-0.122^{***}	0.021^{**}	0.008	0.050
	(0.006)	(0.005)	(0.027)	(0.007)	(0.006)	(0.036)
Income_med:T2	0.001			0.000		
	(0.002)			(0.003)		
Income_high:T2	0.004			0.009^{**}		
	(0.002)			(0.003)		
Income_vhigh:T2	0.006			0.008		
	(0.004)			(0.005)		
T1:NG_lag:Income_med	0.001			-0.008		
	(0.011)			(0.014)		
T1:NG_lag:Income_high	0.056^{***}			-0.054^{**}		
	(0.015)			(0.019)		
T1:NG_lag:Income_vhigh	0.024			-0.005		
	(0.028)			(0.036)		
NG_lag:Income_med:T2	-0.021^{*}			0.003		
	(0.009)			(0.011)		
NG_lag:Income_high:T2	0.041^{***}			-0.017		
	(0.011)			(0.014)		
NG_lag:Income_vhigh:T2	-0.116^{***}			-0.011		
	(0.024)			(0.031)		
T1:pctBlack		0.003			-0.071^{***}	
		(0.004)			(0.005)	
NG_lag:pctBlack		-0.038^{***}			-0.008	
		(0.009)			(0.012)	
pctBlack:T2		0.008^{*}			-0.035^{***}	
		(0.004)			(0.005)	
T1:NG_lag:pctBlack		-0.061^{***}			0.062^{**}	
		(0.017)			(0.021)	
NG_lag:pctBlack:T2		0.048^{***}			0.049^{**}	
		(0.014)			(0.018)	
T1:pctWomen			0.068^{***}			-0.014
			(0.013)			(0.017)
NG_lag:pctWomen			-0.089^{**}			0.137^{**}
			(0.034)			(0.044)
pctWomen:T2			0.055^{***}			-0.013
			(0.012)			(0.016)
T1:NG_lag:pctWomen			0.017			0.023
			(0.066)			(0.085)
NG_lag:pctWomen:T2			0.054			-0.062
			(0.053)			(0.069)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.110	0.107	0.107	0.161	0.160	0.160
Adj. R^2	0.078	0.076	0.076	0.132	0.131	0.130
Num. obs.	241662	257191	257191	241662	257191	257191

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A19 Effect of COVID-19 Policies and Demographics on Non-gig and Gig Work Transitions

	Non-Gig			Gig		
T1	-2.083^{***}	-2.301^{***}	-2.122^{***}	-1.770^{***}	-1.879^{***}	-2.010^{***}
	(0.043)	(0.038)	(0.165)	(0.053)	(0.049)	(0.199)
T2	-1.794^{***}	-1.918^{***}	-1.782^{***}	-1.329^{***}	-1.374^{***}	-1.259^{***}
	(0.067)	(0.062)	(0.150)	(0.080)	(0.075)	(0.168)
NG_lag	1.139^{***}	1.155^{***}	1.160^{***}	-0.531^{***}	-0.524^{***}	-0.524^{***}
	(0.037)	(0.036)	(0.036)	(0.044)	(0.043)	(0.043)
G_lag	0.026	0.038	0.038	1.023^{***}	1.011^{***}	1.011^{***}
	(0.044)	(0.043)	(0.043)	(0.035)	(0.034)	(0.034)
# Jobs_lag	0.025^{***}	0.022^{**}	0.020^{**}	0.164^{***}	0.162^{***}	0.162^{***}
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
week	0.002	0.003	0.003	-0.000	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Income_med x T1	-0.157^{**}			-0.078		
	(0.050)			(0.061)		
Income_high x T1	-0.251^{***}			-0.275^{***}		
	(0.063)			(0.080)		
Income_vhigh x T1	-0.317^{**}			-0.230		
	(0.115)			(0.131)		
Income_med x T2	-0.067			-0.128^{*}		
	(0.044)			(0.051)		
Income_high x T2	-0.118^{*}			-0.065		
	(0.054)			(0.064)		
Income_vhigh x T2	-0.223^{*}			0.047		
	(0.097)			(0.102)		
% Black x T1		0.435^{***}			0.087	
		(0.077)			(0.089)	
% Black x T2		0.186^{**}			0.004	
		(0.071)			(0.078)	
% Women x T1			-0.163			0.294
			(0.313)			(0.373)
% Women x T2			-0.191			-0.218
			(0.266)			(0.292)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-53167.354	-56314.394	-56331.044	-37283.538	-40122.544	-40122.059
Num. obs.	155208	164446	164446	119157	127285	127285

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A20 Effect of COVID-19 Policies and Demographics on Non-gig and Gig Work Transitions - LPM

