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Distributional Impact of COVID-19 Pandemic on Household Employment and Education

By

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Abstract

The economic effects of COVID-19 have been widespread and multifaceted. Researchers are just beginning to understand the extent of the economic recession and the effectiveness of implemented measures. To further expand knowledge around this issue, the current research examines post-pandemic economic shocks and their disproportionate impact on employment and education. The study relies on survey data from CPS (Current Population Survey) and BLS (Bureau of Labor and Statistics) that is aggregated on IPUMS (Integrated Public Use Microdata Series). Multiple regression analysis is performed to isolate specific category effects of the pandemic. The results show the expected distributional effects of the economic recession. These include widespread employment losses and disproportionate effects on low-paying occupations compared to high-paying occupations. Disproportionate impacts are also witnessed in different demographics. Notably, it is observed that African Americans and Hispanics experience higher employment impacts compared to their Caucasian counterparts. In response to the pandemic, liquidity-constrained households seem to have invested less in education.

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Introduction

Research Overview

The COVID-19 pandemic has had a significant impact on virtually all sectors of the U.S. economy (Jackson, 2021). The initial actions of governments, such as closing down businesses and schools, led to an unprecedented economic slowdown (Gupta et al., 2021). The impacts of these actions are likely to have short-term and long-term socio-economic effects. Although it has been almost three years since the disease was discovered, it is still uncertain whether it has entirely been eliminated. This uncertainty is primarily driven by the evolutionary nature of the disease (Altig et al.,2020). Indeed, new variants like Delta, and most recently Omicron, show that the pandemic is far from over. From a recovery perspective, the uncertainty created by the pandemic increases the difficulty of formulating macroeconomic policy responses. Today, it is clear that COVID-19 is not only a pandemic but also a major economic recession.

The severe health impacts of COVID-19 have been followed by equally sharp impacts in the labor market and education sectors (Huang et al.,2020). According to the Organization for Economic Co-operation and Development (OECD), preliminary analysis shows that the economic impact of COVID-19 has been greater than that of the 2007-2008 financial crisis (OECD, 2020). Notably, a combination of fear of new variants and unclear public health guidelines has led to value chain disruption and economic activity contraction (Hobbs, 2020). This has had a huge shock on the labor market and education sector. Millions of workers in the U.S. experienced or are experiencing a reduction or complete loss of employment (Barbieri et al., 2021). As part of the initial mitigation efforts, a lot of companies were forced to close operations.

Given these issues, the current paper attempts to quantify the consequences of COVID-19 in the labor market and education sector. First, the paper describes the distributional effect of

COVID-19 on employment using Current Population Survey (CPS) and Bureau of Labor and Statistics (BLS) data. In particular, the study examines how the pandemic resulted in sharp increases in unemployment, exit rates, and reduced hiring rates. Second, the disproportionate impact of job losses on the wider economic indicators is examined. Third, the study illustrates the effects of labor shocks on education by examining enrollment rates, dropout rates, education spending, and rates of school participation.

CPS data show a significant drop in employment rates at the onset of the pandemic. In April 2020, the unemployment rate had increased to 14.3%, the highest since the start of the collection of unemployment data in 1948 (Falk, 2020). Compared to the February unemployment rate, around 20% of people who were working in February no longer had their jobs by April. Participation in the labor force also declined to 60.2% in April 2020 (Falk, 2020). This was the lowest level since the 1970s. Between January 2020 and April 2020, nonfarm payrolls lost around 22.1 million jobs. Self-employed workers were equally affected. According to BLS data, the number of self-employed workers fell by 12.6% between February 2020 and April 2020, at the height of the pandemic (Falk, 2020). The 12.6% drop includes individuals who were employed but declared themselves absent from work. In a different study, Fairlie (2020) found that the percentage of self-employed workers fell by approximately 28% in the same period.

Anecdotal evidence suggests that some economic sectors were more severely affected compared to others. High job losses were particularly experienced in the service sector compared to other sectors. The hospitality and leisure sector had the highest burden (Falk, 2020). The sector lost the highest number of jobs. The rates of unemployment in this sector have also remained high during the pandemic. Other highly affected sectors include the education and services sectors. Like most governments, the first response to the COVID-19 pandemic by the

U.S. government was the shutdown of schools and all school-related operational activities. As will be illustrated below, this action has resulted in significant losses for the sector.

To quantify the education effects of COVID-19, the current study tests the correlation between high unemployment rates and investment in education. High unemployment rates mean less money for households. It can therefore be expected that high unemployment rates would result in less investment in education (Azevedo et al., 2021). These assumptions can be drawn from the effects of previous economic recessions. For instance, studies have shown that the 2007-2008 financial recession resulted in stretched household budgets for both households and governments (OECD, 2020). As such, it can be argued that the labor shocks of COVID-19 may squeeze household budgets. This may in turn reduce the ability to fund education investments.

There is also the aspect of human capital loss, especially in children. Lack of parental resources and time investment in education can result in a substantial effect on the development of children. According to researchers like Manuelli and Seshadri (2014), the welfare effects of school closures are likely to be felt in the long term. These effects are also likely to have disproportionate effects on households. Children from low-income households may suffer more compared to those in high-income households. This is because low-income households primarily rely on education investments from governments. Moreover, low-income parents may react differently to school closures compared to high-income parents. High-income parents may decide to increase investment in education as a response to the pandemic. Low-income parents may not have the financial resources for such a response.

Inequities in health, income and education have put racial minorities at increased risk of contracting and dying from COVID-19. According to researchers like Cowger et al. (2020), these inequities are a result of decades of unfavorable government policies that have created a socio-economic disadvantage for African Americans and Hispanics. For instance, Blacks and Hispanics are located in high-density neighborhoods that had the most infections at the height of the Pandemic (Hardy and Logan, 2020). Individuals in these areas also significantly rely on public transportation, which increases COVID-19 incidence rates.

The initial restrictions were effective in bringing down the rate of new infections. However, the actions ushered in a full economic crisis. The crisis was accelerated by business closures and industry closedowns. The economy was, therefore, unable to produce and sell goods (Bartik et al., 2020). The U.S. GDP had been rapidly expanding in pre-pandemic periods. The pandemic resulted in the biggest drop in GDP. This was around a 9.1% drop in GDP in the first and second quarters of the pandemic year. This is illustrated in Figure 1 below. Economic shocks had an expected impact on the labor market.

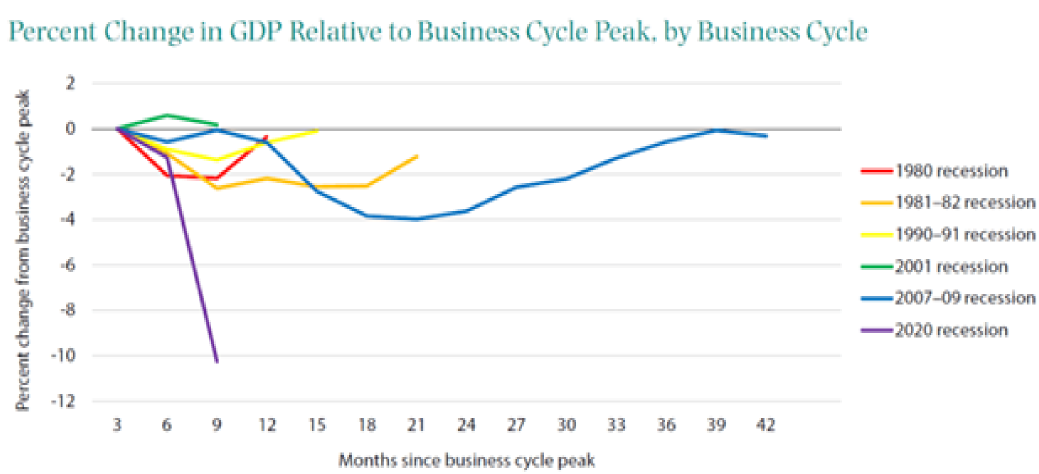

Figure 1. Percent changes in GDP caused by COVID-19 (U.S. Bureau of Economic Analysis)

