Unemployment Gaps During Recessionary Periods among Different Demographic Groups

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I: Introduction

To the layman, recessions are often perceived as short-term events characterized by high unemployment, falling incomes, and reduced economic activity. However, a large body of research shows that recessions have long lasting effects on individuals' economic situations and the overall economy as well. For example, recessions disproportionately affect lower income families. This leads to less opportunity and worse economic outcomes for their children through a variety of mechanisms, such as through nutrition, educational attainment, or access to wealth.[1] Thus, economic downturns impact the future of all family members, including children, for many years after the recession. For these reasons it's important to understand the most vulnerable population during pandemics and construct appropriate relief programs.

Many studies have shown discrimination in the labor market when it comes to employment, wages, and promotions, and it wouldn't be a surprise if women and minorities become disproportionately unemployed during economic downturns. According to the Bureau of Labor Statistics, women were disproportionately affected by the pandemic-related recession from the fourth quarter of 2019 to the second quarter of 2020 with the number of employed women decreasing by 14.5 percent compared with a 12.1 percent decrease for men.[2] Although we have statistics about the percentage of people in each demographic that are unemployed, there is limited research establishing whether there is any statistical significance to these statistics and thus whether there is discrimination in the workplace when it comes to who gets unemployed. This is an important question to look into as it can inform policy-makers who want to construct effective relief policies.

[1] "Economic Scarring: The Long-Term Impacts of the Recession," Economic Policy Institute.

[2] Sean M. Smith, Roxanna Edwards, and Duong, "Unemployment Rises in 2020, as the Country Battles the COVID-19 Pandemic: Monthly Labor Review: U.S. Bureau of Labor Statistics".

This paper will contribute to existing labor economic literature by focusing on the effects of recessions on unenmployment. More specifically, this paper will focus on the probability of becoming unemployed during economic downturn given that an individual is female, and whether the probability is statistically significant and economically sizeable. This paper also looks at differences in unemployment between whites and non-white invidivuals. To my knowledge, there is only one unpublished paper that uses this approach, but with few, yet significant drawbacks such as not controlling for occupation and industry. I hypothesize that women are disproportionally laid off during recessions, but the magnitude of the unemployment gap would diminish after controlling for industry and occupation.

This paper is structured as follows: Section II provides a brief overview of relevant literature. Section III describes the data sets. The empirical strategy used in for this research is described in Section IV. Section V evaluates the results of my findings. Section VI discusses the statistical tests, relevant trends, and further implications on the labor market outcomes during recessions. Lastly, the paper concludes with a summary of the major results of the research. The appendix section includes any relevant tables.

II: Literature Review

The effects of recessions are widely known: unemployment, falling incomes, and reduced economic activity. The Great Recession, which started in December 2007 and ended in June 2009, was especially severe. GDP and the number of jobs declined by about 6 percent, the median family income declined by approximately 8 percent and the high unemployment rate persisted even after the recession was over.[3] However, the effects of the Great Recession varied depending on an individual's gender, race, and ethnicity.

Men were especially hard hit by the Great Recession leading some people to coin this recession as a "man-cession". This difference is explained by differences in occupation and industry employment between men and women. Men made up the vast majority of workers in the construction and building trades which were hit the hardest by the recession. On the other hand, women were more concentrated in the public sector which sustained employment through stimulus spending.[4] At first glance it may seem surprising that more men lost their jobs during the Great Recession given that that women and

[3] Arne L. Kallenberg and Till M. Von Wachter, "The U.S. Labor Market During and After the Great Recession: Continuities and Transformations," The Russell Sage Foundation Journal of the Social Sciences: RSF 3, no. 3 (April 2017)

[4] Michael Hout and Erin Cumberworth, "The Labor Force and the Great Recession," The Stanford Center on Poverty and Inequality, 2012

minority groups tend to get discriminated in the labor market. However, when taking occupation into account, the disproportionate unemployment of men make sense. In terms of race, African Americans and Hispanics are exposed to more unemployment than other groups during healthy economic periods and the increase in unemployment rose proportionally during the Great Recession and thus, in absolute numbers, suffered more than other groups.[5]

