IMF Working Paper

The Distributional Impact of Recessions: the Global Financial Crisis and the Pandemic Recession

by Ippei Shibata

I N T E R N A T I O N A L   M O N E T A R Y   F U N D

IMF Working Paper

Research Department

The Distributional Impact of Recessions: the Global Financial Crisis and the Pandemic Recession[1]

Prepared by Ippei Shibata

Authorized for distribution by Romain Duval

June 2020

Abstract

Using the U.S. Current Population Survey data, this paper compares the distributional impacts of the Pandemic Crisis and those of the Global Financial Crisis in terms of (i) worker characteristics, (ii) job characteristics–"social" (where individuals interact to consume goods), "teleworkable" (where individuals have the option of working at home), and "essential" jobs (which were not subject to government mandated shut-downs during the recent recession), and (iii) wage distributions. We find that young and less educated workers have always been affected more in recessions, while women and Hispanics were more severely affected during the Pandemic Recession. Surprisingly, teleworkable, social and essential jobs have been historically less cyclical. This historical acyclicality of teleworkable occupations is attributable to its higher share of skilled workers. Unlike during the Global Financial Crisis, however, employment in social industries fell more whereas employment in teleworkable and essential jobs fell less during the Pandemic Crisis. Lastly, during both recessions, workers at low-income earnings have suffered more than top-income earners, suggesting a significant distributional impact of the two recessions.

---

1 Introduction

The novel coronavirus, also known as SARS-CoV-2, had significantly impacted the U.S. labor market. The Bureau of Labor Statistics (BLS) data for April 2020 show that the U.S. unemployment rate has increased to 14.7 percent from 3.5 percent in February 2020. During the same period, the employment-to-population ratio has plummeted from 61.1 percent to 51.3 percent. The government's shutdown and social-distancing policies had differential impacts on the types of jobs that had been lost. On one hand, the government allowed continued operations of "essential" industries, such as health care workers, water utilities, and grocery stores. On the other hand, the social-distancing policy prohibited operations of "social jobs" that require physical interactions, such as leisure and hospitality industries. Moreover, while some workers could start working from home, others could not work without going into their workplace, such as workers at grocery stores.

The purpose of this paper is two fold: (i) to study the differential impacts on employment, unemployment rate, and hours worked across different segments of the economy and (ii) to compare the labor market impacts of the current Pandemic Recession to those of the Global Financial Crisis.[1] In particular, we focus on (i) demographic characteristics of workers–age, gender, race, and education, (ii) three types of job characteristics–"essential" (which were not subject to government mandated shutdowns during the current Pandemic recession), "social" (where consumption of goods require human interactions) and "teleworkable" (where individuals have the option of working at home)–, and (iii) wage distributions of workers.

Using U.S. Current Population Survey data, we show that teleworkable and essential jobs are less affected during the current Pandemic Recession while social jobs have been affected severely. Surprisingly, however, we show that all three types of jobs have been less affected (or less cyclical) during the 2008 Global Financial Crisis. Moreover, the resilience (acyclicality) of teleworkable jobs to the negative aggregate shocks during the Global Financial Crisis can be attributable to the fact that a large share of workers in teleworkable jobs is skilled or highly-educated workers–who have been historically less affected in any recession.

Looking at demographic characteristics of workers, this paper corroborates the findings of other research in that Hispanic and female workers have been more severely affected than their counterparts during the current Pandemic Recession. Less educated and young workers have always been affected more severely than their more educated and older counterparts in both recessions (the Global Financial Crisis and the current Pandemic recession). Interestingly, the data still does not show an evidence of older workers, who are known to have a

---

[1]One caveat of this paper is that our latest available data for the current Pandemic is April 2020, which could be the beginning, middle, or end of the current crisis. Empirical results may change as more data become available.

higher mortality risk from COVID-19, getting more severely affected in terms of job loss.

Finally, the Global Financial Crisis and the current Pandemic recession both had a significant negative distributional impact in terms of job prospects. Low-income earners had a much higher chance of job loss than those at the top wage quantile. This differential impact of the job separation rates was much more stark during the current Pandemic recession. This result holds true even after accounting for worker characteristics as well as occupation, industry, and state fixed effects, and corroborates the finding of Cajner et al. (2020), who have used administrative payroll data.

This paper complements the existing literature in several ways: (i) we compare the current recession with the Global Financial Crisis and show that teleworkable jobs have historically been less affected (cyclical) than other jobs, mainly due to their large share of skilled workers; (ii) we also highlight the importance of looking at both occupation and industry by showing large heterogeneity within occupation x industry pairs in terms of their degree of being teleworkable, social, and essential (e.g. Dingel and Neiman (2020), Mongey et al. (2020), and Kaplan et al. (2020)); and (iii) we also corroborate that low wage earners suffer more in terms of job loss both during the current recession and the Global Financial Crisis, but particularly so during the current recession.

A sizable literature has emerged seeking to understand the macroeconomic impact of the novel coronavirus. A subset of this literature employs economic theory to understand the tradeoffs between minimizing adverse health effects and mitigating economic disruptions (Alvarez et al., 2020; Eichenbaum et al., 2020; Jones et al., 2020; Kaplan et al., 2020). Others provide high-frequency data to track the impact of the coronavirus on small businesses (Bartik et al., 2020b), economic uncertainty (Baker et al., 2020a), consumption and debt (Baker et al., 2020c), stock market volatility (Baker et al., 2020b), and broad economic activity (Lewis et al., 2020). Two recent papers – Dingel and Neiman (2020) and Mongey et al. (2020) – predict heterogeneous employment losses during the current recession based on job characteristics, such as the ability to work at home, or whether the sector requires social interaction, which we test in the CPS data.

This paper most closely relates to the rapidly growing segment of empirical literature which monitors the labor market during the beginning of the Pandemic Recession. Cajner et al. (2020) use weekly paycheck data from ADP – the largest U.S. payroll processing company – to study the behavior of different segments of the U.S. labor market through mid-April. They find that employment declines have been concentrated at the bottom of the wage distribution, amongst the youngest and eldest of the population, and in social industries. Similarly, Bartik et al. (2020a) and Kurmann et al. (2020) show enormous declines in both employment and hours in the aggregate economy as well as the leisure and hospi-

tality sector, respectively, using data from Homebase, and online scheduling and time-clock software provider. Coibion et al. (2020) use survey data from the Nielsen Homescan panel in the first week of April to document huge declines in employment, as well as an unprecedented 7 percentage point decline in labor force participation, between early March and early April. Our paper complements these works by using a large, nationally-representative survey to highlight the labor market behavior across demographic groups. Lastly, Montenovo et al. (2020) also study disparities in labor market outcomes using the Current Population Survey until April 2020. Specifically, they study how recent incidence of job loss differed across different demographic groups and face-to-face work, remote, and essential work. However, they do not compare the recent labor market outcome against the Global Financial Crisis in terms of job characteristics unlike this paper.

The paper proceeds as follows. Section 2 describes the Current Population Survey in detail, as well as our approach to sample construction. Section 3 explores the patterns for the aggregate economy, focusing on the share of both employed and unemployed workers and hours worked. Section 4 explores heterogeneity in the labor market behavior of workers according to their demographics and education. Section 5 studies the heterogeneity in labor market outcomes across occupation and industry between the Global Financial Crisis and the Pandemic crisis. Section 6 conducts regression analysis to understand the cyclicality of teleworkable, social, and essential jobs between the Global Financial Crisis and the current Pandemic recession. Section 7 studies the distributional impact of the Global Financial Crisis and the Pandemic recession in terms of job separation rates based on wage quantiles. Section 8 concludes.

2   Data

We use the Current Population Survey (CPS), a national representative survey for the U.S., between 2007 to April 2020. The Current Population Survey (CPS) has several advantages over high-frequency datasets that have been used to track the coronavirus' influence on the labor market thus far. The CPS is a large, nationally-representative survey and is the source data underlying official employment statistics released by the Bureau of Labor Statistics (BLS). The CPS contains information regarding workers' labor force status, industry, occupation, and demographics (e.g. sex, age, race, geographical locations, and education), permitting new insight into the effects of the coronavirus across a variety of individual types.