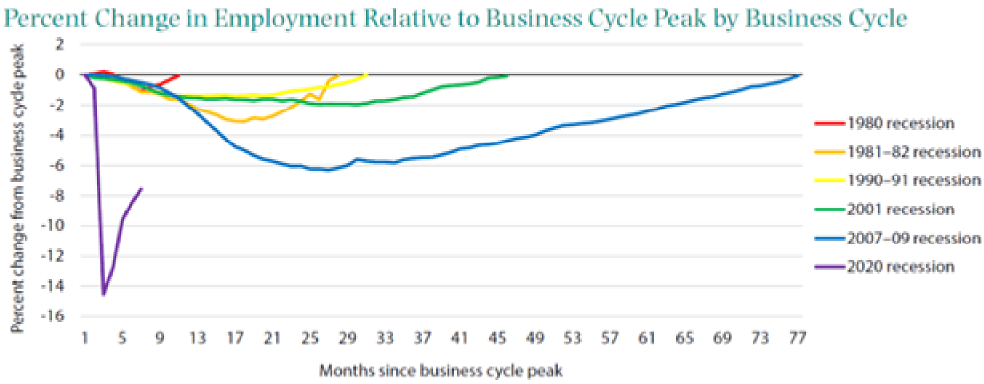

Figure 2. Percent changes in employment caused by COVID-19 (U.S. Bureau of Economic Analysis)

Figure 2 shows the changes in employment caused by percent changes in GDP. Before COVID-19, the U.S. had 113 months of job growth. As indicated earlier, nonfarm employment fell by 20.5 million. The employment crisis was felt by all categories of workers. However, researchers like Stevenson (2020) have shown that the impact was severe for women, Blacks, and low-wage earners. For instance, in May 2020, the gender with the highest nonfarm jobs was men. This was different from historical trends where women had more nonfarm jobs compared to men (Stevenson, 2020). Less educated workers were also heavily affected.

The effect of COVID-19 on employment can also be assessed by changes in consumer spending. Recent studies, like that of Chetty et al. (2020), have illustrated the effect of COVID-19 on the labor market caused by a significant reduction in the spending of consumers, especially affluent consumers. At the onset of the pandemic, spending in high-income households was reduced. Spending cuts in the high-income level were influenced by health reasons rather than reductions in income levels. Reduction in spending was specifically concentrated in businesses that provide in-person services, such as restaurants and schools (Cox et al., 2020). This resulted in the loss of revenues for businesses. Businesses then passed the loss to employees, especially low-wage workers (Chetty et al., 2020). As a result, unemployment rates increased.

Figure 3 shows the huge decline in household spending. The decline was around 8.7% in comparison to pre-pandemic periods. This was the largest month-to-month decrease in U.S. history. The decrease in retail spending was, however, not consistent across all areas. Expectedly, areas such as pharmacies and groceries experienced demand increases. Plunges in spending volume were high in retail areas such as leisure spending, clothes, and food services. In August, retail sales had increased to a higher level compared to its 2019 level. These shifts in spending are illustrated in Figure 3 below. The Figure shows changes in retails in different recessions.

COVID-19's effect on employment and education sectors can also be assessed from the ripple effect of reduced industrial production. Output in mining and utility sectors has significantly been disrupted by COVID-19. Approximately 13 million Americans are employed in these sectors (BLS, 2020). This is especially true for companies with physical jobs that cannot be completed remotely. The sector that had less severe effects compared to the 2007-2008 crisis is the construction machinery sector.

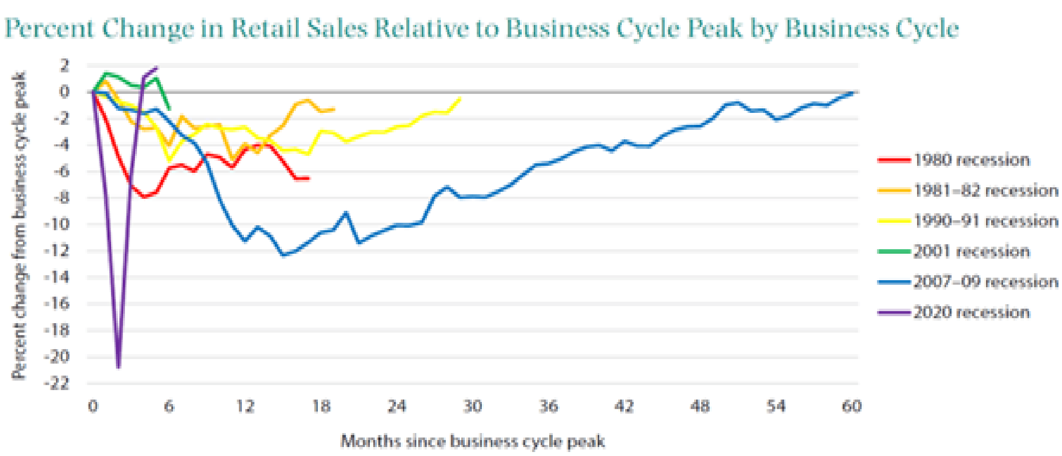

Figure 3. Changes in Retail Sales at different Business Cycles (U.S. Bureau of Economic Analysis)

The sectoral impact of COVID-19 has been particularly severe on small businesses. In the U.S., half of the private sector workers are employed by small businesses. The majority of businesses in the U.S. are, therefore, small businesses. Any economic shocks in small businesses result in a direct effect on the employment rate. Between February and April, small businesses reported a significant fall in revenue which impacted their ability to retain workers.

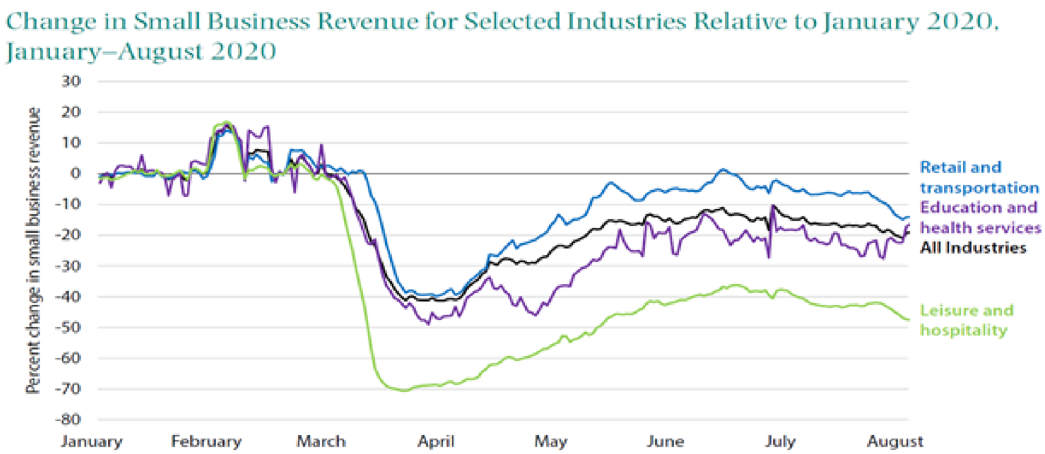

Figure 4. Changes in Small Business revenue during COVID-19 (U.S. Bureau of Economic Analysis)

Severe declines were experienced in the Leisure and Hospitality Sector, followed by the Education and Health services sector. In comparison to January 2020, the August 2020 average revenues for these businesses had fallen by 47.5% in the Leisure and Hospitality Sector and by 16.4% in the Education and Health services sector. In all businesses, revenues had fallen by 19.1% in comparison to the levels in January 2020.