Although there has been some progress towards equality in the labor market in terms of wages, the racial and gender gap continues to persist. In 2015, for example, Blacks earned 75 percent as much as Whites in median hourly earnings and women earned 83% as much as men. Even when looking only at the individuals with a bachelor's degree and more education, Black and Hispanic men earn approximately 80 percent of the hourly wages of White men, and Black and Hispanic women earn only about 70 percent the hourly wages of White men of similar education level.[6]

The gender wage gap has been narrowing between 1980 to 2018 which can be attributed to women's more prevalent role in high-skilled jobs and higher levels of education. However, when accounting for relevant observable factors such as education, industry, occupation, work experience, and hours worked, there is still about 12 cents, down from 15 cents to the dollar gender wage gap which could be attributed to gender stereotypes and discrimination and differences in professional networking and in the inclination to negotiate for raises and promotions.[7]

The pandemic recession is very different from previous recessions and has even been coined "shecession", a word that first appeared in the New York Times. Alon et al. (2021) explore the women's employment in regular and pandemic recessions in various developing countries, including the United States, the United Kingdom, Canada, German, Spain, and the Netherlands. There are two main observable factors that disproportionately affected women during the pandemic recession. First, the pandemic recession had the biggest impact on sectors such as hospitality and tourism which have high female employment shares. Furthermore, the pandemic led to school and daycare closures. Mothers provide a larger share of childcare compared to fathers, so this strongly affected women's ability to work given the increased childcare needs.[8] However, even when controlling for occupation and increase in child needs which disproportionately affect women, Alon et al. (2021) find that there are still remaining

[5] Ibid.

[6] Eileen Patten, "Racial, Gender Wage Gaps Persist in U.S. despite Some Progress," Pew Research Center.

[7] Rakesh Kochhar, "Women Are Narrowing the Gender Wage Gap," Pew Research Center's Social & Demographic Trends Project.

[8] Titan Alon et al., "From Mancession to Shecession: Women's Employment in Regular and Pandemic Recessions," in NBER Macroeconomics Annual 2021, Volume 36 (University of Chicago Press, 2021),

gender gaps whose cause is not yet well understood.

The pandemic recession could also have a substantial impact on gender equality. Alon et al. (2020) find that the pandemic recession erodes women's position in the labor market in the short and medium term. This happens because of loss in labor market experience and further widens the gender wage gap in its immediate aftermath.[9] Interestingly, the researchers argue that there could be a reduction in gender inequality in the long run because of the rise in work flexibility which would disproportionally benefit women, and possible shifting of social norms in terms of sharing the sharing of childcare obligations between mothers and fathers. Their quantitative analysis shows that the pandemic recession can ultimately reduce the gender wage gap, but it would take many years to make up for women's initial skill losses.[10] Thus, it's still important to construct strategic and effective relief policies to mitigate the immediate burden that some demographics face.

III: Data

Most of the data that will be used for this research paper will come from IPUMS-CPS which integrates and disseminates microdata from the Current Population Survey (CPS). The data is a monthly U.S. household survey conducted by the U.S. Census Bureau and the Bureau of Labor Statistics. The variables used for this paper are the following:

1. *Age* which gives each person's age at last birthday. One small shortcoming as stated by the U.S. Census Bureau is that there may be inaccurate age values in the 2003-2010 samples. However, this should not have significant impact in this research paper since the age related inaccuracies mostly affect studies of people ages 65 and older.

2. *Sex* takes on two values: 1 for male and 2 for female.

3. *Race* which includes nearly 30 categories in the IPUMS CPS. I simplified this into two categories: White and Non-White.

4. *Industry* which reports the type of industry in which the person performed his or her primary occupation. There are various industry variables, such as IND, $IND1950$, and $IND1990$. The variable chosen for this study is $IND1990$ since it provides a consistent set of industry codes for IPUMS-CPS from 1968 forward.