The CPS conducts monthly interviews of approximately 60,000 households and 100,000 to 150,000 individuals based on physical address. Households are interviewed for four consecutive months, and then rotated out for the next eight months before being interviewed again

four more months. This structure allows researchers to track workers' labor force status for a maximum of eight months during a 16-month period. In the fourth and eighth month in the survey (outgoing rotation groups), workers in the sample are asked about their wage information, which we will use to rank workers into different wage quantiles.

We use cross-sectional aspect of the CPS for majority of our analysis but also use its longitudinal aspect to study the distributional impact of the current Pandemic recession. To construct longitudinal CPS dataset, we follow the algorithm in Madrian and Lefgren (2000) to match individuals over 5 months over the period of 13 months. Individuals are matched across months based on their household identifier, personal identifier, sex, age, and race. Age is allowed to differ by increment of one between consecutive months. Based on this algorithm, close to 90 percent of the eligible sample can be matched for four consecutive months.[2] More than 60 percent of the eligible sample can be followed for five monthly surveys across 13 months.

Because only a subsample of the individuals can be matched in the survey due to various reasons including simple attrition and coding errors, longitudinal data do not necessarily line up with the aggregate cross-sectional statistics. If the matching attrition is completely random and independent of any demographic characteristics, we can simply scale up the weights by the ratio of the total sample number in the original survey to the number in the matched sample. However, attrition is often not random. To ensure that demographic representations in the matched sample mirror those in the original survey, we rescale the sample weights of the matched individuals by multiplying them by the inverse of matching probability conditional on the individual's demographic characteristics and labor force status. Specifically, we estimate a logit model and calculate the predicted probability of matching conditional on gender, age, race, education, and labor force status. We then multiply the original weights by the inverse of the corresponding predicted probabilities. This partially alleviates the problem arising from non-random attrition. Throughout we focus on a broad definition of prime-age workers by only considering those between the ages of 21 and 70. We additionally exclude military workers.

---

[2] In each month, the survey contains 8 rotational groups based on the number of month in the sample. Between two consecutive months, only a subset of the workers belonging to the rotation groups 1-3 and 4-7 in the first month can be matched to the following month's survey. These eligible groups from the first survey will appear as the rotation groups 2-4 and 5-8 in the second survey while the rotation groups 5 and 8 from the first survey will leave the CPS sample, either for the next 8 months (for rotation group 5) or permanently (rotation group 8). Thus, around 75 percent of the total sample from the first month is eligible to be matched.

Figure 1: Aggregate Employment and Average Hours Decline
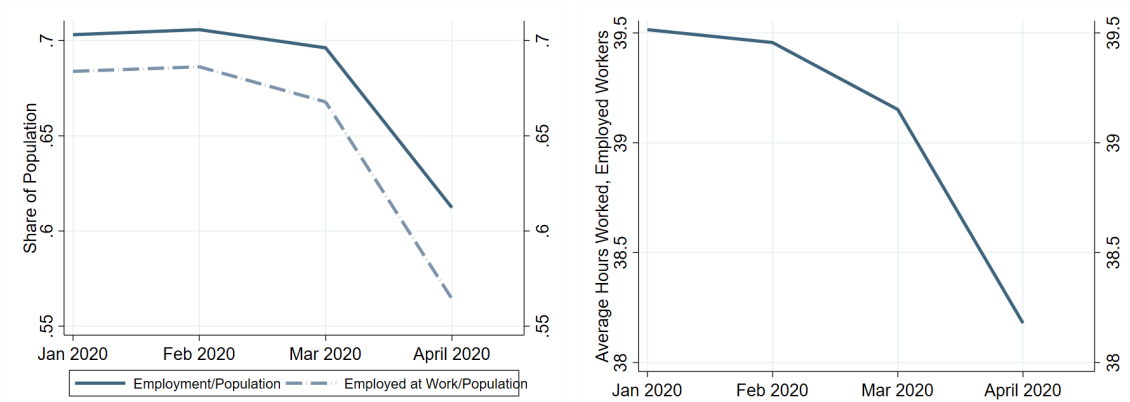
3 Aggregate Employment and Hours Declines during the Pandemic Recession

This section summarizes the aggregate employment decline in the United States during the first few months of the Pandemic recession. Figure 1 shows the trend in the aggregate employment rate for individuals aged 21 to 70 between January and April 2020. We highlight two employment rate series: the first tracks those who report being employed while the second excludes those who report being employed but were absent from work during the survey week. As seen from the figure, the U.S. employment to population rate for this age groups fell by almost nine percent during this period. The decline was even steeper – at 12 percent – excluding workers who were absent from work from the employment measure.[3] Figure 1 also shows the average hours worked for all individuals aged 21 to 70 who remained employed with positive hours through April 2020 (solid line). Hours worked for those that remained employed fell by 3.3 percent or 1.3 hrs.

How much of total decline in hours worked has occurred on the extensive margin vs the intensive margin? Aggregate hours worked including both the extensive and intensive margin changes has fallen by 17.3 percent between January and April 2020. Using the results above, 80 percent of the decline in aggregate hours (or -13.8 percent) is attributable to the extensive margin (decline in employment rate) while 20 percent (or -3.4 percent) is attributable to the intensive margin (hours worked).

Figure 2 plots trends in the unemployment rate for 21-70 year old during the same period. Again, we compute two unemployment measures. First, we measure the unemployed as

---

[3]Note that in this study, we use non-seasonally adjusted data and different age groups (21-70 years old) from the Employment Situation Report by Census. Therefore, the numbers here may be slightly different from the Census report.

Figure 2: Unemployment Rate
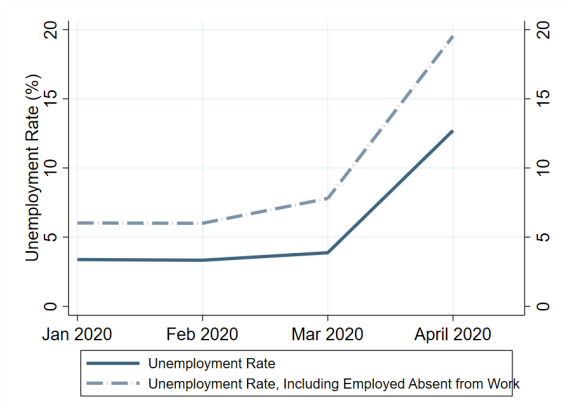
those who are not employed but who are actively looking for a job. This is the standard unemployment measure. For our second measure, we also include those who report being employed but were absent from work as also being unemployed. The unemployment rate for workers between 21-70 years old have increased by 9.3 percent between January and April 2020. An alternative measure of unemployment rate, which includes those who report being employed but were absent from work as also being unemployed, has increased by 13.5 percent from 6 percent to 19.5 percent during the same period.

4   The Distributional Effects of the Pandemic Recession vs the Global Financial Crisis by Demographic Groups

In this section, we investigate whether the group of workers who have been more severely affected during the current Pandemic recession had also been severely affected during the 2008 Global Financial Crisis. Specifically, we study changes in both the extensive (employment rate) and intensive (average hours worked) margin of employment between 2007 and 2009 against those between 2019 and April 2020 across (i) gender, (ii) race, (iii) age group, and (iv) educational attainment. We show that while the magnitude of decline in employment and hours worked is much severe during this current recession than during the Global Financial Crisis, the groups of workers suffered relatively more (younger, less educated and non-whites workers) were similar between the two recessions. One key difference between the two recessions is that women saw a sharper decline in employment during the current recession than during the Global Financial Crisis.