	Non-Gig			Gig		
T1	-0.267^{***}	-0.279^{***}	-0.286^{***}	-0.160^{***}	-0.159^{***}	-0.141^{***}
	(0.005)	(0.004)	(0.017)	(0.005)	(0.004)	(0.017)
T2	-0.244^{***}	-0.257^{***}	-0.255^{***}	-0.121^{***}	-0.124^{***}	-0.101^{***}
	(0.007)	(0.006)	(0.017)	(0.007)	(0.007)	(0.017)
NG_lag	0.241^{***}	0.243^{***}	0.244^{***}	-0.109^{***}	-0.108^{***}	-0.109^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
G_lag	-0.017^{**}	-0.016^{**}	-0.016^{**}	0.220^{***}	0.218^{***}	0.217^{***}
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
# Jobs_lag	0.005^{***}	0.005^{***}	0.005^{***}	0.028^{***}	0.028^{***}	0.028^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income_med x T1	-0.011^{*}			-0.004		
	(0.005)			(0.006)		
Income_high x T1	-0.015^{*}			-0.005		
	(0.006)			(0.007)		
Income_vhigh x T1	0.007			-0.014		
	(0.011)			(0.011)		
Income_med x T2	-0.009			-0.013^{*}		
	(0.005)			(0.005)		
Income_high x T2	-0.014^{*}			-0.003		
	(0.006)			(0.007)		
Income_vhigh x T2	-0.003			0.001		
	(0.010)			(0.011)		
% Black x T1		0.026^{**}			-0.026^{**}	
		(0.008)			(0.008)	
% Black x T2		0.020^{*}			-0.011	
		(0.008)			(0.008)	
% Women x T1			0.025			-0.046
			(0.032)			(0.033)
% Women x T2			0.004			-0.049
			(0.030)			(0.031)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.182	0.181	0.181	0.152	0.151	0.151
Num. obs.	155208	164446	164446	119157	127285	127285

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A21 Effect of COVID-19 Policies on Non-gig Gig Work Transitions

	FTNG			PTNG		
T1	-2.389^{***}	-3.024^{***}	-2.442^{***}	-1.104^{***}	-1.653^{***}	-1.190^{***}
	(0.039)	(0.049)	(0.039)	(0.060)	(0.070)	(0.064)
T2	-2.015^{***}	-2.716^{***}	-2.048^{***}	-0.969^{***}	-1.349^{***}	-1.021^{***}
	(0.069)	(0.074)	(0.069)	(0.107)	(0.111)	(0.108)
NG_lag	1.247^{***}	0.642^{***}	1.226^{***}	0.461^{***}	-0.041	0.433^{***}
	(0.044)	(0.048)	(0.043)	(0.054)	(0.064)	(0.054)
G_lag	-0.053	-0.099	-0.285^{***}	0.358^{***}	0.325^{***}	0.213^{**}
	(0.051)	(0.051)	(0.060)	(0.062)	(0.062)	(0.074)
# Jobs_lag	0.010	0.006	0.013	0.038^{***}	0.037^{***}	0.042^{***}
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
week	0.003	-0.001	0.003	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
NG_lag x T1		1.244^{***}			1.337^{***}	
		(0.051)			(0.079)	
NG_lag x T2		1.245^{***}			0.688^{***}	
		(0.045)			(0.067)	
G_lag x T1			0.733^{***}			0.427^{***}
			(0.092)			(0.097)
G_lag x T2			0.394^{***}			0.167^{*}
			(0.068)			(0.076)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-43759.726	-43252.082	-43719.915	-19199.526	-19041.753	-19189.417
Num. obs.	134787	134787	134787	71191	71191	71191

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A22 Effect of COVID-19 Policies on Non-gig Work Transitions - LPM

	FTNG			PTNG		
T1	-0.291^{***}	-0.293^{***}	-0.301^{***}	-0.083^{***}	-0.106^{***}	-0.083^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
T2	-0.270^{***}	-0.282^{***}	-0.279^{***}	-0.077^{***}	-0.097^{***}	-0.076^{***}
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
NG_lag	0.242^{***}	0.225^{***}	0.236^{***}	0.043^{***}	0.005	0.043^{***}
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
G_lag	-0.032^{***}	-0.032^{***}	-0.085^{***}	0.028^{***}	0.027^{***}	0.029^{***}
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
# Jobs_lag	0.003^{*}	0.002^{*}	0.003^{**}	0.007^{***}	0.007^{***}	0.007^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NG_lag x T1		-0.014^{*}			0.086^{***}	
		(0.006)			(0.007)	
NG_lag x T2		0.067^{***}			0.054^{***}	
		(0.005)			(0.006)	
G_lag x T1			0.107^{***}			0.003
			(0.009)			(0.009)
G_lag x T2			0.079^{***}			-0.004
			(0.008)			(0.007)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.209	0.211	0.210	-0.002	0.000	-0.002
Num. obs.	134787	134787	134787	71191	71191	71191

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A23 Effect of COVID-19 Policies and work type choices on Non-gig and Gig Work Transitions - LPM

	Non-Gig		Gig	
	(1)	(2)	(3)	(4)
T1	-0.274^{***}	-0.285^{***}	-0.177^{***}	-0.161^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
T2	-0.261^{***}	-0.264^{***}	-0.139^{***}	-0.132^{***}
	(0.006)	(0.006)	(0.007)	(0.007)
NG_lag	0.230^{***}	0.234^{***}	-0.134^{***}	-0.109^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
G_lag	-0.016^{**}	-0.074^{***}	0.216^{***}	0.208^{***}
	(0.005)	(0.006)	(0.004)	(0.005)
# Jobs_lag	0.004^{***}	0.006^{***}	0.028^{***}	0.028^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
week	0.000	0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
NG_lag x T1	-0.011^{*}		0.057^{***}	
	(0.005)		(0.007)	
NG_lag x T2	0.052^{***}		0.045^{***}	
	(0.005)		(0.006)	
G_lag x T1		0.109^{***}		-0.037^{***}
		(0.008)		(0.006)
G_lag x T2		0.085^{***}		0.043^{***}
		(0.006)		(0.005)
COVID controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Adj. R^2	0.182	0.182	0.152	0.152
Num. obs.	164944	164944	127560	127560