Research Significance

The COVID-19 pandemic is not over. Therefore, the current research provides a highly uncertain assessment of disruptions in both the labor market and the education sector. After the 2007-2008 financial crisis, the recovery in the labor market was prolonged. This led to a further negative cycle that further slowed down economic recovery. Some researchers argue that some sectors have not fully recovered from the 2007-2008 financial crisis (Lee et al., 2020). Although it is still early to assess the full economic effect of the pandemic, it is essential to recognize any economic effect early (Lee et al., 2020). This allows the enactment of policy measures that can prevent further deterioration of economic activity.

The need for the current research is borne from the unique nature of the economic effect of the COVID-19 pandemic and its unprecedented ripple effect. Indeed, the labor and education sector effects of the pandemic is not fully understood. Unlike other financial crises, the standard ways of measuring employment and unemployment may not be applicable to the recession caused by the pandemic. Although most people were not working, they did not entirely lose their jobs. Some people lost their jobs but were not looking for new jobs because of personal responsibilities at home. Some people also worked shorter hours than usual.

Review of related Literature

Effects of COVID-19 on employment and education have in the past year grown to an area of significant scholarly interest. For instance, a wide range of studies has attempted to assess the impact of the pandemic on different job types. In a study by Dingel and Neiman (2020), the researchers assess the type of occupations that can be performed from home (remotely). Building on the study, research by B´eland et al. (2020) and Montenovo et al. (2020) show that jobs that require less contact are better suited for remote conditions. In a study by Kahn et al. (2020), the researchers assess the relationship between COVID-19 and job postings.

Several studies have attempted to highlight the disproportionate impact of COVID-19 on disadvantaged groups. These include minority workers, women, children, and less educated workers. According to Reichelt et al. (2020), Gezici and Ozay (2020), and Alon et al. (2020), these groups appear to be highly affected by the COVID-19 pandemic compared to other groups. Some studies have also attempted to examine the impact of state interventions on the labor market. In this context, the studies examine the variations and timings of the impact of intervention strategies. Studies report different findings. Researchers like Rojas et al. (2020) and Chen et al. (2020) report adverse labor market shocks.

According to these studies, countries, and states that had the most significant outbreaks had the most enormous impact on the labor market. Some studies also examine the role of voluntary social distancing. This is where people voluntarily adjusted their social behaviors during the pandemic (Kong and Prinz, 2020). According to Dreger and Gros (2021), stay-at-home closures had a significant effect on the revenues generated by businesses. Most studies attempting to assess the initial impact of COVID-19 relied on economic data between February and April 2020. This initial data captured the early market effects of the pandemic, especially during the implementation of restrictive market measures.

Some researchers have also attempted to offer global and regional assessments of the impact of COVID-19 on the labor market. For instance, a cross-country study by Adian et al. (2020) found that SMEs (Small and Medium Sized Enterprises) in 13 countries suffered the highest effect compared to large companies. In a study by Apedo-Amah et al. (2020), the researchers find significant adjustments in the intensive margin of hours and temporary work stoppages. In Bachas et al. (2020), the researchers model the economic shocks to firms using administrative data from different countries. The study finds a 5-10% reduction in annual payroll.

Very few studies have assessed the distributional effects of the pandemic. In a study by Dang et al. (2020), the researchers assess the distributional impacts of the pandemic on income levels. The researchers use country-level surveys from China, Italy, Japan, the UK, and South Korea. The findings show that poor people felt the biggest impact of the pandemic. The study also shows that the poor were less likely to undertake behavioral changes. In a different study, Decerf et al. (2020) examine the poverty effect of the pandemic using mortality and poverty level data. Specifically, the researchers use mortality and poverty data to investigate how COVID-19 influences the number of years spent in poverty. The findings show that poor people may spend 15 additional years in poverty because of the pandemic.

An interesting trend in this field is the use of alternative data to measure the impact of COVID-19. These types of analyses usually rely on official labor statistics from government agencies. However, these types of data are published in very low frequencies. Researchers have resorted to the use of proxies that can infer labor market adjustments. Examples include job postings, electricity consumption, and bank data. For instance, a study by Kahn et al. (2020) utilizes job postings to measure the economic effects of COVID-19. Chetty et al. (2020) use private-sector data to measure the economic impacts of COVID-19. In a different study, Cox et al. (2020) used household-level bank data to assess the economic impacts of COVID-19.

In a study by Abay et al. (2020), the researchers use data from google searches to assess the economic demand for different services in different countries. The study finds a substantial drop in demand for services in the restaurant, leisure, and retail sectors. In a study by Sampi and

Jooste (2020), google mobility data are used to forecast economic data in different sectors. The analysis predicted a fall in industrial production caused by the direct effects of the pandemic. All these studies point to market-level disruptions caused by a significant reduction in spending.

Several studies have also examined the ability of workers to work from home in different sectors. In a study by Garrote Sanchez et al. (2020), the researchers investigate the job market in the EU and find that only 30% of the jobs can be completed remotely. In a similar assessment, Gottlieb et al. (2020) find that only 20% of jobs can be completed remotely in low-income countries. In comparison, 37% of jobs can be completed remotely in high-income countries. These findings were consistent with that of Hatayama, Viollaz, and Winkler (2020), who found that more jobs in developed counties can be completed from home compared to developing countries.

A different set of studies sought to examine different policy decisions and their impacts. In research by Alon et al. (2020), the researchers developed a macroeconomic model that measures the effectiveness of COVID-19 policies in developed and developing countries. Precisely, the studies measure the effectiveness of lockdowns. Expectedly, the researchers conclude that lockdowns are not effective in developing countries. In the study by Maloney and Taskin (2020), the relation between social distancing and economic activity is assessed. The study shows the reduced economic activity as a result of social distancing behaviors.

A number of studies have also focused on the educational impact of COVID-19. Studies by Psacharopoulos et al. (2020) and Azevedo et al. (2020) assess the economic impact of school closures among affected cohorts. The researchers predict poor quality learning, which may result in reduced income among the cohorts. While assessing the impact of non-pharmaceutical interventions, a study by Demirgu¨c et al. (2020) found that early implementation of economic restrictions resulted in better economic outcomes. From a similar standpoint, the International Monetary Fund (2020) explained that early mitigation efforts had better economic outcomes compared to late efforts. An investigation by the International Labor Organization (2020) investigates economic disruptions in the labor market. The investigations found that workplace closures resulted in significant losses in labor income.

The current research complements these studies in several ways. First, the study shows how CPS data and data from IPMUS can be used to assess the distributional effects of COVID-19 on the labor market and the education sector. By doing this, the study examines the differential impacts of employment losses at different levels of the labor force. Second, inequalities in the sectors are assessed using stocks and flow from CPS data. Going by the above literature review, it can be hypothesized that employment shocks will be greater in disadvantaged levels of the economy, such as less educated workers, women, Blacks, Hispanics, and younger workers. In the education sector, the study measures employment effects on investment in education and potential human capital losses.

The current paper contributes to the growing literature that attempts to study the effects of COVID-19. As assessed above, previous studies have correctly shown the impact of COVID-19 on the employment rate. However, very few studies have focused on the distributional effects of COVID-19. In this context, distributional effects refer to the resultant redistribution of costs and gains from the COVID-19 pandemic. This is expressed as a cost to a particular group (sector) and a gain to another group. Further, the research links employment effects to outcomes in the education sector. This is advantageous in several ways. First, the study gives more macroeconomic insight than what is available on the association between employment and investment in education. Second, the study can be used to make future inferences about trends in economic inequalities. Overall, the study makes a significant empirical contribution to the study of the effects of COVID-19 on the labor and education sector.