Figure 3: Extensive/Intensive Margin during 2007-2009 and 2019-April 2020 by Sex
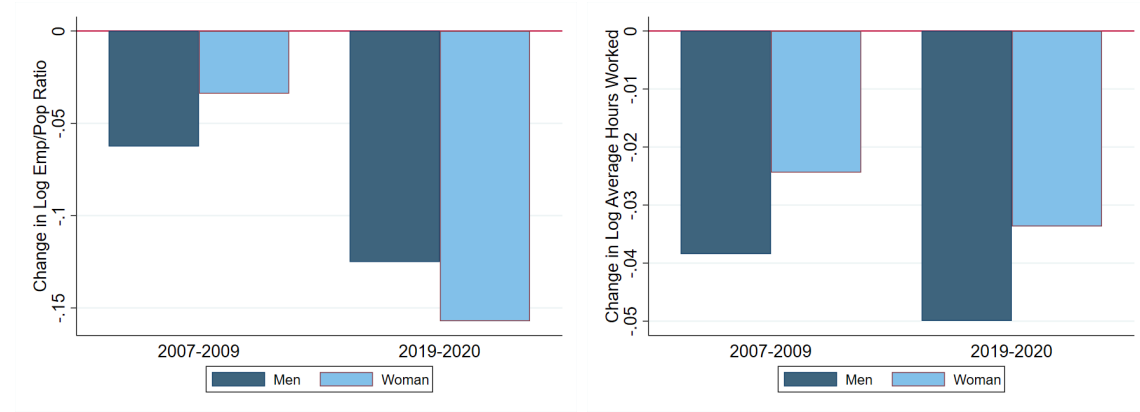
4.1 Gender

Figure 3 plots the changes in log employment to population ratio and the log average hours worked by gender between 2007-2009 and 2019-April 2020. Whereas men suffered more in terms of employment (extensive margin) in 2007-2009, women got more heavily affected during the current Pandemic recession. However, conditional on being employed, the average hours worked declined less for women during both during the Global Financial Crisis and the current Pandemic recession. However, as we show later in Section 6, a major part of the decline in employment rate for women during this recession is attributable to the fact that women are more likely to work in the industries and occupations that were affected more severely during the current Pandemic recession.

4.2 Age Group

Figure 4 plots the changes in extensive and intensive margin of employment for 2007-2009 and 2019-April 2020 for age groups by every 10 years. Compared to the GFC, younger workers, particularly the workers between 21-30 years old, saw a sharper decline in employment during the current Pandemic recession than the other age groups. The magnitude of decline in log average hours worked (intensive margin) was similar across different age group, with the exception of the older workers between 61-70 years old.

4.3 Race

Figure 5 plots the changes in extensive and intensive margin of employment for 2007-2009 and 2019-April 2020 by race. Compared to the Global Financial Crisis, employment rates for black and Hispanic workers declined more severely than other racial groups, particularly

Figure 4: Extensive/Intensive Margin during 2007-2009 and 2019-April 2020 by Age Group
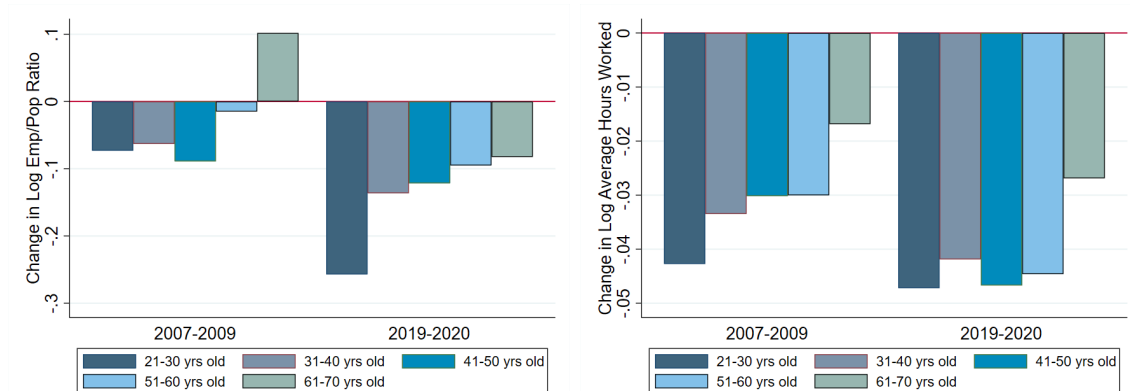
Figure 5: Extensive/Intensive Margin during 2007-2009 and 2019-April 2020 by Race
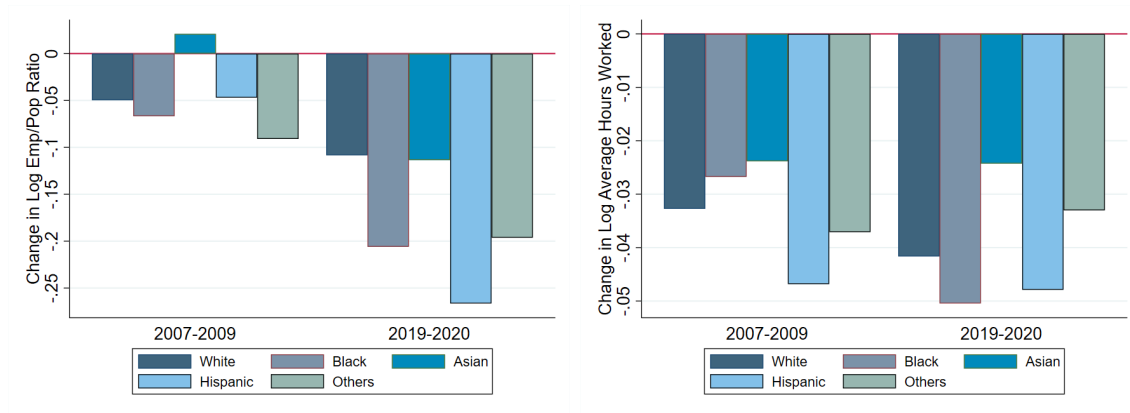
during the current recession. The hours worked declined least for Asian workers.

4.4 Education

Figure 6 plots the changes in extensive and intensive margin of employment for 2007-2009 and 2019-April 2020 by educational attainment level. While the magnitudes of decline in both employment rate and average hours worked are more severe during the current recession, the pattern of relative decline is very similar across educational groups between the two recessions. Less educated workers have seen a much sharper decline in both the employment rate and the average hours worked than more educated workers.

Figure 6: Extensive/Intensive Margin during 2007-2009 and 2019-April 2020 by Education
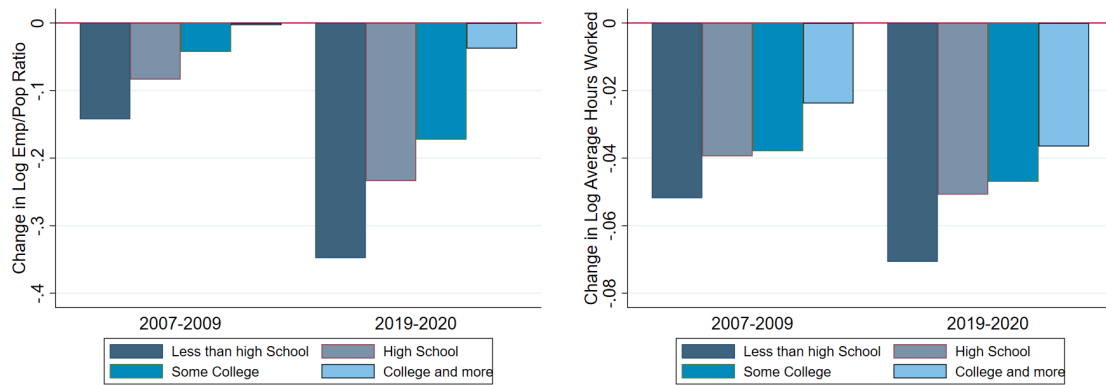
5 The Distributional Effects of the Pandemic Recession vs the Global Financial Crisis by Occupation and Industry

5.1 Occupation

In this section, we first compare the changes in unemployment rate and average hours worked by occupation. Here, we focus on the unemployment rate rather than employment because only employed and unemployed workers, but not those out of the labor force, report their occupation and industry.[4] Figure 7 plots the changes in unemployment rate and the log average hours worked by occupation between 2007-2009 and 2019-April 2020. Whereas service occupations were affected less during the Global Financial Crisis, workers in that sector suffered most during the current recession. Sales and office and administrative support also saw relatively sharper increase in the unemployment rate during the current recession than the previous recession. On the other hand, conditional on being employed, the patterns of changes in the average hours worked were very similar between the past recession and the current recession. Workers in management, business and financial occupations have been less affected than workers in other occupations both during the current recession and the Global Financial Crisis.