[9] Titan Alon et al., "This Time It's Different: The Role of Women's Employment in a Pandemic Recession," Working Paper, Working Paper Series (National Bureau of Economic Research, August 2020).

[10] Ibid.

5. *Occupation* will also be controlled for. As with the *Industry* variable, there are several options for *Occupation*: OCC, OCC19650, and OCC1990. According to IPUMS-CPS, OCC1990 may be prefarable for samples from 1980 onward, which is the reason why this *Occupation* variable was chosen. This variable is very granular with over 800 occupations. As IPUMS-CPS mentiones in the variable description, it's possible to aggregate the categories into 7 broader occupational categories.

    (a) Managerial & Professional, which includes a wide variety of occupations, such as legislators, managers, engineers, scientists, therapists, lawyers, writers, artists, and entertainers.

    (b) Technical, Sales & Administrative Support: this includes occupations such technologists, technicians, pilots, computer software developers, and sales representatives.

    (c) Service Occupations: such as police, detectives, guards, waiters, guides, and barbers.

    (d) Farming, Forestry & Fishing: such as farmers, gardeners, and animal caretakers.

    (e) Precision, Production, Craft& Repairs: such as mechanics and repairers.

    (f) Operatives & Laborers: this includes machine operators, assemblers, and inspectors.

    (g) Non-Occupation Responses

6. Lastly, the dependent variable will be *WHYUNEMP* which is grouped into 7 categories. The first category includes individuals who have not lost their job during the time of the survey. The other 6 categories are all related to unemployment. The goal of this paper is to examine the unemployment gap between various demographic groups. However, the data has 7 categories and running a multinomial logit model is beyond the scope of this paper. Thus, I aggregated the 6 unemployment categories into one single group. Individuals who were not unemployed during the time of the CPS survey receive a value of 0 while individuals who were unemployment receive a value of 1. Lastly, this data includes observations who are not in the work force which were filtered out since we only care about people in the work force.

To determine which period was a recessionary period, I will be using the FRED which has data on the dates of recessions as inferred by GDP-based recessions.[11]

[11] Hamilton, James, Dates of U.S. recessions as inferred by GDP-based recession indicator, retrieved from FRED, Federal Reserve Bank of St. Louis

IV: Empirical Strategy

Since the dependent variable is binary, the most natural model to use is a logistic regression. The variable has a value of 1 if the individual is unemployed and a value of 0 otherwise. The baseline model I intend to estimate is

$$Unemployed_i = \beta_0 + \beta_1 Female_i + \beta_2 NonWhite_i + \beta_3 Age_i + \varepsilon_i \tag{1}$$

to see what the likelihood is of becoming unemployed during a recession given that an individual is a women and that an individual is a person of color. This model will be run separately for various recessions.

Next, I intend to estimate the logistic regression similar to equation 1, but include two important control variables: industry and occupation. The model is

$$Unemployed_i = \beta_0 + \beta_1 Female_i + \beta_2 NonWhite_i + \beta_3 Age_i + \delta X_i + \varepsilon_i \tag{2}$$

where the X vector is composed of industry and occupation fixed effects. Again, this model will be run separately for various recessions.

V: Results

The omitted category for gender is male, so the interpretation of the female coefficient will be relative to male. Similarily, the coefficient interpretation for Non-White is relative to Whites as that is the omitted race category. Lastly, since a logistic regression was used, the coefficient values in the result tables are the log-odds ratios, instead of probabilities. When discussing the coefficiets, however, the values will be interpreted in terms of probability. To do this conversion, I exponentiate the log-odds to get the odds ratio and then convert that to probability using the formula below.

$$probability = \frac{odds}{1 + odds}$$

In the baseline model, the coefficient for female for the 2001 recession is -0.191 and is statistically