Association between COVID-19 Labor Shocks and Self-Employment

There has also been research interest towards the impact of the pandemic on the state of self-employed individuals. Unlike formally employed individuals, self-employed workers may have been impacted by the pandemic as a result of an increase in household-related activities. For instance, it can be argued that given the closing of schools and day-care facilities, the role of self-employed individuals in homes doubled (Sevilla and Smith, 2020). Moreover, gender differences may have contributed to the increased complexities of these issues. Female self-employed individuals are likely to have higher effects compared to men. This is primarily because of gender norms.

According to BLS data, between Feb-April 2020, there was a 12.6% reduction in the percentage of self-employed workers in the U.S (BLS, 2020). This estimate includes individuals who are absent but employed. The fall in employment rates also affected unincorporated self-employed workers. The success of self-employed individuals is usually affected by general economic factors and the prevailing state of employment (Rissman 2006). These individuals engage in work that requires a high level of manual activities. Such jobs were in lower demand during the pandemic. Extant research shows that the employment hours of self-employed individuals are affected by cyclic economic patterns (Pabilonia, 2014). As such, high employment rates result in increased inflows because of a lack of viable job opportunities. However, increased entry leads to reduced pay in the sector.

Labor shock dynamics also have an impact on coupled households and childcare. Coupled households make collective decisions regarding income, parenting, and time spent on childcare. Because of pandemic-related restrictions, there has been an increase in the demand for childcare. In previous recessions, pandemics led to men spending more time in childcare (Morrill and Pabilonia, 2014). This action points to a more favorable labor effect of the pandemic from the perspective of reversed gender roles.

Even for self-employed individuals, service-oriented industries suffered the highest effect compared to other formal industries. Women, especially those with children, were highly affected compared to men. Notably, service-oriented industries that mainly employed self-employed women were classified as non-essential (Alon et al., 2020). As illustrated above, the inability to work in these areas could also be exacerbated by increased childcare responsibilities in homes brought about by the closure of schools and child-care centers. Cumulatively, these affected the ability of self-employed individuals to find meaningful employment opportunities.

According to Alon et al. (2020), the effects of the pandemic on self-employed individuals were highest in April 2020. The effects were reduced a little around May 2020. As a result of shutdowns, coupled women who are primarily engaged in self-employed activities could not find time to work. The hours spent in employment were therefore significantly reduced. The negative effect of such situations was high if their spouse could not work at home. In households where spouses could work at home, the effects were reduced.

Impact of COVID-19 on Education

The pandemic increased reliance on remote learning. However, the pandemic came at a time when most educational institutions were not prepared to exclusively offer remote learning. According to the OECD, most schools found that the inadequacy of learning facilities significantly impacted learning during the pandemic. COVID-19 measures are particularly not ideal within a school environment. The distances cannot accommodate schools with high numbers of students and limited resources, such as public schools (OECD, 2021). Moreover, there is a variation in the effect of the pandemic between different education levels. According to OECD, universities have better adapted to remote learning because of the low number of learners and ease of access to resources.

The pandemic has had a tremendous effect on vocational training institutions (VET) in the U.S. Compared to universities and other educational institutions, VETs are dependent on work-based learning. This was significantly affected by social distancing measures during the pandemic period. This is a considerable concern given the role of the institutions in ensuring alignment between training and job requirements. The institutions also play a critical role in enabling economic recovery during recessions. 60% of total learning time in VETs is practical. Such learning cannot be completed remotely.

Data and Methodology

The current study examines these factors using data from the CPS and the U.S. Census and American Community Survey microdata (IPMUS). CPS is the premier source of labor, and statistical data in the U.S. IPMUS harmonizes microdata from different sources. The analysis will map the unemployment rate of individuals across different categories and within the pandemic period. This is through February, March, and April of 2020. Changes in employment rates between these months will be measured. Different occupations and sectors are compared according to the level of wages before the pandemic and after the pandemic. To isolate the effect of the pandemic on employment, a regression model is developed. Specifically, the model assesses the impact of the pandemic at different points of the period and in different industries.

The first step is the construction of employment flows. This analysis is based on monthly data from the Current Population Survey (CPS). The employment flows are extracted from the CPS data as per the methodology given by Madrian & Lefgren (1999). In this case, monthly filings are matched using IDs. The matches are then confirmed using sex, age, and race. The sample only includes non-institutionalized civilians. The target population is 16 years and above.

Usually, the CPS records employment data using a specific reference week. At the beginning of the pandemic, the reference week for March 2020 was used. This was the week of March 8th to 14th. For April, the reference week was April 12th to April 18th. Notably, the March survey did not fully capture the effects of the pandemic. There were no restrictions or social distancing measures in the early periods of the pandemic. March data are therefore not conclusive. For instance, initial unemployment insurance claims were 250,892 in the week of March 14 (ended) (BLS, 2020). This number significantly increased in the weeks after to unprecedented levels.

The current analysis focuses on CPS data given in April 2020. Seasonal adjustments are made using data from previous years. The patterns are computed using CPS weights. Each month, the CPS surveys between 95,000 and 100,000 individuals. During the pandemic, the response rate was meager. Only 85,000 people were surveyed in March, and only 82,000 were surveyed in April (BLS, 2020). It can therefore be observed that attrition from the sample reached 13% during the pandemic.

Figure 5 shows the aggregate patterns over time – extracted from CPS data. The data compared the aggregate employment patterns since 1976. The employment rate is given as the blue line. The line shows all individuals categorized as employed per month. The red line also shows the employment rate but excludes individuals thought to have been incorrectly classified during the pandemic. In April 2020, a large number of individuals classified themselves as 'employed but out of work". These reasons were initially not enumerated by the CPS. This group grew from 0.5% at the beginning of the pandemic to 5% in April 2020. According to the BLS, the individuals should have been classified as temporary layoffs.

CPS data further shows that almost 20% of individuals who were employed but absent from work still received salaries from their employers. For these reasons, the adjusted rate was computed. This is shown by the redline. The redline adjusts for individuals with three sets of circumstances; absent from work because they were unemployed, absent from work for other reasons, and those paid but absent from work.

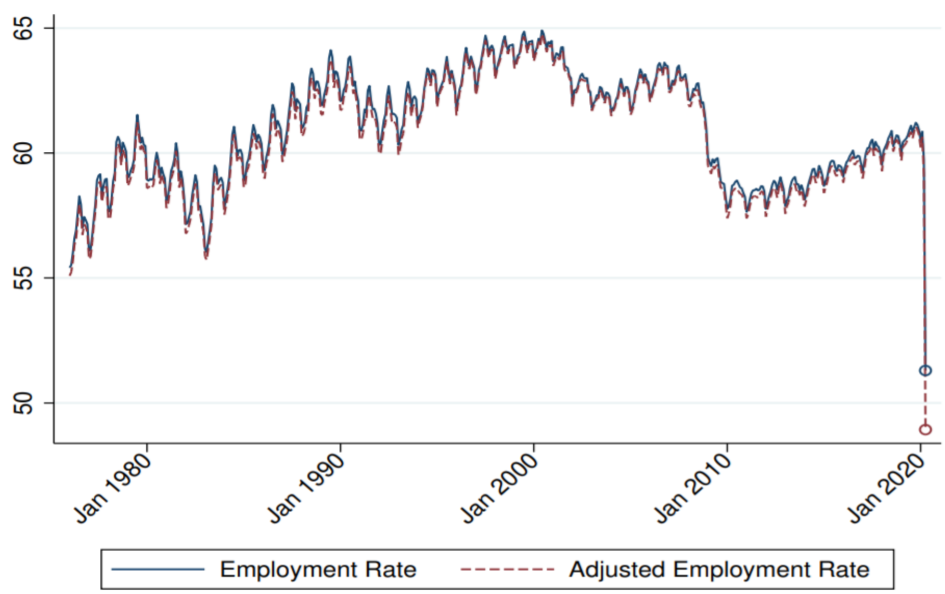

Figure 5. Movement of the Employment Rate (BLS, 2020)

Irrespective of whether the decline is adjusted or not, it is very unprecedented/dramatic compared to historical trends. According to statistics from BLS, the official employment rate moved from around 60% in February to 51% in April 2020. In the adjusted employment rate, the employment rate falls from the above rates to 59% and 48%, respectively. The rest of the analysis utilizes the adjusted employment rates for the period between February and April.