---

[4]This prohibits one from calculating an appropriate sub-population of group that individuals belong to.

Figure 7: Change in Unemployment Rate and Hours Worked during 2007-2009 and 2019-April 2020 by Occupation
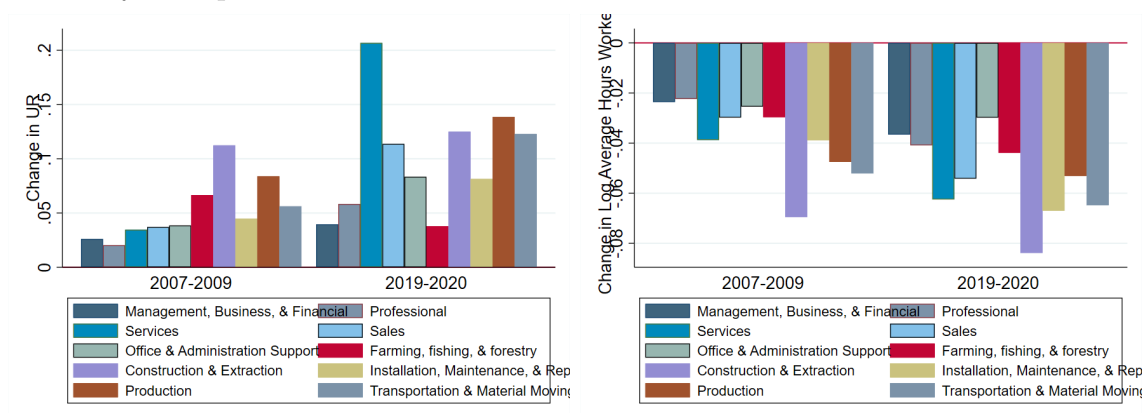
Figure 8: Change in Unemployment Rate and Average Hours Worked during 2007-2009 and 2019-April 2020 by Teleworkability
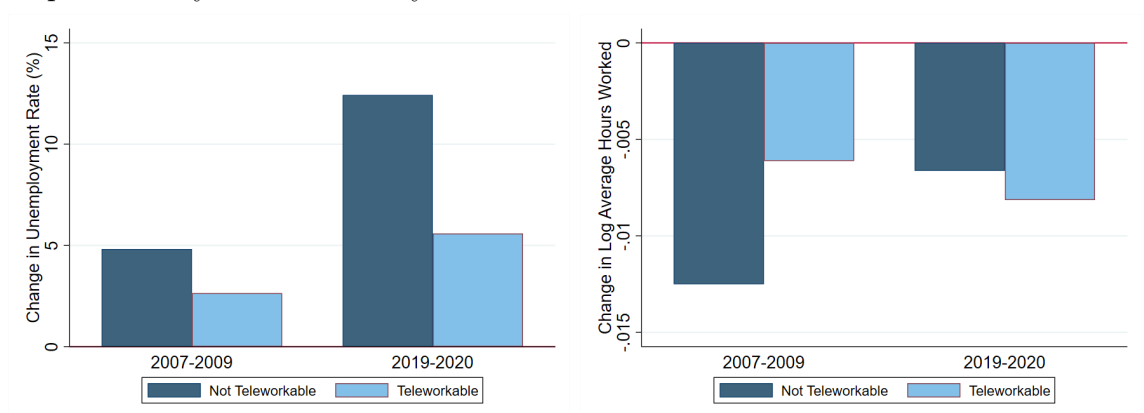
5.1.1 Teleworkable Occupations

Due to social distancing measure and lock-down policies, workers who are able to work from home are postulated to be less affected during the current crisis. Following Dingel and Neiman (2020) and Mongey et al. (2020), we classify jobs into teleworkable and non-teleworkable occupations. Figure 8 plots the changes in unemployment rate for teleworkable and non-teleworkable occupations. We see that workers in teleworkable occupations are less affected during any recession, but workers in non-teleworkable occupations have been much more severely affected during the current recession. Figure 8 looks very similar when we plot changes in the log employment-to-aggregate population changes. However, conditional on being employed, workers in teleworkable occupation have also seen a decline in the average hours worked.

Figure 9: Change in Unemployment Rate and Average Hours Worked during 2007-2009 and 2019-April 2020 by Industry
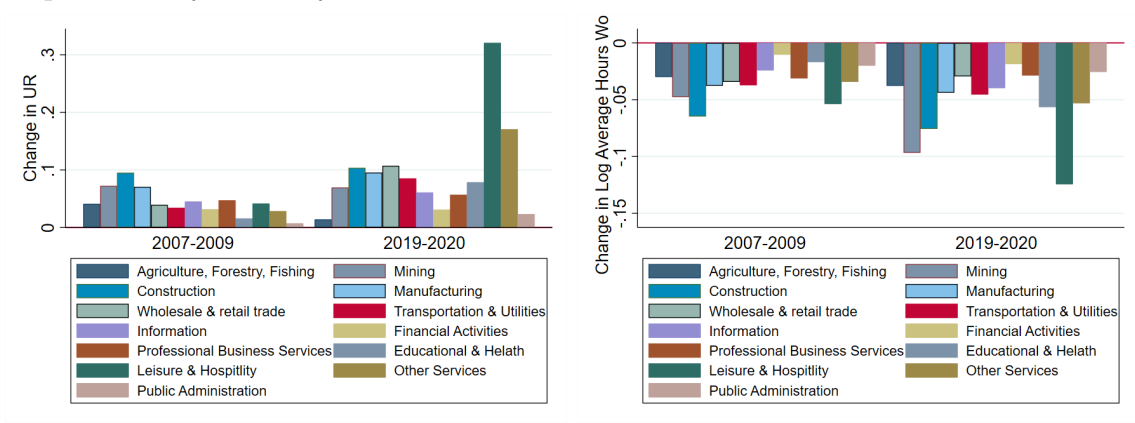
5.2 Industry

Figure 9 plots changes in unemployment rate and the average hours worked during the Global Financial Crisis and the current Pandemic recession. Almost all the industries except for agriculture, construction, and financial sectors have seen a sharper rise in the unemployment rate during the current recession than the previous recession. In particular, workers in leisure and hospitality have seen a sharp increase in the unemployment rate. These workers have also seen a sharp decline in the average hours worked.

5.2.1 Social Industry

Following Kaplan et al. (2020), we categorize industries into social and non-social (consumption). Industries are considered as social if their output requires interpersonal interaction to consume. If you need to work in a factory or a warehouse close to other people in order to produce the output, that does not count as social, but if you need to meet someone to consume the output then it does. Therefore, manufacturing makes a consumption good whereas restaurants make a social good. Some industries could be harder to categorize, for instance, retail and finance. We categorize finance industry as non-social even though you may need to meet with a branch manager to open an account, because the majority of financial services are performed without interpersonal interaction. Retail is classified as social because you need to go to a store and interact with a clerk to purchase goods. The rise in online retail over the last 15 years has made that less true today, but we still classify retail industry as social. Even within a broad industry category, some more finely defined industries are considered social while others are not. For instance, the financial services that are social are automotive rental and leasing, and other consumer goods are rental and