Table 1: Results: Baseline Model

	Dependent variable:					
	Unemployed					
	2001 Recession	P-Value	Great Recession	P-Value	Covid Recession	P-Value
Female	−0.191	0.000	−0.438	0.000	0.047	0.000
	(0.029)		(0.017)		(0.011)	
Non-White	0.585	0.000	0.290	0.000	0.394	0.000
	(0.033)		(0.020)		(0.012)	
Age	−0.041	0.000	0.003	0.000	−0.017	0.000
	(0.001)		(0.0004)		(0.0004)	
Constant	−1.550	0.000	−3.303	0.000	−1.938	0.000
Industry FE	No		No		No	
Occupation FE	No		No		No	
Observations	109,193		414,325		536,004	

Notes: Standard errors in paranthesis

significant at the 1% level. This means that being $Female$ is associated with the probability of being being unemployed decreasing by 45.2%. Being $Non-White$ is associated with the log odds of becoming unemployed increasing by 0.585, which translates to a probability of 64.2%. These values make sense since men-dominated industries were strongly affected by the 2001 recession and given race-discrimination in the work force. The coefficients for $Female$ and $Non-White$ for the Great Recession regression have the same sign as the coefficients for the 2001 Recession period, as expected. However, the magnitude of Great Recession was significantly greater than that of the 2001 Recession, and this is reflected in the $Female$ coefficient of −0.438 (39.2% less probable), as industries such as Construction were severely impacted.

When looking at the coefficients for the Covid Recession, we see that the $Female$ coefficient is 0.047 and is statistically significant at the 1% leve. This translates to a probability of becoming unemployed increasing by 51.2%. The sign of the $Non-White$ coefficient has the same sign as for the other two regressions. The positive and significant $Female$ coefficient for the Covid Recession could suggest that female employees are disproportionately unemployed. However, the $Female$ coefficients for the other two recessionary periods would suggest the opposite for those recessions. The concern here is that certain sectors are more strongly affected during recessions than others. For example, the 2001 Recession and Great Recession affected male-dominated industries more, while the Covid-Recessions affected women-dominated industries more, such as services. Thus, it is important to control for Occupation and Industry.

Table 2: Results: Full Model

	Dependent variable: Unemployed					
	2001 Recession	P-Value	Great Recession	P-Value	Covid Recession	P-Value
Female	0.131	0.000	0.015	0.450	0.116	0.000
	(0.035)		(0.020)		(0.012)	
Non White	0.578	0.000	0.417	0.000	0.339	0.000
	(0.035)		(0.020)		(0.013)	
Age	−0.026	0.000	−0.017	0.000	−0.007	0.000
	(0.001)		(0.001)		(0.0004)	
Constant	−1.381	0.000	−1.430	0.000	−2.558	0.000
	(0.084)		(0.051)		(0.040)	
Industry Fixed Effects	Yes		Yes		Yes	
Occupation Fixed Effects	Yes		Yes		Yes	
Observations	109,193		414,325		536,004	

Notes: Standard errors in paranthesis

There are several interesting findings when controlling for Occupation and Industry. First of all, for the 2001 Recession, the sign for the $Female$ coefficient is now positive, suggesting that during the 2001 Recession, women disproportionately became unemployed even after controlling for industry and occupation. More specifically, women were approximately 53.3% more likely to become unemployed. The $Non-White$ coefficient for the 2001 Recession remains nearly identical as in the baseline model. During the Great Recession, the $Female$ coefficient loses its significance, which is what was initially expected. Furthermore, the probability of becoming unemployed $Non-White$ employees decreases from 64.2% to 60.3%. However, this is still an economically significant difference in unemployment probabilities between whites and non-whites. Lastly, the $Female$ coefficient for the Covid Pandemic increased and remained statistically significant, which was not expected. The probability of becoming unemployed for women during the Covid induced pandemic was 52.9%. The probability of becoming unemployed for non-whites during the Covid induced pandemic was 58.4%.The initial hypothesis was that the mangnitutde would decrease since we're controlling for occupation and industry. This results suggest that women and people of color during the Covid Recession lost their jobs disproportionately to white men.