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

Table A24 EFFECT OF COVID-19 POLICIES AND DEMOGRAPHICS ON NON-GIG WORK TRANSITIONS

	FTNG			PTNG		
T1	-2.278^{***}	-2.499^{***}	-2.291^{***}	-0.925^{***}	-1.190^{***}	-1.029^{***}
	(0.050)	(0.044)	(0.192)	(0.075)	(0.068)	(0.275)
T2	-1.915^{***}	-2.068^{***}	-1.726^{***}	-0.895^{***}	-0.989^{***}	-1.298^{***}
	(0.076)	(0.071)	(0.173)	(0.118)	(0.110)	(0.254)
NG_lag	1.243^{***}	1.244^{***}	1.248^{***}	0.410^{***}	0.454^{***}	0.461^{***}
	(0.045)	(0.044)	(0.044)	(0.057)	(0.054)	(0.054)
G_lag	-0.054	-0.050	-0.051	0.355^{***}	0.358^{***}	0.360^{***}
	(0.053)	(0.051)	(0.051)	(0.064)	(0.062)	(0.062)
# Jobs_lag	0.012	0.011	0.010	0.043^{***}	0.039^{***}	0.038^{***}
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
week	0.002	0.004	0.003	0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
Income_med x T1	-0.138^{*}			-0.215^{*}		
	(0.057)			(0.087)		
Income_high x T1	-0.283^{***}			-0.226^{*}		
	(0.074)			(0.103)		
Income_vhigh x T1	-0.106			-0.914^{***}		
	(0.127)			(0.229)		
Income_med x T2	-0.114^{*}			0.056		
	(0.051)			(0.077)		
Income_high x T2	-0.110			-0.176		
	(0.062)			(0.094)		
Income_vhigh x T2	-0.193			-0.300		
	(0.110)			(0.170)		
% Black x T1		0.511^{***}			0.387^{**}	
		(0.088)			(0.133)	
% Black x T2		0.285^{***}			0.088	
		(0.080)			(0.124)	
% Women x T1			-0.179			-0.149
			(0.363)			(0.523)
% Women x T2			-0.550			0.636
			(0.307)			(0.447)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-41369.812	-43659.264	-43675.996	-17902.464	-19135.736	-19138.844
Num. obs.	127287	134445	134445	66789	71005	71005

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A25 EFFECT OF COVID-19 POLICIES AND DEMOGRAPHICS ON NON-GIG WORK TRANSITIONS - LPM

	FTNG			PTNG		
T1	-0.286^{***}	-0.299^{***}	-0.272^{***}	-0.074^{***}	-0.088^{***}	-0.099^{***}
	(0.005)	(0.004)	(0.018)	(0.006)	(0.005)	(0.021)
T2	-0.261^{***}	-0.278^{***}	-0.232^{***}	-0.073^{***}	-0.078^{***}	-0.110^{***}
	(0.007)	(0.007)	(0.018)	(0.009)	(0.008)	(0.021)
NG_lag	0.242^{***}	0.242^{***}	0.242^{***}	0.038^{***}	0.042^{***}	0.042^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
G_lag	-0.033^{***}	-0.032^{***}	-0.032^{***}	0.029^{***}	0.028^{***}	0.029^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
# Jobs_lag	0.003^{**}	0.003^{*}	0.003^{*}	0.007^{***}	0.007^{***}	0.007^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income_med x T1	-0.010			-0.007		
	(0.006)			(0.007)		
Income_high x T1	-0.011			-0.012		
	(0.007)			(0.008)		
Income_vhigh x T1	0.010			-0.029^{*}		
	(0.012)			(0.014)		
Income_med x T2	-0.014^{**}			0.008		
	(0.005)			(0.007)		
Income_high x T2	-0.012			-0.012		
	(0.007)			(0.008)		
Income_vhigh x T2	-0.009			-0.014		
	(0.011)			(0.013)		
% Black x T1		0.037^{***}			0.022^{*}	
		(0.009)			(0.011)	
% Black x T2		0.037^{***}			0.006	
		(0.009)			(0.011)	
% Women x T1			-0.037			0.030
			(0.035)			(0.040)
% Women x T2			-0.073^{*}			0.064
			(0.033)			(0.037)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.210	0.209	0.209	-0.004	-0.002	-0.002
Num. obs.	127287	134445	134445	66789	71005	71005

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A26 Effect of COVID-19 Policies Gig Work Transitions - LPM

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-0.212^{***}	-0.219^{***}	-0.092^{***}	-0.107^{***}	-0.081^{***}	-0.097^{***}
	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)
T2	-0.190^{***}	-0.187^{***}	-0.089^{***}	-0.102^{***}	-0.041^{***}	-0.051^{***}
	(0.011)	(0.008)	(0.010)	(0.008)	(0.011)	(0.011)
NG_lag	-0.148^{***}	-0.133^{***}	-0.075^{***}	-0.088^{***}	-0.123^{***}	-0.049^{***}
	(0.007)	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)
G_lag	-0.012^{*}	0.042^{***}	0.005	-0.002	0.238^{***}	0.339^{***}
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
# Jobs_lag	0.025^{***}	0.021^{***}	0.009^{***}	0.012^{***}	0.037^{***}	0.018^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.001	0.000	0.001^{*}	0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
NG_lag x T1	0.070^{***}	0.075^{***}	0.056^{***}	0.051^{***}	0.009	0.028^{**}
	(0.010)	(0.008)	(0.010)	(0.008)	(0.011)	(0.011)
NG_lag x T2	0.054^{***}	0.069^{***}	0.022^{*}	0.022^{**}	0.023^{*}	0.029^{**}
	(0.009)	(0.008)	(0.009)	(0.007)	(0.010)	(0.010)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.099	0.079	-0.008	-0.005	0.254	0.226
Observations	42171	75022	37374	72499	47425	51939