CPS data can also be used to illustrate outflows and inflows in the U.S. economy. Outflows and inflows are assessed as a percentage of the previous month's employment rate. This results in Figure 6 and Figure 7 below.

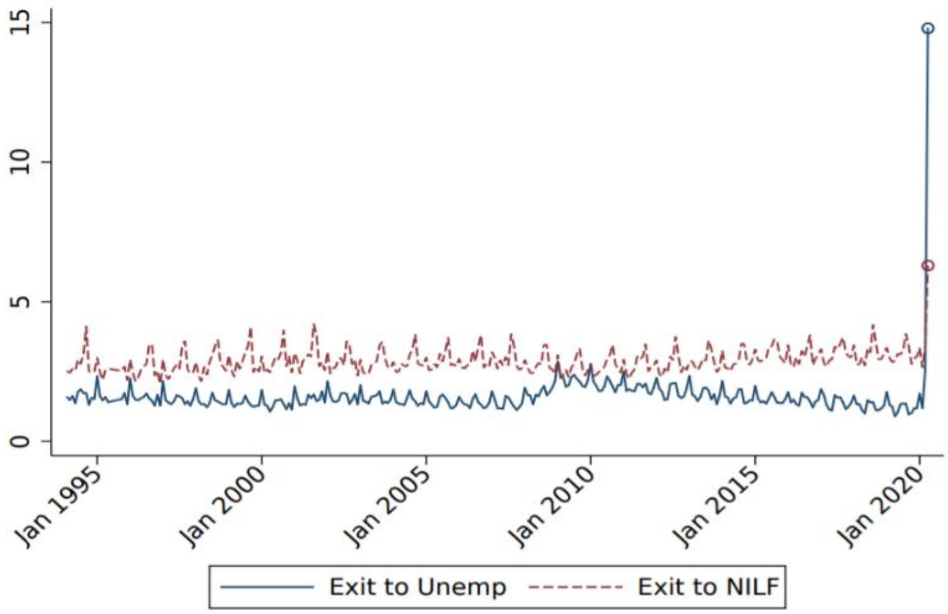

Figure 6. Employment outflows (BLS, 2020)

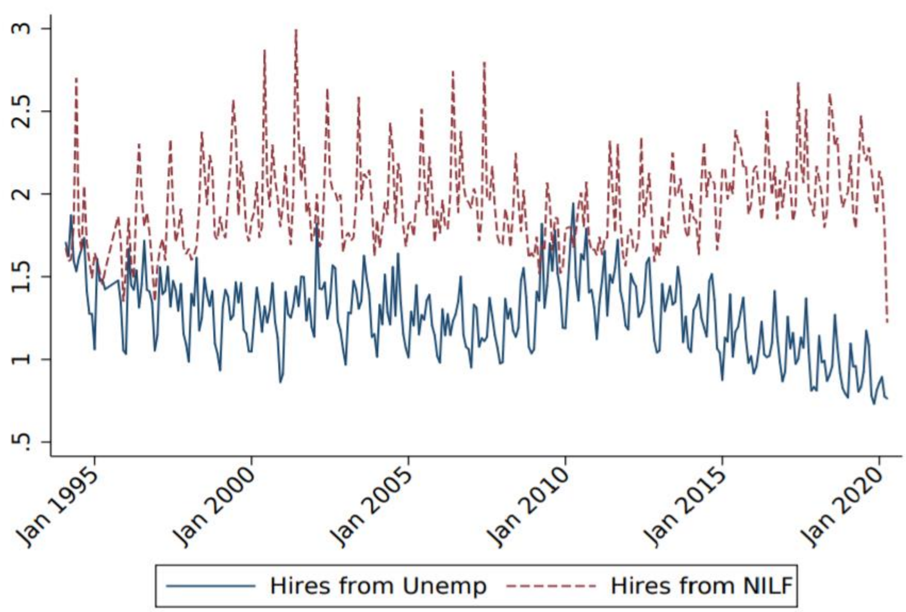

Figure 7. Employment outflows (BLS, 2020)

The Figures show the percentage of flows in the labor market, which includes the percentage of individuals exiting employment and those employed. The adjustment excludes individuals who are absent from work but are considered employed. From Figure 7, it can be seen that outflows from employment, both in adjusted and non-adjusted terms, increased significantly in April 2020. The exit rate from employment rose to unprecedented levels compared to other months. This shows that around 20% of individuals lost their jobs between February and April.

According to Figure 7, the inflow rate also changed dramatically. Between 2015 and 2019, the inflow into employment was around 1%. However, in March 2020, the rate dropped to 0.78%. In April 2020, the rate had reached 0.76%. Although the unemployment rate reduced, hiring was very stable in April 2020. As such, the result shows that unemployment was because of non-employment as opposed to a reduction in hiring. Notably, this is different from patterns observed in other recessions. In previous recessions, unemployment rates increased primarily because of reduced hiring. This is as described in studies by Elsby et al. (2009), Shimer (2012), and Fujita & Ramey (2009).

Modeling the exact Effect of the Pandemic from Adjusted Time Trends

The current paper attempts to assess the heterogeneous effects of the pandemic from different perspectives. These include different industries, demographic groups, and occupations. Distinguishing pandemic-related effects from seasonal adjustment facilitates accurate estimation of the heterogeneities of employment effects. Using CPS data from between January 2015 to April 2020, several multiple regressions are performed. Specifically, regression is performed on grouped data according to the factor of interest. The groups may be occupations, industries, and demographic groups.

In general, the following regression model is used for the specific group of interest;

$Y \ = \gamma_g D_{m(t)} + \alpha_g D_{y(t)} + \theta_g D_{2020M3} + \delta_g D_{2020M3} + \epsilon$ **Equation 1**

In this case;

Y is the dependent variable in the period under analysis. This is period between g *(February)* and t *(April)*. For any specific group, this is the unemployment rate.

The regression also incorporates hires and exits data. The specific month under analysis is given by the variable $D_{m(t)}$. The model also considers seasonal variation of the employment rate in the group under analysis. The seasonal variation is captured by γ_g. The variable $\alpha_g D_{y(t)}$ captures the year-by-year variation in a specific group. $\theta_g D_{2020M3} + \delta_g D_{2020M3}$indicates the months under analysis. In this case, the months are March and April 2020.

March 2020 is included to capture the initial effects of the pandemic. The main coefficient under investigation is δ_g. The coefficient shows the level of changes in the variable of interest. The analysis aims to show the pandemic related effects on the employment rate. Specifically, a two-month period is used because the effects of the pandemic starts to gain trend in March 2020.

Distributional Effects of COVID-19 on different Sectors

The pandemic resulted in a wide range of effects in many sectors. An unprecedented production slowdown was witnessed in the manufacturing sector. There was a time when only essential businesses were required to operate, and other businesses were to operate remotely. As illustrated above, consumer spending was severely reduced in restaurants, hotels, gyms, and other non-essential service businesses. The current analysis, therefore, hypothesizes a wide range of heterogeneous impacts on different facets of the economy.

Impacts on Occupations and Industries

To assess the impact of the pandemic on occupations and industries, the current paper relies on the methodology given by Acemoglu and Autor (2011). The analysis begins by ranking different occupations according to wage. The rankings are based on hourly wages at different periods (after pandemic and pre-pandemic periods). This is from January to February 2020. Occupations are ranked from lowest to highest in terms of pay. The categories are based on the 2-digit occupation SOC (Standard Occupational Classification) codes. This is a federal classification system that categorizes workers.