Figure 10: Change in Unemployment Rate and Average Hours Worked during 2007-2009 and 2019-April 2020 by Social and Non-Social Industry

leasing. The professional services that are social are vets, security guards, and services to buildings and dwellings (except cleaning during construction). The manufacturing sector that is social is retail bakeries.
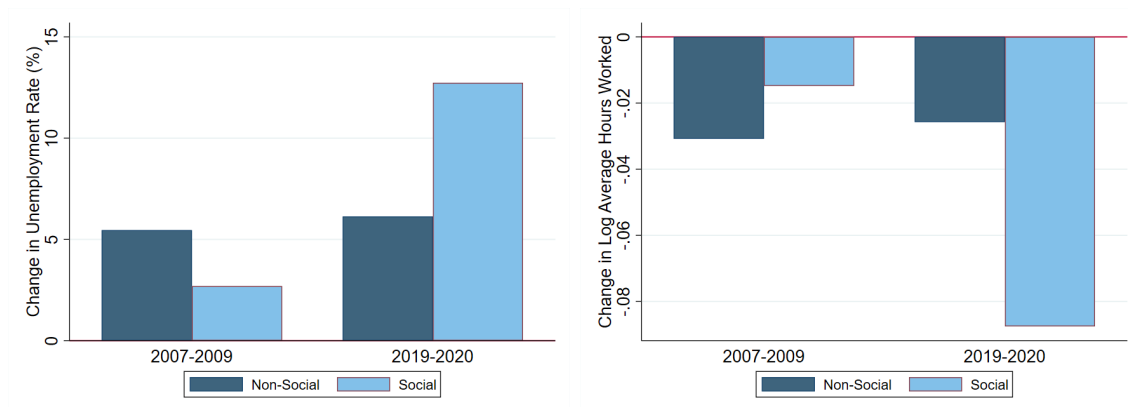
Figure 10 plots changes in unemployment rate and the average hours worked during the Global Financial Crisis and the current Pandemic recession by social and consumption (non-social) industries. Between 2007-09, the social industries saw a small increase in the unemployment rate. However, during this current Pandemic, the unemployment rate of social jobs has increased sharply, almost twice as much as that of non-social jobs. The hours worked of workers in social sectors has also sharply declined.

5.2.2 Essential Industry

During the current Pandemic crisis, the government has allowed the business operations of essential industries while restricting those of non-essential industries (Tomer and Kane, 2020). These include health care facilities, grocery stores, and water utilities.

Figure 11 plots changes in the unemployment rate and average hours worked for non-essential and essential industries during the Global Financial Crisis and the current Pandemic Crisis. Interestingly, the essential industries have suffered less in terms of unemployment rate during the Global Financial Crisis. However, during the current crisis, the non-essential industries have seen much sharper changes in both unemployment rate and average hours worked.[5]

---

[5]Log employment to aggregate population ratios show similar patterns.

Figure 11: Change in Unemployment Rate and Average Hours Worked during 2007-2009 and 2019-April 2020 by Essential and Non-Essential Industry
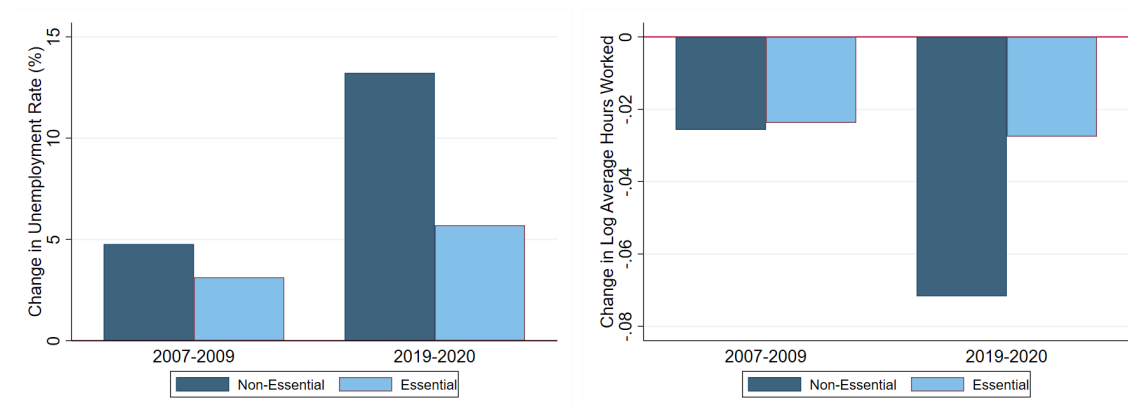
5.3 Importance of Looking at Teleworkable, Social, and Essential Jobs

The previous subsections showed general patterns of changes in unemployment rates and average hours worked during the two recessions. This section emphasizes the importance of looking at both occupation and industry by showing significant heterogeneity even within teleworkable occupations.

Table 1 shows the share of employment in teleworkable, social and essential jobs by broad occupation categories.[6] It shows a significant degree of heterogeneity even at the broad level of occupations. For instance, workers in managerial, financial, and professional occupations tend to have a larger share of teleworkable employment and have a higher share of workers with bachelor's degree or above. Nevertheless, professional and related occupations are more likely to be social than those in managerial, financial, and professional occupations. Construction and extraction occupations and transportation and material moving occupations are both not teleworkable. However, construction and extraction occupations are less social and non-essential than transportation and material moving occupations.

Table 2 shows the share of employment in teleworkable, social, and essential jobs by broad industry categories. Leisure and hospitality and educational and health services are both social, but only educational and health services are essential. Leisure and hospitality is also less likely to be teleworkable than education and health services. Moreover, a larger fraction of workers in education and health service industries is with bachelor's degree than those working in leisure and hospitality. While agriculture, forestry, fishing and hunting industries

---

[6]Employment share is calculated based on 2019 data to avoid the potential bias from using the data during the Pandemic recession.

Table 1: Share Employment in teleworkable, social, and essential jobs by broad occupation classification

	Share of Employment with:			
	Teleworkable (1)	Essential (2)	Social (3)	Bachelor's (4)
Management, business, and financial occupations	0.83	0.44	0.29	0.60
Professional and related occupations	0.63	0.43	0.67	0.73
Service occupations	0.05	0.38	0.89	0.17
Sales and related occupations	0.21	0.37	0.63	0.34
Office and administrative support occupations	0.53	0.56	0.47	0.27
Farming, fishing, and forestry occupations	0.00	0.96	0.03	0.12
Construction and extraction occupations	0.00	0.09	0.03	0.09
Installation, maintenance, and repair occupations	0.01	0.54	0.45	0.10
Production occupations	0.00	0.59	0.14	0.11
Transportation and material moving occupations	0.00	0.69	0.59	0.12

and construction industry are both non-social, but the former is considered essential while the latter is not.

Figure 12 plots the changes in unemployment rates by broad occupation category and broad industry category between the Global Financial Crisis and the current recession. We see that more teleworkable occupations tend to be less affected during this recession than the previous recession. Workers in management and professional occupations have been less affected during the current recession than the previous recession. Social and non-essential industries, particularly, jobs in leisure and hospitality, have been much more severely affected than jobs in other industries during the current recession than the previous recession.

Table 3 shows the share of employment in terms of female and skilled workers within each type of jobs. First, we see that there are more skilled workers in 2019 (40 percent) than in 2007 (33 percent). Second, the share of aggregate employment in all the three jobs have increased between 2007 and 2019. Social jobs have increased by 2 percentage points. Third, we see that teleworkable jobs have a higher share of skilled workers, those who have college and more education, (63 percent in 2019) than the average (40 percent in 2019). However, average educational level of workers in essential and social jobs are very similar to the average. Lastly, teleworkable and social jobs have higher share of female workers but, particularly true for social jobs, partially explaining a sharper decline in female employment during the current Pandemic recession.

Lastly, Figure 13 shows a Venn diagram for the employment share for teleworkable,

Table 2: Share of Employment in teleworkable, social, and essential jobs by broad industry classification

	Share of Employment with:			
	Teleworkable (1)	Essential (2)	Social (3)	Bachelor's (4)
Agriculture, forestry, fishing, and hunting	0.08	1.00	0.00	0.21
Mining	0.28	0.84	0.00	0.26
Construction	0.20	0.00	0.00	0.16
Manufacturing	0.30	0.64	0.01	0.30
Wholesale and retail trade	0.20	0.40	0.78	0.26
Transportation and utilities	0.23	0.82	0.57	0.23
Information	0.59	0.59	0.00	0.56
Financial activities	0.70	0.70	0.03	0.54
Professional and business services	0.65	0.32	0.14	0.56
Educational and health services	0.51	0.54	1.00	0.56
Leisure and hospitality	0.14	0.00	1.00	0.24
Other services	0.31	0.27	0.73	0.29
Public administration	0.47	.	.	0.52

social, and essential jobs. We see that large fractions of jobs overlap across categories. For instance, while social jobs comprise 50.9% (52.9%) of total employment in 2007 (2019), 68.4 (=34.8%/50.9%) % (69.7%) of them are also categorized as teleworkable and essential jobs in 2007 (2019). A 16.1% (16.0%) of total employment is purely social that is neither teleworkable nor essential. Thus, the Venn diagram illustrates a large overlap of different types of jobs.