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

Table A27 Effect of COVID-19 Policies and Gig work types on Gig Work Transitions

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-3.089^{***}	-2.766^{***}	-1.779^{***}	-1.718^{***}	-1.649^{***}	-1.786^{***}
	(0.122)	(0.075)	(0.115)	(0.073)	(0.101)	(0.091)
T2	-2.525^{***}	-2.169^{***}	-1.548^{***}	-1.494^{***}	-0.957^{***}	-0.949^{***}
	(0.167)	(0.110)	(0.173)	(0.115)	(0.134)	(0.122)
NG_lag	-0.435^{***}	-0.342^{***}	-0.519^{***}	-0.517^{***}	-0.373^{***}	-0.084
	(0.065)	(0.048)	(0.082)	(0.057)	(0.060)	(0.054)
G_lag	0.224^{**}	0.273^{***}	-0.058	-0.106	1.592^{***}	1.796^{***}
	(0.073)	(0.052)	(0.090)	(0.062)	(0.069)	(0.060)
# Jobs_lag	0.111^{***}	0.082^{***}	0.062^{***}	0.065^{***}	0.211^{***}	0.126^{***}
	(0.007)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)
week	0.003	0.001	0.016^{*}	0.019^{***}	-0.035^{***}	-0.036^{***}
	(0.006)	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)
G_lag x T1	0.609^{***}	0.688^{***}	0.896^{***}	0.810^{***}	0.654^{***}	1.060^{***}
	(0.117)	(0.077)	(0.118)	(0.081)	(0.099)	(0.090)
G_lag x T2	0.400^{***}	0.344^{***}	0.440^{***}	0.343^{***}	0.303^{***}	0.423^{***}
	(0.086)	(0.059)	(0.098)	(0.067)	(0.082)	(0.073)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-11001.166	-22172.774	-8741.642	-18601.526	-14114.856	-16556.652
Num. obs.	42171	75022	37374	72499	47425	51939

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A28 Effect of COVID-19 Policies and Gig work types on Gig Work Transitions - LPM

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-0.150^{***}	-0.177^{***}	-0.086^{***}	-0.100^{***}	-0.063^{***}	-0.081^{***}
	(0.007)	(0.005)	(0.006)	(0.005)	(0.007)	(0.007)
T2	-0.141^{***}	-0.154^{***}	-0.085^{***}	-0.096^{***}	-0.042^{***}	-0.047^{***}
	(0.011)	(0.009)	(0.010)	(0.008)	(0.011)	(0.011)
NG_lag	-0.101^{***}	-0.086^{***}	-0.057^{***}	-0.072^{***}	-0.110^{***}	-0.031^{***}
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
G_lag	0.048^{***}	0.078^{***}	-0.002	-0.005	0.239^{***}	0.341^{***}
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
# Jobs_lag	0.024^{***}	0.020^{***}	0.009^{***}	0.012^{***}	0.037^{***}	0.018^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.001	0.000	0.001^{*}	0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
G_lag x T1	-0.127^{***}	-0.098^{***}	0.012	0.011	-0.059^{***}	-0.039^{***}
	(0.009)	(0.007)	(0.008)	(0.007)	(0.009)	(0.009)
G_lag x T2	-0.049^{***}	-0.022^{***}	0.011	0.005	0.034^{***}	0.020^{**}
	(0.008)	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.102	0.079	-0.009	-0.006	0.256	0.226
Num. obs.	42171	75022	37374	72499	47425	51939

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A29 EFFECT OF COVID-19 POLICIES AND INCOME ON GIG WORK TRANSITIONS

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-2.714^{***}	-2.362^{***}	-1.222^{***}	-1.328^{***}	-1.047^{***}	-0.817^{***}
	(0.111)	(0.074)	(0.111)	(0.076)	(0.094)	(0.087)
T2	-2.225^{***}	-1.881^{***}	-1.204^{***}	-1.297^{***}	-0.612^{***}	-0.426^{***}
	(0.169)	(0.113)	(0.177)	(0.120)	(0.136)	(0.125)
NG_lag	-0.355^{***}	-0.284^{***}	-0.445^{***}	-0.448^{***}	-0.329^{***}	0.002
	(0.067)	(0.050)	(0.084)	(0.059)	(0.061)	(0.056)
G_lag	0.479^{***}	0.540^{***}	0.342^{***}	0.225^{***}	1.891^{***}	2.212^{***}
	(0.061)	(0.044)	(0.071)	(0.051)	(0.048)	(0.044)
# Jobs_lag	0.108^{***}	0.080^{***}	0.057^{***}	0.059^{***}	0.209^{***}	0.118^{***}
	(0.008)	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)
week	0.008	0.003	0.017^{*}	0.019^{***}	-0.036^{***}	-0.035^{***}
	(0.007)	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)
Income_med x T1	-0.070	-0.115	-0.067	0.011	-0.192	-0.394^{***}
	(0.134)	(0.089)	(0.133)	(0.089)	(0.105)	(0.098)
Income_high x T1	-0.140	-0.095	-0.536^{**}	-0.390^{**}	-0.292^{*}	-0.315^{**}
	(0.203)	(0.130)	(0.195)	(0.123)	(0.133)	(0.117)
Income_vhigh x T1	-1.453^{*}	-0.964^{**}	0.035	-0.239	-0.106	-0.464^{**}
	(0.570)	(0.338)	(0.409)	(0.248)	(0.204)	(0.175)
Income_med x T2	-0.108	-0.092	-0.130	0.023	-0.186^{*}	-0.226^{**}
	(0.097)	(0.068)	(0.116)	(0.078)	(0.089)	(0.082)
Income_high x T2	-0.213	-0.080	-0.193	-0.123	0.017	-0.124
	(0.151)	(0.096)	(0.154)	(0.102)	(0.107)	(0.098)
Income_vhigh x T2	-1.760^{***}	-1.008^{***}	-0.042	-0.020	0.187	-0.060
	(0.411)	(0.245)	(0.356)	(0.197)	(0.160)	(0.140)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-10121.349	-20357.550	-8022.370	-17222.751	-13189.902	-15533.645
Num. obs.	38834	69349	34467	67621	44498	48667