VI: Conclusion

The results of my full model disproved my hypothesis that after controlling for occupation and industry, the likelihood of being unemployed during the Covid Pandemic for women would be similiar to that of men. However, my results show the opposite. Being a women during the Covid Pandemic is associated with 53.3% more likelihood of becoming unemployed. Although the model controls for important variables such as race, age, occupation, and industry. There are some limitations that have to be considered. The most important one being the impact of the pandemic on school closures. School closures disproportionately affect women because they tend to play a larger role than men when it comes to childrens upbringing. Thus, it could be that the $Female$ coefficient is picking up the effect of being a mother. This can be added to the full model as IPUMS-CPS data includes this information. Lastly, the Covid Recession also disproportionately affected people of color. Even after controlling for Industry and Occupation, being $Non-White$ is associated with a log odds increase of being unemployed by 0.339 which is a probability of approximately 60.3%. Literature on recessions and employment has shown that recessions have a long-lasting impact on the people affected which can span for generations. Thus, it is important to construct policies that sufficiently aid the individuals most impacted by economic downturns.

Appendix

Table 3: Results: Full Model

	Dependent variable:		
	Unemployed		
	2001 Recession	Great Recession	Covid Recession
Female	0.131***	0.015	0.116***
	(0.035)	(0.020)	(0.012)
Non White	0.578***	0.417***	0.339***
	(0.035)	(0.020)	(0.013)
Age	−0.026***	−0.017***	−0.007***
	(0.001)	(0.001)	(0.0004)
Business and Repair Services	0.544***	0.016	0.266***
	(0.147)	(0.090)	(0.058)
Construction	1.036***	0.782***	0.546***
	(0.148)	(0.087)	(0.058)
Durable Goods Manufacturing	0.181	0.182**	0.247***
	(0.147)	(0.088)	(0.059)
Entertainment	0.495***	0.280***	1.290***
	(0.154)	(0.095)	(0.058)
Finance, Insurance, and Real Estate	−0.071	−0.161*	−0.215***
	(0.159)	(0.094)	(0.062)
Mining	0.152	−0.197*	0.154**
	(0.191)	(0.116)	(0.073)
Industry NA	19.175	−2.251***	18.979
	(75.575)	(0.094)	(35.692)
Non Durable Goods Manufacturing	0.285*	0.050	0.207***
	(0.153)	(0.092)	(0.062)
Personal Services	0.090	−0.156	0.916***
	(0.157)	(0.095)	(0.058)
Professional	−0.264*	−0.315***	0.141**
	(0.146)	(0.086)	(0.056)
Public Administration	−0.461***	−0.911***	−0.751***
	(0.169)	(0.104)	(0.066)
Retail	0.343**	0.100	0.662***
	(0.143)	(0.085)	(0.055)
Telecommunications	0.069	0.071	0.027
	(0.222)	(0.134)	(0.111)
Transportation	−0.123	−0.245**	0.447***
	(0.162)	(0.097)	(0.061)
Wholsesale	−0.001	−0.301***	0.020
	(0.162)	(0.103)	(0.069)
Managerial and Professional	−1.728***	−1.210***	−0.235***
	(0.153)	(0.090)	(0.055)
Occupation NA	−1.905***	−1.341***	−0.854***
	(0.139)	(0.084)	(0.054)
Non-Occupation Responses	−1.596	0.354*	19.036
	(392.637)	(0.193)	(185.883)
Operatives and Laborers	−0.520***	−0.101	0.233***
	(0.134)	(0.082)	(0.054)
Precision Production, Craft, and Repair Services	−1.349***	−0.552***	−0.210***
	(0.140)	(0.083)	(0.055)
Services	−0.853***	−0.512***	0.224***
	(0.135)	(0.082)	(0.053)
Technical, Sales and Administrative Support	−1.255***	−0.734***	−0.244***
	(0.134)	(0.081)	(0.053)
Constant	−1.381***	−1.430***	−2.558***
	(0.084)	(0.051)	(0.040)
Observations	109,193	414,325	536,004
Log Likelihood	−18,292.990	−53,287.620	−129,023.500
Akaike Inf. Crit.	36,637.990	106,627.200	258,099.000
Note:			*p<0.1; **p<0.05; ***p<0.01