Table 3: Share of Employment, Female and Skilled Workers in teleworkable, social, and essential jobs

	Share of Total Employment					
	Employment		Women		High Skill	
Year	2007	2019	2007	2019	2007	2019
Aggregate			.476	.480	.333	.400
Teleworkable	.384	.393	.583	.559	.555	.633
Essential	.465	.475	.494	.497	.324	.395
Social	.509	.529	.592	.596	.342	.398

Figure 12: Changes in Unemployment Rate during 2007-2009 and 2019-April 2020 by Occupation and Industry

Slope coefficient: 0.86 (Robust SE: 0.45). R-squared: 0.13

Slope coefficient: 0.46 (Robust SE: 0.32). R-squared: 0.02
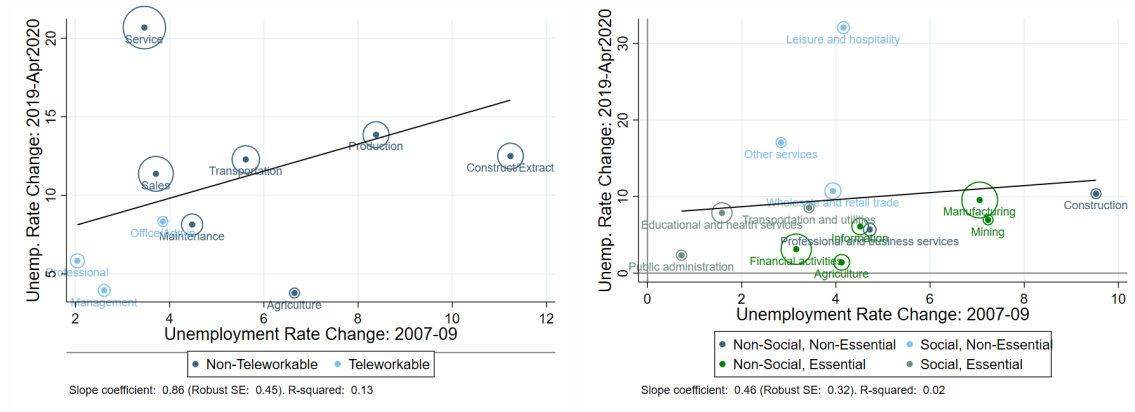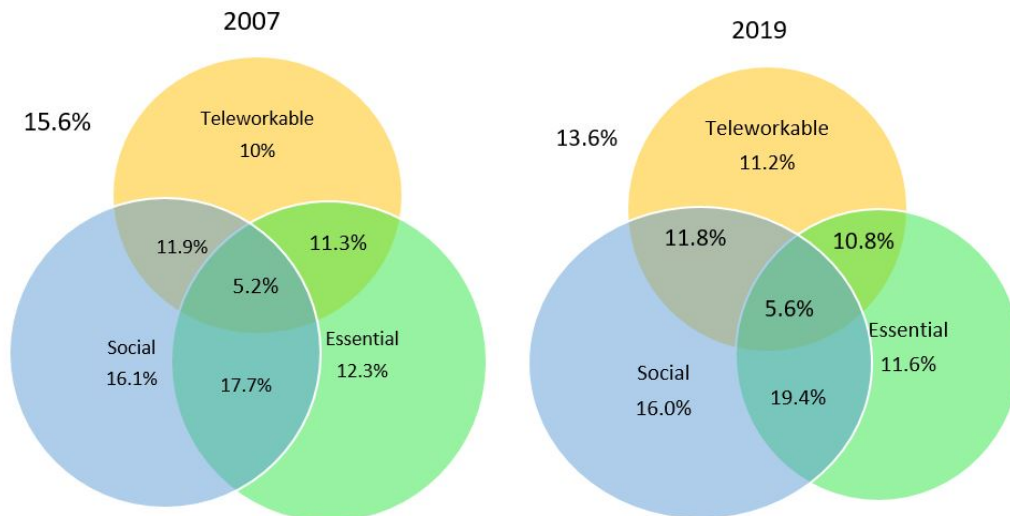
Figure 13: Employment Share by Teleworkable, Social, and Essential Jobs: 2007-09 vs 2019-20

19

6 Empirical Analysis of Labor Market Outcomes during the Pandemic Recession vs the Global Financial Crisis

Previous sections showed changes in employment, unemployment, and average hours worked across different demographic groups and different occupation and industries, with special focus on their teleworkability, socialbility, and essentiability. In this section, we formally test if the current recession has seen a very different pattern from the previous recession in terms of the decline in employment and average hours worked. Our empirical specification is as follows:

$$\Delta(Y_{it}-Y_t) = \alpha_{tw}Occ_{TW}+\alpha_s Ind_S+\alpha_e Ind_E+\gamma X_{it}+Pandemic*(\beta_{tw}Occ_{TW}+\beta_s Ind_S+\beta_e Ind_E+\Gamma_p X_{it})+\epsilon_{it} \tag{1}$$

where $(\Delta Y_{it} - \Delta Y_t)$ is a change in log employment or unemployment rate at a occupation $\times$ industry cell level (ΔY_{it}) after subtracting the aggregate change in the variable (ΔY_t) for each recession to control for the difference in the size of shocks between the Global Financial Crisis and the current Pandemic recession. Occ_{TW}, Ind_S and Ind_E are indicator variables if a occupation $\times$ industry cell belongs to a teleworkable occupation, a social industry, or an essential industry. Pandemic is an indicator variable that is equal to 1 if ΔY_{it} is the change between 2019 and April 2020 and zero if it is the change between 2007 and 2009. α's capture the relative change in log employment or unemployment rate for teleworkable, social, and essential jobs during the Global Financial Crisis. β's are the variables of our interest, which captures differential changes in log employment or unemployment rate during the Pandemic recession. The total changes in the left hand side variables for the pandemic recession are given by the sum of α_k and β_k for $k \in \{TW, S, E\}$. We restrict our occupation x industry pairs to the ones with more than 10 observations, leaving us with 700 observations for our regression analysis.

Table 4 shows the regression results of equation (1). Column (1)-(3) show the regressions with teleworkable occupation dummy, social industry dummy, and essential industry dummy and their cross-product with the pandemic dummy without any demographic controls. Standard errors shown are all robust standard errors. Column (4) shows the results including all three categories of teleworkable, essential and social jobs. We first see that all teleworkable, social and essential industries were less affected than their counterparts during the Global Financial Crisis, which is implied by significant and positive coefficients.

Table 4: Regression Results: Change in Log Employment

	(1)	(2)	(3)	(4)	(5)	(6)
Teleworkable Occ.	0.064**			0.048***	-0.016	-0.024
	(0.029)			(0.018)	(0.013)	(0.016)
Social Ind.		0.061***		0.119***	0.115***	0.088***
		(0.020)		(0.019)	(0.019)	(0.016)
Essential Ind.			0.067*	0.049***	0.052***	0.041**
			(0.035)	(0.018)	(0.018)	(0.016)
Teleworkable × Pandemic	0.080***			0.133***	0.102***	0.099***
	(0.019)			(0.031)	(0.034)	(0.036)
Social × Pandemic		-0.123**		-0.218***	-0.230***	-0.132***
		(0.060)		(0.064)	(0.064)	(0.039)
Essential × Pandemic			0.041*	0.107***	0.093***	0.123***
			(0.024)	(0.038)	(0.034)	(0.041)
Skill					0.185***	0.184***
					(0.037)	(0.035)
Skill × Pandemic					0.035	-0.013
					(0.051)	(0.065)
Men						-0.005
						(0.031)
Men × Pandemic						0.113
						(0.086)
Education Control:	N	N	N	N	Y	Y
Demographic Controls:	N	N	N	N	N	Y
Observations	700	700	700	700	700	700
R-squared	0.085	0.055	0.058	0.272	0.319	0.379

Note: Regression results are of equation 1. Robust standard errors are in parentheses.