The rankings are computed by assessing the mean hourly wages in the pre-pandemic period between January and February 2020. The hourly wages are taken directly from CPS data and divided over the given time period. Examples of low-paying occupations are Cleaning and maintenance, Personal care, and Food Preparation. The highest paying professions are Legal, Management, Computer and Mathematical Operations, and Finance. These occupations are ranked in Table 1 below. The current analysis also focuses on different industries. There are 13 different industries under analysis. Using the same criteria, industries are ranked from highest to lowest. Expectedly, the highest paying industries are Mining, Financial Services, and Legal consulting. On the other hand, the lowest paying industries are Trade, Hospitality, and Leisure. These are highlighted in Table 2 below.

The second assessment focuses on the impact of employment losses on different occupations. This is summarized in Figure 8 below. Figure 8 is a plot of the coefficient of the regression equation. The plot is computed for all the occupations under analysis. The analysis is completed at a 95% confidence interval. It shows the changes in the dependent variable as of

April 2020. The Figure shows percentage changes in the employment rate across different occupations (highest to lowest paying) as per the SOC categorized table.

Type of Occupation	2-digit SOC Code	Ranking 22-highest, 1-lowest	Changes in Employment (Emp/Pop) (Feb- April 2020)
Computer and Mathematical	15	22	0.023
Legal Profession	23	21	-0.069
Architecture	17	20	-0.11
Management	11	19	-0.49
Financial Operation	13	18	-0.27
Science Sector	19	17	-0.01
Healthcare	29	16	-0.44
Arts and Media	27	15	-0.33
Education	25	14	-0.57
Social Work/Community	21	13	-0.05
Maintenance	49	12	-0.33
Construction	47	11	-0.82
Protection Service	33	10	-0.17
Sales	41	9	-1.32
Admin	43	8	-1.01
Production	51	7	-0.83
Transportation	53	6	-1.01
Healthcare Support	31	5	-0.27
Cleaning	37	4	-0.5
Fishing Farming and Forestry	45	3	-0.03
Personal Care	39	2	-1.02
Food Preparation	35	1	-1.79

Table 1. Ranking of different employments and changes caused by pandemic (BLS, 2020)

Figure 8 shows a clear pattern observed during the pandemic. The impact of the pandemic was diverse across different occupations. Notably, lower-paying occupations had a huge percent change in occupations compared to higher-paying occupations. Specifically, in 12 of the low-paying occupations, there is a significant change (decline) in the rate of employment.

Some occupations did not have a big dip in the employment rate. These occupations were Farming and Fishing. The opposite effect was experienced in high-paying occupations such as Architecture. There were mild increases in employment rates in high-paying occupations such as Architecture.

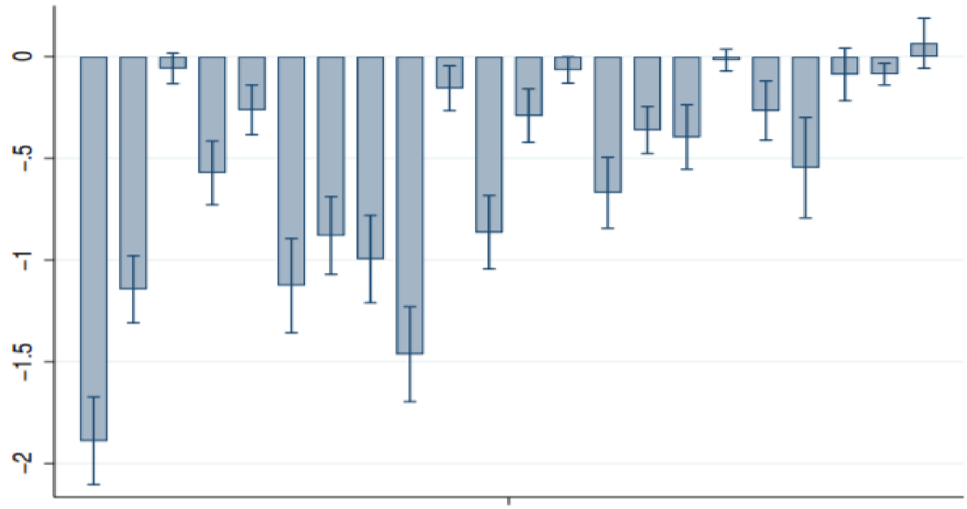

Figure 8. Percentage change of employment (Across occupations)

The graphs candlesticks correspond to the values in Table 1. For instance, the left most bar represent the food preparation occupation (-1.79). Computer and mathematical occupation is represented by the right most bar (0.023).

Type of Industry	BLS Code	Ranking 13-highest, 1-lowest	Changes in Employment (Emp/Pop)
Mining and Extraction	2	13	-0.04
Financial Services	8	12	-0.33
Professional Services	9	11	-0.91
Administration	13	10	-0.14
Information Tech	7	9	-0.14
Manufacturing	4	8	-0.94
Construction	3	7	-0.95
Education	10	6	-2.23
Transportation	6	5	-0.47
Services	12	4	-1.05
Trade	5	3	-1.47
Agriculture	1	2	-0.03

Hospitality	11	1	-2.54

Table 2. Employment changes according to industry (BLS, 2020)

Figure 9 and 10 show the exit and hire rate of employment across occupations. The hires and exit rates are computed in the same order as in Table 1. The rates are computed as a percentage of employment in the period under analysis. In this case, the rate in April is cumulative for the two months period. In this context, the employment inflows and outflows are easily comparable. These Figures are also consistent with the findings given in Figure 8. Comparing Figure 9 and 10, it is clear that the magnitude of exits was higher compared to hires.