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A30 EFFECT OF COVID-19 POLICIES AND INCOME ON GIG WORK TRANSITIONS - LPM

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-0.193^{***}	-0.207^{***}	-0.079^{***}	-0.100^{***}	-0.065^{***}	-0.060^{***}
	(0.007)	(0.006)	(0.007)	(0.005)	(0.008)	(0.008)
T2	-0.168^{***}	-0.167^{***}	-0.076^{***}	-0.096^{***}	-0.030^{*}	-0.025^{*}
	(0.011)	(0.009)	(0.011)	(0.008)	(0.012)	(0.012)
NG_lag	-0.114^{***}	-0.095^{***}	-0.058^{***}	-0.071^{***}	-0.112^{***}	-0.031^{***}
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
G_lag	-0.009	0.046^{***}	0.005	-0.000	0.243^{***}	0.341^{***}
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
# Jobs_lag	0.026^{***}	0.021^{***}	0.009^{***}	0.012^{***}	0.037^{***}	0.018^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.001	0.000	0.001^{*}	0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Income_med x T1	-0.009	0.015^{*}	0.004	0.012	-0.027^{**}	-0.044^{***}
	(0.009)	(0.007)	(0.008)	(0.006)	(0.009)	(0.009)
Income_high x T1	-0.008	0.041^{***}	-0.017	-0.006	-0.017	-0.045^{***}
	(0.013)	(0.009)	(0.011)	(0.008)	(0.011)	(0.011)
Income_vhigh x T1	-0.214^{***}	-0.024	0.015	0.011	0.007	-0.054^{***}
	(0.032)	(0.020)	(0.025)	(0.015)	(0.016)	(0.015)
Income_med x T2	-0.015	0.003	-0.006	0.008	-0.024^{**}	-0.033^{***}
	(0.008)	(0.007)	(0.008)	(0.006)	(0.009)	(0.009)
Income_high x T2	-0.018	0.012	-0.012	-0.003	-0.002	-0.029^{**}
	(0.013)	(0.009)	(0.011)	(0.008)	(0.011)	(0.011)
Income_vhigh x T2	-0.254^{***}	-0.066^{***}	0.009	0.009	0.027	-0.017
	(0.030)	(0.019)	(0.023)	(0.014)	(0.016)	(0.015)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.101	0.077	-0.009	-0.006	0.258	0.225
Num. obs.	38834	69349	34467	67621	44498	48667

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A31 Effect of COVID-19 Policies and Race on Gig Work Transitions

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-2.765^{***}	-2.573^{***}	-1.589^{***}	-1.623^{***}	-1.099^{***}	-1.053^{***}
	(0.119)	(0.078)	(0.117)	(0.076)	(0.080)	(0.073)
T2	-2.380^{***}	-2.041^{***}	-1.504^{***}	-1.448^{***}	-0.598^{***}	-0.502^{***}
	(0.167)	(0.111)	(0.175)	(0.116)	(0.125)	(0.115)
NG_lag	-0.383^{***}	-0.287^{***}	-0.439^{***}	-0.450^{***}	-0.328^{***}	-0.016
	(0.065)	(0.048)	(0.081)	(0.057)	(0.059)	(0.054)
G_lag	0.470^{***}	0.523^{***}	0.324^{***}	0.209^{***}	1.874^{***}	2.205^{***}
	(0.058)	(0.042)	(0.068)	(0.049)	(0.047)	(0.042)
# Jobs_lag	0.109^{***}	0.079^{***}	0.057^{***}	0.061^{***}	0.208^{***}	0.121^{***}
	(0.008)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)
week	0.005	0.004	0.018^{*}	0.021^{***}	-0.035^{***}	-0.036^{***}
	(0.007)	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)
% Black x T1	0.091	0.376^{**}	0.759^{***}	0.768^{***}	-0.325^{*}	-0.031
	(0.182)	(0.121)	(0.183)	(0.124)	(0.158)	(0.143)
% Black x T2	0.345^{*}	0.293^{**}	0.686^{***}	0.525^{***}	-0.273^{*}	-0.186
	(0.137)	(0.095)	(0.164)	(0.114)	(0.138)	(0.127)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-11002.770	-22163.955	-8740.932	-18583.315	-14127.594	-16624.031
Num. obs.	42079	74806	37283	72287	47393	51939

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A32 Effect of COVID-19 Policies and Race on Gig Work Transitions - LPM