During the pandemic, teleworkable and essential jobs remained to be less affected than their counterparts. However, social jobs have been affected more severely than their counterparts, and its total impact (sum of coefficients on essential industry and its interaction term with pandemic dummy) is negative.

There is a tight link between teleworkable jobs and its composition of skilled workers. Although teleworkable jobs have been less affected than their counterparts both during the Global Financial Crisis and the current Pandemic without any control variables (Table 4: Column (1)-(4)), the impact on teleworkable jobs was similar to their counterparts during the Global Financial Crisis once we control for the composition of educated workers (Column (5)). In other words, the sensitivity of teleworkable jobs to negative aggregate shocks are in GFC can be attributable to its composition of skilled workers. Nevertheless, during the current Pandemic recession, teleworkable jobs, even after accounting for the composition of skilled workers, have been less affected than the counterparts.[7]

On the other hand, social jobs are much more severely affected during the Pandemic, and essential jobs are even less affected during the current Pandemic than during the Global Financial Crisis. This holds true even after controlling for the demographic compositions (Column 6). Moreover, column (6) shows that the difference in job loss between men and women becomes statistically insignificant (Men x Pandemic) once we control for the types of jobs (teleworkable occupaitons, and social and essential industries) and demographic characteristics (age, race, and education) at occupation x industry level. This is different from the naive comparison of total employment decline from Figure 3, which suggests that women have been affected more during the Pandemic than men.[8]

7 Distributional Impact at Individual Level: the Pandemic Recession vs the Global Financial Crisis

Many researchers have shown that this Pandemic recession is impacting the most vulnerable and low income group more severely than their less vulnerable and richer counterparts in terms of health and income (Cajner et al. (2020) and Schmitt-Grohé et al. (2020)). In this section, we study the distributional effects in terms of employment outcome between the

---

[7]However, the relative change in unemployment rate is similar between teleworkable and non-teleworkable jobs during the Pandemic (Table 6 Column (6) in Appendix). This difference in results based on log employment-to-population ratio and the unemployment rate can be attributable to the movement into out of labor force.

[8]Using individual level regression, Montenovo et al. (2020) show that women still suffered more during this recession than men. However, the degree of gender explaining the increase in temporary layoff declines by two-thirds once occupations and industries are controlled for.

Pandemic Recession and the Global Financial Crisis. Specifically, we investigate how much of the higher job separation probabilities for the lowest quantile in wage distribution can be explained by workers' demographic characteristics, occupations (e.g. teleworkability), and industries (social and essential).

We exploit the panel dimension of the Current Population Survey for this section. We focus our analysis on the month-to-month job separation probability between February and April 2020 compared to the Global Financial Crisis period of 2008 to 2009. Using the wage information for the outgoing rotation groups, we can observe wage information between 9 and 11 months prior to the observation month and group the individuals into four wage quantiles.[9] We then follow the month-to-month transition rates during the Global Financial Crisis (2008 and 2009) and the Pandemic recession (February-April 2020). We define job separation as movement from being employed in month t-1 to either being unemployed or out of labor force in month t. We do so to take into account the results of Coibion et al. (2020), which claim that many of those who lost jobs are not actively looking for a job and thus may be classified as out of the labor force. However, the results are generally robust when we restrict our sample to March-April 2020 transition only and to movement from employment to unemployment (and excluding out of labor force) (See Table 7 in Appendix for robustness check).

Following Cajner et al. (2020), our empirical specification is a linear probability model with OLS with standard errors clustered at broad occupation x industry categories:

$$JSR_{it} = \sum_{q=1}^{Q} \mathbf{I}\{\text{i's quantile is q}\} \times (\alpha_q + \beta_q Pandemic) + \Gamma X_{it} + \Phi X_{it} \times Pandemic + \sum_{t=1}^{T} \theta_t I_{M_t} + \epsilon_{it}$$

(2)

where JSR_{it} is a dummy variable which is equal to 1 if a worker has separated from a job between $t-1$ and t and 0 otherwise. In our baseline specification, we define job separation as a movement from employment to either unemployment or out of the labor force. As a robustness check, we alternatively define job separation as the movement from employment to unemployment. α_q measures the job separation probabilities during the pre-Pandemic period for a worker belonging to quantile q relative to the top-wage earner, and β_q measures the job separation probabilities relative to the top-wage earners during the Pandemic for a worker who belonged to wage quantile q prior to the recession. X_{it} includes demographic characteristics of workers, and $\theta_t I_{M_t}$ are the time fixed effects for each month.

Our specification differs in several dimensions from Cajner et al. (2020). While Cajner

---

[9]To increase the sample size, we treat both February-March and March-April 2020 as the Pandemic period

Table 5: Regression Results: Monthly Job Separation for Wage Quantiles

	(1)	(2)	(3)	(4)
Wage Quantile: 1	0.017***	0.013***	0.011***	0.010***
	(0.001)	(0.002)	(0.002)	(0.002)
Wage Quantile: 2	0.007***	0.005***	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Wage Quantile: 3	0.003**	0.002*	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Pandemic × Wage Quantile: 1	0.078***	0.076***	0.058***	0.038***
	(0.012)	(0.011)	(0.008)	(0.007)
Pandemic × Wage Quantile: 2	0.049***	0.047***	0.033***	0.025***
	(0.011)	(0.010)	(0.008)	(0.006)
Pandemic × Wage Quantile: 3	0.020***	0.019***	0.011***	0.009**
	(0.005)	(0.005)	(0.004)	(0.004)
Demographic Controls:	N	Y	Y	Y
Education Control:	N	N	Y	Y
Occ x Ind Fixed Effects:	N	N	N	Y
State Fixed Effects:	N	N	N	Y
Observations	245,149	245,149	245,149	245,149
R-squared	0.023	0.025	0.027	0.041

Note: Table shows regression results of equation 2. "Wage Quantile: q" and "Wage Quantile: q" × Pandemic show the coefficients $\alpha'_q s$ and $\beta'_q s$ from the regression. The coefficient shows the differential job separation rate for workers in quantile q relative to the top (4th) quantile. Standard Errors are clustered at occupation x industry Level.

et al. (2020) split the sample into five different wage quanties, we separate into four different quantiles (i.e. 0-25th percentile, 25th-50th percentile, 50th-75th percentile, and 75th-100th percentile) to allow more observations within the cell. Unlike Cajner et al. (2020), we control for educational attainment level of workers but do not control for business size. Moreover, we use wage information from a year ago while they use early March wage data to categorize the sample into different wage quantiles.

Table 5 shows the regression results of equation (2). Column (1) shows the baseline results with no control. We see that the workers at the bottom wage quantiles have a much higher chance of separating from a job than workers in the top wage quantile during the Global Financial Crisis and the current Pandemic recession. Column (2) shows the results controlling for non-education demographic information (i.e. gender, race, and age). The demographic information explains about 20 percent of job separation rate for the workers at the bottom wage quantile $(0.013 - 0.017)/(0.017) \approx 0.23)$ during the Global Financial Crisis. Column (3) further controls for the educational attainment, which explains additional 11 percent of job separation probabilities of workers in the bottom quantile or total of 40 percent combining demographic and educational information during the Global Financial Crisis. During the Pandemic, the workers in the bottom three quantiles suffered from a higher chance of losing job than those in the top quantile.

Column (4) controls for broad occupation x industry and state fixed effects. Even after controlling for broad occupation x industry and state fixed effects, workers in the bottom wage quantile got more severely affected during the current Pandemic than the Global Financial Crisis, suggesting a severe distributional impact of the current Pandemic. Results are robust to alternatively defining job separation probability as those moving from employment to unemployment but excluding movement to out of the labor force (see Table 7 in Appendix). In sum, during both recessions, workers at the bottom wage quantile had suffered more than those in the top wage quantile. However, the current recession had shown a even stronger distributional impact than the previous recession in terms of job prospects for the workers at the bottom wage quantile.