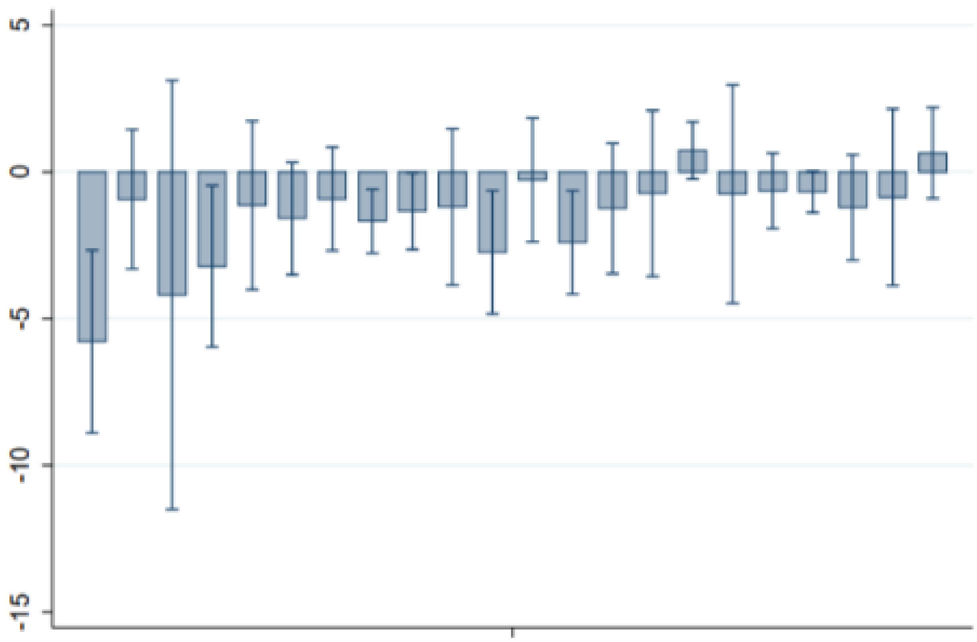

Figure 9. Hires in the period of analysis

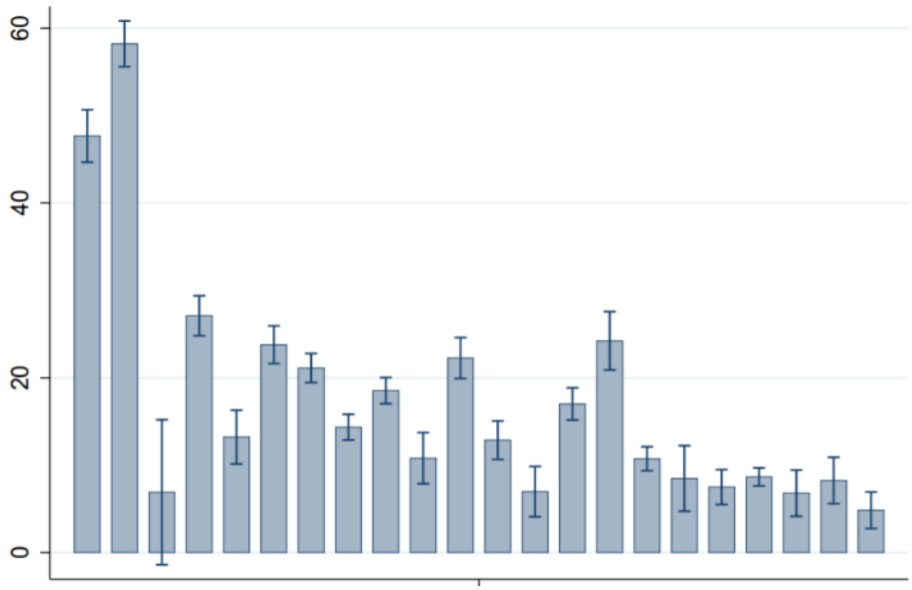

Figure 10. Exits during the period under analysis

In Figure 9 and 10, most occupations don't show statistically significant reductions in hiring in the month of April 2020. The cleaning and hiring occupation registered a slight decline in new hires. Similarly, other low-paying occupations have decreased new hires. Figure 10 shows a significant drop in the number of people employed between February and April. This reduction is similar across other low occupations such as transportation, maintenance, trade, and production.

Changes in employment during the period can also be examined at the industry level. This assessment is given in Figure 11. The Figure illustrates employment losses across all 13 industries and according to the listing given in Table 2. Expectedly, there is a visible disproportionate impact of the pandemic. Industries such as Leisure suffered the highest effect compared to industries such as Mining, Public Administration, and Agriculture. Changes in employment rate during the pandemic are also measured. This is given in Figure 12. The Figure shows the shared distribution of employment losses across industries.

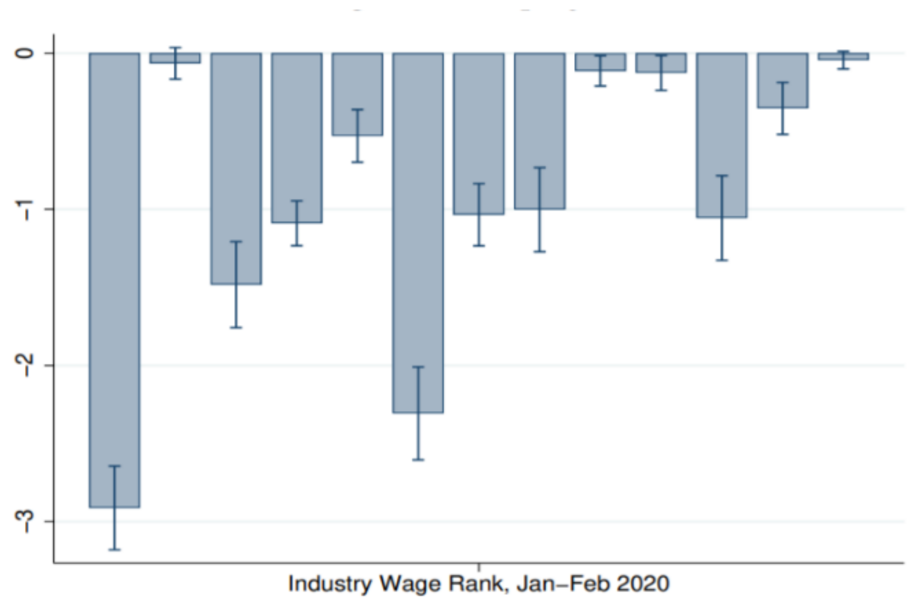

Figure 12. Changes in employment rate across industries in the pandemic period

Changes in industry flow are also examined in terms of hires and exits. This analysis is given in Figure 13 and 14. For most industries, the rate of hiring did not drop significantly in the period under analysis. As expected, some industries have larger declines than others. These are Hospitality, Information, and Construction. Low exit rates were experienced in higher-paying industries such as Financial Services, Professional Services, and Mining.

Figure 13. Hires across industries

Figure 14. Exits across industries

The changes in raw employment rates in the period under analysis are also examined. This is performed using the refined industry and occupation data. Each occupation is assessed using percentiles that are weighted as per the average wage in the period just before the pandemic. These changes are plotted in Figure 11 below. The Figure gives an overview of the per capita changes in the rate of employment for all occupations. The Figure gives a more detailed illustration of the heterogenous and disproportionate impact of the pandemic. According to the Figure, occupations with the significant declines are those that are ranked lower.

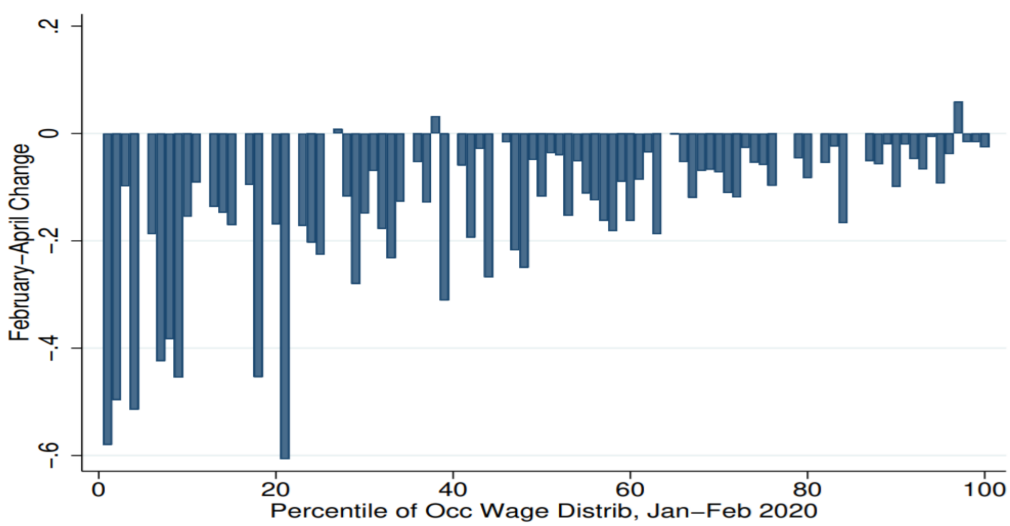

Figure 15. Percentile changes in employment rate across occupations

The findings show the heterogenous impact of labor effects on education. At the initial phase of the pandemic, the spatial effects for educated and less educated workers were similar. However, the effects changed as the pandemic progressed. Less educated workers experienced higher job losses.

The analysis shows a general disproportionate impact of the pandemic on the rate of employment. Changes and declines in employment rates and hires seem to be higher in low-paying occupations compared to high-paying industries. To gain deeper insights into the impacts of the pandemic, two industries are independently assessed. These are the Leisure and Services industries. These industries had the largest exit rates from employment. This analysis is given in Figure 15. The Figure shows a positive correlation between exit rates and wage rank for the two industries. Service industries and occupations have the highest exit rates.