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-0.192^{***}	-0.191^{***}	-0.091^{***}	-0.106^{***}	-0.078^{***}	-0.092^{***}
	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)	(0.007)
T2	-0.182^{***}	-0.172^{***}	-0.093^{***}	-0.103^{***}	-0.033^{**}	-0.040^{***}
	(0.011)	(0.009)	(0.011)	(0.008)	(0.011)	(0.011)
NG_lag	-0.115^{***}	-0.095^{***}	-0.056^{***}	-0.071^{***}	-0.113^{***}	-0.034^{***}
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
G_lag	-0.010	0.044^{***}	0.006	-0.001	0.238^{***}	0.339^{***}
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
# Jobs_lag	0.026^{***}	0.021^{***}	0.009^{***}	0.012^{***}	0.037^{***}	0.018^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.001	0.001	0.001^{**}	0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
% Black x T1	-0.014	-0.036^{***}	0.027^{*}	0.028^{**}	0.001	0.010
	(0.012)	(0.010)	(0.012)	(0.009)	(0.014)	(0.014)
% Black x T2	0.020	0.006	0.039^{***}	0.032^{***}	-0.018	-0.023
	(0.012)	(0.010)	(0.012)	(0.009)	(0.014)	(0.014)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.098	0.077	-0.009	-0.006	0.253	0.226
Num. obs.	42079	74806	37283	72287	47393	51939

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A33 EFFECT OF COVID-19 POLICIES AND GENDER ON GIG WORK TRANSITIONS

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-2.652^{***}	-2.817^{***}	-1.060^{*}	-1.635^{***}	-0.677^{*}	-0.878^{**}
	(0.439)	(0.289)	(0.424)	(0.287)	(0.343)	(0.303)
T2	-2.789^{***}	-2.029^{***}	-1.554^{***}	-1.466^{***}	-0.596^{*}	-0.185
	(0.339)	(0.227)	(0.383)	(0.256)	(0.293)	(0.261)
NG_lag	-0.382^{***}	-0.289^{***}	-0.429^{***}	-0.443^{***}	-0.331^{***}	-0.017
	(0.065)	(0.048)	(0.081)	(0.057)	(0.059)	(0.054)
G_lag	0.475^{***}	0.526^{***}	0.338^{***}	0.219^{***}	1.872^{***}	2.204^{***}
	(0.058)	(0.042)	(0.068)	(0.049)	(0.047)	(0.042)
# Jobs_lag	0.109^{***}	0.079^{***}	0.054^{***}	0.058^{***}	0.208^{***}	0.121^{***}
	(0.008)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)
week	0.004	0.003	0.016^{*}	0.019^{***}	-0.035^{***}	-0.035^{***}
	(0.006)	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)
% Women x T1	-0.129	0.736	-0.468	0.504	-0.965	-0.360
	(0.821)	(0.536)	(0.792)	(0.535)	(0.646)	(0.566)
% Women x T2	1.032	0.175	0.560	0.346	-0.129	-0.688
	(0.570)	(0.384)	(0.659)	(0.443)	(0.513)	(0.453)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-11004.193	-22170.299	-8752.864	-18605.180	-14129.274	-16624.073
Num. obs.	42079	74806	37283	72287	47393	51939

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A34 EFFECT OF COVID-19 POLICIES AND GENDER ON GIG WORK TRANSITIONS - LPM

	FTFD	PTFD	FTGD	PTGD	FTDR	PTDR
T1	-0.240^{***}	-0.176^{***}	-0.043	-0.087^{***}	-0.040	-0.052
	(0.028)	(0.022)	(0.027)	(0.020)	(0.030)	(0.029)
T2	-0.242^{***}	-0.153^{***}	-0.080^{**}	-0.093^{***}	-0.036	0.018
	(0.028)	(0.022)	(0.026)	(0.020)	(0.030)	(0.029)
NG_lag	-0.115^{***}	-0.096^{***}	-0.055^{***}	-0.071^{***}	-0.113^{***}	-0.033^{***}
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
G_lag	-0.010	0.044^{***}	0.007	-0.000	0.238^{***}	0.339^{***}
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
# Jobs_lag	0.026^{***}	0.021^{***}	0.009^{***}	0.012^{***}	0.037^{***}	0.018^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
week	0.001	0.000	0.001^{*}	0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
% Women x T1	0.083	-0.049	-0.074	-0.021	-0.074	-0.074
	(0.052)	(0.041)	(0.050)	(0.037)	(0.056)	(0.055)
% Women x T2	0.128^{**}	-0.031	-0.001	-0.003	-0.002	-0.120^{*}
	(0.049)	(0.039)	(0.047)	(0.035)	(0.053)	(0.051)
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.098	0.077	-0.009	-0.006	0.253	0.226
Num. obs.	42079	74806	37283	72287	47393	51939

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

10.4. Additional summaries for Work hours

Table A35 EFFECT OF COVID-19 POLICIES ON MEAN WEEKLY GIG WORK HOUR PROXIES

	Average weekly Gig work hour proxies - Negative Binomial					
	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.626^{***}	-0.078^{***}	-0.068	-0.045^{*}	-0.405^{***}	-0.271^{***}
	(0.057)	(0.022)	(0.055)	(0.022)	(0.033)	(0.029)
T2	-0.525^{***}	-0.096^{**}	-0.056	-0.046	-0.391^{***}	-0.347^{***}
	(0.083)	(0.033)	(0.088)	(0.035)	(0.047)	(0.045)
week	-0.000	0.000	-0.002	-0.000	0.007^{**}	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-20601.921	-36107.098	-5322.094	-11492.391	-72530.974	-62001.761
Observations	6325	12874	3233	7432	12427	12402