8   Conclusion

This paper studies the differential impacts of recessions on employment, unemployment rate, and hours worked across different segments of the economy during the current Pandemic Recession and the Global Financial Crisis. In particular, we focus on (i) demographic characteristics of workers–age, gender, race, and education, (ii) three types of job characteristics–"essential" (which were not subject to government mandated shutdowns during the current

Pandemic recession), "social" (where consumption of goods require human interactions) and "teleworkable" (where individuals have the option of working at home)–, and (iii) wage distributions of workers.

We document that teleworkable and essential jobs are less affected during the current Pandemic Recession while social jobs have been affected severely. Surprisingly, however, we show that all three types of jobs have been less affected (or less cyclical) during the 2008 Global Financial Crisis. Furthermore, the resilience (acyclicality) of teleworkable jobs to the negative aggregate shocks during the Global Financial Crisis can be attributable to the fact that a large share of workers in teleowrkable jobs consists of skilled or highly-educated workers–who have been historically less affected in any recession.

With regards to workers' demographic characteristics, this paper corroborates the findings of other research in that Hispanic and female workers have been more severely affected than their counterparts during the current Pandemic Recession. Less educated and young workers have always been affected more severely than their more educated and older counterparts in both recessions (the Global Financial Crisis and the current Pandemic recession).

Finally, the Global Financial Crisis and the current Pandemic recession both had a significant negative distributional impact in terms of job prospects. Low-income earners had suffered more from job loss than top-income earners. This differential impact of the job separation rates was much more stark during the current Pandemic recession.

References

Alvarez, Fernando E, David Argente, and Francesco Lippi, "A Simple Planning Problem for COVID-19 Lockdown," Working Paper 26981, National Bureau of Economic Research April 2020.

Baker, Scott R, Nicholas Bloom, Steven J Davis, and Stephen J Terry, "COVID-Induced Economic Uncertainty," Working Paper 26983, National Bureau of Economic Research April 2020.

Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle J. Kost, Marco C. Sammon, and Tasaneeya Viratyosin, "The Unprecedented Stock Market Impact of COVID-19," Working Paper 26945, National Bureau of Economic Research April 2020.

Baker, Scott, Robert Farrokhnia, Seffen Meyer, Michaela Pagel, and Constantine Yannelis, "How Does Household Spending Respond to an Epidemic? Consumption and Debt During the 2020 COVID-19 Pandemic," *Work in Progress*, 2020.

Bartik, Alexander W., Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matt Unrath, "Labor Market Impacts of COVID-19 on Businesses: Update with Homebase Data Through April 8," mimeo 2020.

Bartik, Alexander W, Marianne Bertrand, Zoë B Cullen, Edward L Glaeser, Michael Luca, and Christopher T Stanton, "How Are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey," Working Paper 26989, National Bureau of Economic Research April 2020.

Cajner, Tomaz, Leland Crane, Ryan Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz, "The U.S. Labor Market During the Beginning of the Pandemic Recession," Working Paper 27159, National Bureau of Economic Research May 2020.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, "Labor Markets During the COVID-19 Crisis: A Preliminary View," Working Paper 27017, National Bureau of Economic Research April 2020.

Dingel, Jonathan I and Brent Neiman, "How Many Jobs Can be Done at Home?," Working Paper 26948, National Bureau of Economic Research April 2020.

Eichenbaum, Marty, Sergio Rebelo, and Mathias Trabandt, "The Macroeconomics of Epidemics," *Work in Progress*, 2020.

Jones, Callum J, Thomas Philippon, and Venky Venkateswaran, "Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home," Working Paper 26984, National Bureau of Economic Research April 2020.

Kaplan, Greg, Ben Moll, and Gianluca Violante, "Pandemics According to Hank," *Work in Progress*, 2020.

Kurmann, André, Etienne Lalé, and Lien Ta, "The Impact of COVID-19 on U.S. Employment and Hours: Real-Time Estimates With Homebase Data," Working Paper April 2020.

Lewis, Daniel, Karel Mertens, and James H Stock, "U.S. Economic Activity During the Early Weeks of the SARS-Cov-2 Outbreak," Working Paper 26954, National Bureau of Economic Research April 2020.

Madrian, Brigitte C and Lars J. Lefgren, ""An Approach to Longitudinally Matching Current Population Survey (CPS) Respondents," *Journal of Economic and Social Measurement*, 2000, *26*, 31–62.

Mongey, Simon, Laura Pilossoph, and Alex Weinberg, "Which Workers Bear the Burden of Social Distancing Policies," BFI Working Paper 2020-51, Becker Friedman Institute Working Paper April 2020.

Montenovo, Laura, Xuang Jiang, Felipe Lozano Rojas, Ian M. Schmutte, I Simon Kosali, Bruce A Weinberg, and Coady Wing, "Determinants of Disparities in COVID-19 Job Losses," Working Paper 27132, National Bureau of Economic Research May 2020.

Schmitt-Grohé, Stephanie, Ken Teoh, and Uribe Martín, "COVID-19: TESTING INEQUALITY IN NEW YORK CITY," April 2020, (27019).

Tomer, Adie and Joseph W. Kane, "How to protect essential workers during COVID-19," *Brookings Report, Brookings Institute*, March 2020.

9 Appendix: Robustness Check Results

Table 6: Regression Results: Change in Unemployment Rate

	(1)	(2)	(3)	(4)	(5)	(6)
Teleworkable Occ.	-0.035***			-0.029***	-0.008*	0.001
	(0.012)			(0.006)	(0.005)	(0.004)
Social Ind.		-0.008		-0.035***	-0.036***	-0.025***
		(0.008)		(0.007)	(0.006)	(0.004)
Essential Ind.			-0.033**	-0.022***	-0.025***	-0.016***
			(0.014)	(0.006)	(0.006)	(0.004)
Teleworkable × Pandemic	-0.027***			-0.044***	-0.014	-0.013
	(0.008)			(0.013)	(0.012)	(0.011)
Social × Pandemic		0.052*		0.097***	0.108***	0.077***
		(0.029)		(0.029)	(0.028)	(0.016)
Essential × Pandemic			-0.028***	-0.064***	-0.054***	-0.067***
			(0.009)	(0.018)	(0.016)	(0.018)
Skill					-0.068***	-0.048***
					(0.013)	(0.009)
Skill × Pandemic					-0.049***	-0.044*
					(0.017)	(0.023)
Men						0.017*
						(0.009)
Men × Pandemic						-0.017
						(0.037)
Education Control:	N	N	N	N	Y	Y
Demographic Controls:	N	N	N	N	N	Y
Observations	682	682	682	682	682	682
R-squared	0.118	0.082	0.123	0.426	0.500	0.566

Note: Table shows regression results of equation 1. Robust standard errors are in parentheses.

Table 7: Regression Results: Monthly Job Separation for Wage Quantiles (Only Employment to Unemployment)

	(1)	(2)	(3)	(4)
Wage Quantile: 1	0.007***	0.006***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Wage Quantile: 2	0.003***	0.003***	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Wage Quantile: 3	0.002***	0.002***	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Pandemic × Wage Quantile: 1	0.054***	0.052***	0.039***	0.024***
	(0.009)	(0.009)	(0.007)	(0.005)
Pandemic × Wage Quantile: 2	0.036***	0.035***	0.025***	0.019***
	(0.006)	(0.006)	(0.005)	(0.005)
Pandemic × Wage Quantile: 3	0.018***	0.017***	0.011***	0.010***
	(0.005)	(0.004)	(0.004)	(0.004)
Demographic Controls:	N	Y	Y	Y
Education Control:	N	N	Y	Y
Occ x Ind Fixed Effects:	N	N	N	Y
State Fixed Effects:	N	N	N	Y
Observations	245,149	245,149	245,149	245,149
R-squared	0.022	0.023	0.024	0.040

Note: Table shows regression results of equation 2. *"Wage Quantile: q"* and *"Wage Quantile: q"* × *Pandemic* show the coefficients $\alpha'_q s$ and $\beta'_q s$ from the regression. The coefficient shows the differential job separation rate for workers in quantile q relative to the top (4th) quantile. Standard Errors are clustered at occupation x industry Level.