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

Table A36 EFFECT OF COVID-19 POLICIES AND INCOME ON GIG WORK HOUR PROXIES

	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.690^{***}	-0.090^{***}	-0.001	-0.056^{*}	-0.378^{***}	-0.285^{***}
	(0.073)	(0.026)	(0.062)	(0.028)	(0.050)	(0.040)
T2	-0.581^{***}	-0.111^{**}	0.011	-0.066	-0.455^{***}	-0.379^{***}
	(0.098)	(0.036)	(0.093)	(0.039)	(0.068)	(0.055)
week	-0.001	0.000	-0.001	0.000	0.003	0.001
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
Income_med x T1	0.078	0.014	-0.124	0.006	-0.024	-0.005
	(0.113)	(0.032)	(0.089)	(0.030)	(0.078)	(0.047)
Income_high x T1	-0.123	0.073	-0.257^{*}	0.035	-0.089	-0.036
	(0.142)	(0.050)	(0.107)	(0.038)	(0.089)	(0.059)
Income_vhigh x T1	0.067	-0.074	-0.053	0.068	-0.174	-0.012
	(0.138)	(0.109)	(0.097)	(0.068)	(0.155)	(0.092)
Income_med x T2	-0.017	0.013	-0.054	0.037	0.041	-0.039
	(0.069)	(0.024)	(0.068)	(0.026)	(0.067)	(0.041)
Income_high x T2	-0.044	-0.007	-0.163	0.027	0.001	-0.011
	(0.082)	(0.038)	(0.086)	(0.033)	(0.082)	(0.051)
Income_vhigh x T2	0.022	0.095	0.054	0.021	0.064	0.079
	(0.091)	(0.091)	(0.065)	(0.033)	(0.106)	(0.070)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-23391.176	-33288.254	-4850.916	-10561.487	-317980.704	-137123.251
Observations	5845	11754	2949	6828	11575	11500

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A37 Effect of COVID-19 Policies and Income on Gig Work Hour Proxies - Negative Binomial model

	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.632^{***}	-0.087^{***}	-0.001	-0.056^{*}	-0.381^{***}	-0.277^{***}
	(0.070)	(0.026)	(0.062)	(0.028)	(0.048)	(0.040)
T2	-0.508^{***}	-0.109^{**}	0.011	-0.066	-0.425^{***}	-0.360^{***}
	(0.096)	(0.036)	(0.093)	(0.039)	(0.063)	(0.055)
week	0.001	0.000	-0.001	0.000	0.007^{**}	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
Income_med x T1	0.029	0.015	-0.124	0.006	-0.038	0.001
	(0.103)	(0.032)	(0.089)	(0.030)	(0.062)	(0.047)
Income_high x T1	-0.114	0.072	-0.257^{*}	0.035	-0.069	-0.004
	(0.118)	(0.052)	(0.107)	(0.038)	(0.081)	(0.059)
Income_vhigh x T1	-0.011	-0.070	-0.053	0.068	-0.117	0.006
	(0.144)	(0.110)	(0.097)	(0.068)	(0.139)	(0.101)
Income_med x T2	-0.083	0.013	-0.054	0.037	0.032	-0.019
	(0.061)	(0.024)	(0.068)	(0.026)	(0.059)	(0.041)
Income_high x T2	-0.094	-0.009	-0.163	0.027	0.006	-0.002
	(0.077)	(0.038)	(0.086)	(0.033)	(0.072)	(0.050)
Income_vhigh x T2	-0.085	0.098	0.054	0.021	0.025	0.098
	(0.088)	(0.093)	(0.065)	(0.033)	(0.101)	(0.072)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-19101.087	-32971.313	-4851.117	-10562.283	-67632.336	-57441.906
Observations	5845	11754	2949	6828	11575	11500

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A38 Effect of COVID-19 Policies and Race on Gig Work Hour Proxies

	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.641^{***}	-0.079^{**}	-0.108	-0.042	-0.390^{***}	-0.303^{***}
	(0.087)	(0.028)	(0.077)	(0.025)	(0.046)	(0.033)
T2	-0.583^{***}	-0.102^{**}	-0.079	-0.027	-0.404^{***}	-0.394^{***}
	(0.086)	(0.035)	(0.095)	(0.037)	(0.052)	(0.046)
week	-0.002	0.000	-0.002	-0.000	0.003	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
% Black x T1	-0.076	-0.004	0.095	-0.005	-0.025	0.059
	(0.152)	(0.043)	(0.122)	(0.043)	(0.098)	(0.069)
% Black x T2	0.046	0.009	0.055	-0.055	-0.053	0.083
	(0.096)	(0.034)	(0.089)	(0.039)	(0.096)	(0.063)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-25106.101	-36392.799	-5314.034	-11467.201	-336214.206	-148194.871
Observations	6321	12855	3228	7416	12419	12402

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A39 EFFECT OF COVID-19 POLICIES AND RACE ON GIG WORK HOUR PROXIES - NEGATIVE BINOMIAL MODEL

	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.591^{***}	-0.076^{**}	-0.108	-0.042	-0.394^{***}	-0.280^{***}
	(0.074)	(0.028)	(0.077)	(0.025)	(0.038)	(0.033)
T2	-0.547^{***}	-0.099^{**}	-0.079	-0.027	-0.385^{***}	-0.360^{***}
	(0.087)	(0.035)	(0.095)	(0.037)	(0.049)	(0.046)
week	-0.000	0.000	-0.002	-0.000	0.007^{**}	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
% Black x T1	-0.099	-0.004	0.095	-0.005	-0.044	0.035
	(0.125)	(0.044)	(0.122)	(0.043)	(0.082)	(0.070)
% Black x T2	0.054	0.008	0.055	-0.055	-0.026	0.059
	(0.086)	(0.034)	(0.089)	(0.039)	(0.087)	(0.063)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-20589.566	-36053.265	-5314.254	-11468.062	-72474.797	-62000.905
Observations	6321	12855	3228	7416	12419	12402

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A40 EFFECT OF COVID-19 POLICIES AND GENDER ON GIG WORK HOUR PROXIES

	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.568	-0.036	-0.127	-0.001	-0.507^{*}	-0.273
	(0.340)	(0.105)	(0.226)	(0.091)	(0.208)	(0.140)
T2	-0.757^{**}	-0.055	-0.284	-0.155	-0.623^{**}	-0.371^{***}
	(0.274)	(0.083)	(0.220)	(0.082)	(0.223)	(0.104)
week	-0.002	0.000	-0.002	-0.000	0.003	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
% Women x T1	-0.187	-0.084	0.115	-0.085	0.210	-0.027
	(0.647)	(0.193)	(0.450)	(0.171)	(0.402)	(0.264)
% Women x T2	0.362	-0.081	0.437	0.204	0.395	-0.009
	(0.505)	(0.147)	(0.376)	(0.144)	(0.424)	(0.180)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-25104.727	-36392.522	-5313.889	-11467.087	-336105.069	-148228.341
Observations	6321	12855	3228	7416	12419	12402

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A41 Effect of COVID-19 Policies and Gender on Gig Work Hour Proxies - Negative Binomial model

	FTFG	PTFG	FTGG	PTGG	FTDD	PTDD
T1	-0.714^{*}	-0.031	-0.128	-0.001	-0.412^{*}	-0.197
	(0.300)	(0.106)	(0.226)	(0.091)	(0.175)	(0.139)
T2	-0.879^{***}	-0.047	-0.284	-0.155	-0.605^{**}	-0.278^{**}
	(0.231)	(0.083)	(0.220)	(0.082)	(0.186)	(0.108)
week	-0.000	0.000	-0.002	-0.000	0.007^{**}	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
% Women x T1	0.168	-0.089	0.115	-0.085	0.014	-0.140
	(0.571)	(0.195)	(0.450)	(0.171)	(0.331)	(0.262)
% Women x T2	0.672	-0.092	0.437	0.204	0.408	-0.132
	(0.421)	(0.147)	(0.376)	(0.144)	(0.345)	(0.190)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-20587.591	-36052.976	-5314.108	-11467.948	-72472.135	-62001.363
Observations	6321	12855	3228	7416	12419	12402

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A42 EFFECT OF COVID-19 POLICIES AND DEMOGRAPHICS ON NON-GIG WORK HOURS

	FTWH	FTWH	FTWH	PTWH	PTWH	PTWH
T1	-0.093^{***}	-0.103^{***}	-0.061	-0.149^{***}	-0.129^{***}	-0.099
	(0.010)	(0.009)	(0.046)	(0.032)	(0.030)	(0.152)
T2	-0.131^{***}	-0.138^{***}	-0.137^{***}	-0.152^{***}	-0.171^{***}	-0.152
	(0.012)	(0.011)	(0.036)	(0.041)	(0.038)	(0.139)
week	-0.000	-0.000	-0.000	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Income_med x T1	-0.016			0.084^{*}		
	(0.013)			(0.042)		
Income_high x T1	0.004			-0.016		
	(0.021)			(0.054)		
Income_vhigh x T1	0.022			-0.268^{*}		
	(0.035)			(0.123)		
Income_med x T2	-0.017			0.003		
	(0.011)			(0.040)		
Income_high x T2	0.006			-0.037		
	(0.015)			(0.053)		
Income_vhigh x T2	-0.021			-0.208		
	(0.031)			(0.122)		
% Black x T1		0.035			0.007	
		(0.019)			(0.069)	
% Black x T2		0.023			0.072	
		(0.017)			(0.062)	
% Women x T1			-0.065			-0.051
			(0.090)			(0.291)
% Women x T2			0.010			-0.001
			(0.069)			(0.259)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-1180641.341	-1239199.109	-1239442.786	-278301.198	-302348.493	-302520.272
Observations	32882	34434	34434	7515	8121	8121

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A43 EFFECT OF COVID-19 POLICIES AND DEMOGRAPHICS ON NON-GIG WORK HOURS - NEGATIVE BINOMIAL MODEL

	FTWH	FTWH	FTWH	PTWH	PTWH	PTWH
T1	-0.097^{***}	-0.104^{***}	-0.070	-0.132^{***}	-0.124^{***}	-0.053
	(0.010)	(0.009)	(0.044)	(0.031)	(0.029)	(0.144)
T2	-0.131^{***}	-0.137^{***}	-0.149^{***}	-0.136^{***}	-0.157^{***}	-0.117
	(0.012)	(0.011)	(0.036)	(0.040)	(0.036)	(0.143)
week	-0.000	-0.000	-0.000	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Income_med x T1	-0.011			0.071		
	(0.013)			(0.041)		
Income_high x T1	0.010			-0.052		
	(0.020)			(0.054)		
Income_vhigh x T1	0.017			-0.285^{*}		
	(0.033)			(0.115)		
Income_med x T2	-0.016			0.007		
	(0.011)			(0.037)		
Income_high x T2	0.007			-0.062		
	(0.015)			(0.054)		
Income_vhigh x T2	-0.020			-0.190		
	(0.032)			(0.101)		
% Black x T1		0.031			0.026	
		(0.019)			(0.063)	
% Black x T2		0.021			0.068	
		(0.017)			(0.060)	
% Women x T1			-0.050			-0.122
			(0.085)			(0.277)
% Women x T2			0.032			-0.046
			(0.067)			(0.268)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-240159.193	-251517.898	-251520.396	-51754.990	-55940.336	-55941.913
Observations	32882	34434	34434	7515	8121	8121

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$