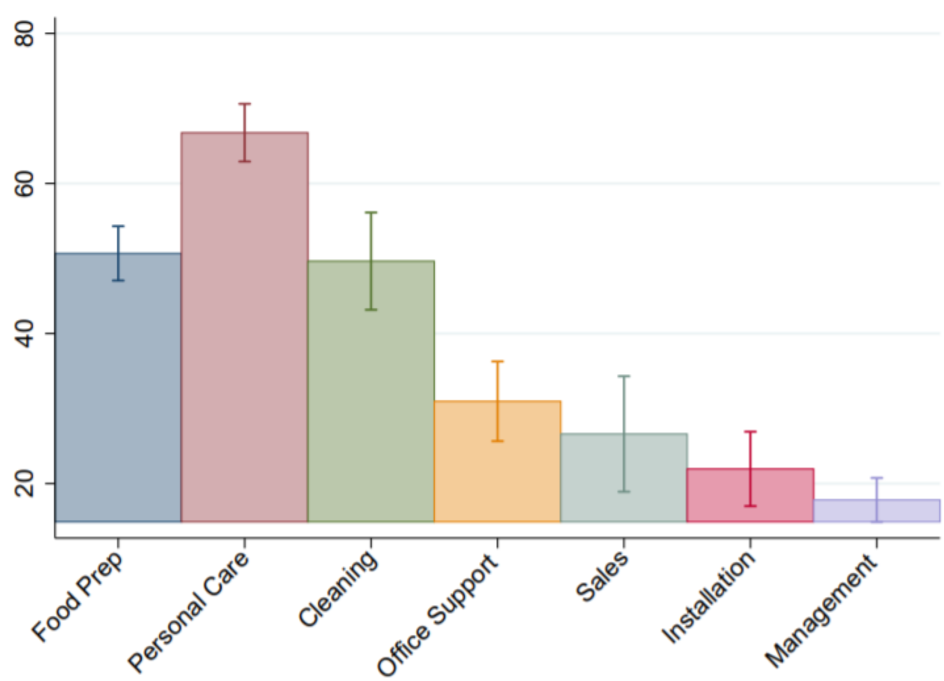

Figure 15. Pandemic impact on exit rates across occupations in service industries.

Impact of the Pandemic on Different Demographic Groups

The above analysis shows a clear difference in the impact of the pandemic across wage levels and occupations. Given the association between wage and demographic groups, these differences can be used to infer other demographic-related impacts. In fact, it is well known that specific populations occupy low-paying or high-paying jobs more than others. For instance, ethnic minorities who are less educated are more likely to take up low-paying jobs.

A similar regression approach, as given in Equation 1, is used to assess the demographic impacts of the pandemic. The results of the regression are given in Table 3 below. The objective of the regression was to show the unit changes/impact of the pandemic. As such, the statistical test outcome of interest is the change coefficients. It has already been determined, from CPS data, that there were employment changes in these sectors. The table shows the impact of the pandemic on exit and hires rates according to specific demographic groupings. The first column shows the employment to population ratio in the period before the pandemic. The second and third column shows the impact of the employment to population ratio in terms of percentages. The rest of the columns, four and five, show the impact of the pandemic as a proportion of the total employment.

		Employment Rate (Feb-2020)- 1	Employment Rate Coef (Feb-2020)- 2	Pre-pandemic changes- 3	Employment Change Coef (Feb-2020)- 4	% SE- 5	Exits Coefficient -6	Exits SE- 7	Hires Coefficient -8	Hires SE-9	Hire-Exits – 10
Gender	Men	66	-12.2	0.17	-17.8	0.4	16.1	0.32	-1.1	0.3	-17.2
	Women	56	-12.1	0.24	-21.8	0.6	19.3	0.37	-1.6	0.3	-20.9
Education	No Deg (High Sch)	34	-11.8	0.7	-34.8	3	28.6	1.5	-4.7	1.3	-33.3
	HS Grad	56	-14.6	0.36	-28.4	1.3	22.9	0.48	-1.6	0.4	-24.5
	College	61	-14.4	0.35	-22.8	1.2	20.1	0.44	-1.3	0.4	-21.4
	College Grad	72	-9	0.29	-9	0.9	11	0.32	-0.5	0.2	-11.5
Race											

	Caucasian	60	-10.6	0.15	-17.5	0.4	15.8	0.28	-1.1	0.2	-16.1
	African American	58	-12.6	0.45	-21.4	1.1	17.6	0.87	-1.4	0.7	-18.1
	Hispanic	65	-16.6	0.54	-25.5	1.1	22.2	0.67	-2.1	0.6	-24.3
	Others	61	-13.7	0.43	-21	1.3	21.2	0.8	-1.1	0.9	-22.3
Age											
	16-25	54	-18.2	0.56	-35.2	1.6	26.8	1.14	-4.2	1.11	-30.9
	26-35	80	-14.7	0.37	-17.3	0.8	15.7	0.4	-0.7	0.4	-16.4
	36-55	80	-12.7	0.27	-15.8	0.5	15.3	0.3	-0.9	0.3	-16.3
	56-85	37	-7.5	0.25	-19.4	0.9	18	0.6	-0.9	0.4	-18.9

Table 3. Pandemic impact on different demographic groups (BLS, 2020)

The results of the analysis reveal several insights. First, there was no significant difference in the impact of the pandemic across men and women. This is determined by looking at the employment rate coefficient, which is -12.2 in men and 12.1in women. The difference is, however, noticeable in terms of the percentage of employment lost. The percentage of employment lost seems to be more prominent in women (22%) compared to men (18%). This is primarily because of the reduced base of women's employment. It can therefore be concluded that the pandemic affected women compared to men. This is because a higher percentage of women lost employment compared to men.

Differences in the impact of the pandemic can also be assessed in terms of education groups. As shown in the fourth column of Table 3, the impact of the pandemic on education groups shows a monotonic pattern. In particular, high employment losses are experienced by individuals with only high school qualifications or without a high school degree. In this category, the pandemic led to a loss of 33% of employment. On the other hand, workers with a college degree experienced 9% of job losses. As shown in the other rows of the same table, non-Caucasian workers experienced high job losses compared to their Caucasian counterparts. Employment losses were notably higher among Hispanics.

From the sixth column to the tenth column, the labor impact of the pandemic is assessed according to demographic data. The employment hires and exits are represented on the basis of previous levels of employment. These changes are represented as a coefficient in April 2020, which is compared to pre-pandemic periods. As such, the coefficients show changes in employment relative to pre-pandemic periods. The analysis controls for typical transition movements. Similar to the above findings, the results show more significant employment exits in specific demographic groups. These are non-Caucasians, women, and young workers. These groups are also associated with low levels of education.

All in all, it is clear that these patterns are similar to that of other recessions. This is as documented by researchers like Hoynes et al. (2012). Perhaps the biggest difference in this study is the labor shocks experienced by men. In other recessions, the pandemic had a more considerable impact on men. This finding is consistent with the hypothesis given by Alon et al. (2020). Despite the high levels of exit rates, labor shocks were also driven by reduced hiring rates in certain areas of the economy (Le et al., 2021). This is consistent with the analysis given by Forsythe (2020) and Brodeur et al. (2021). Specifically, hiring was significantly reduced in older workers compared to young workers. This shows that there was a disproportionate reduction in hiring across populations.

Association between Occupations and Industries and Heterogeneous impact across Demographic Groups

The current study has so far shown how the pandemic affected different demographic groups across occupations and industries. However, it can be argued that these impacts may have been a result of the high representation of these groups in the occupations or industries. This section examines whether the high impact was a result of the overrepresentation of these groups.

This clarifies whether the pandemic had a disproportionate impact on the groups. To perform this analysis, outflows from employment are first examined. Compared to reduced inflows, outflows are the primary drivers of unemployment in the pandemic period.

By using outflow data, the pre-displacement activities during the pandemic can be examined. Specifically, the analysis can account for individuals who transition out of the labor force. Therefore, the extent of the differential impact of COVID-19 in different groups is factored in the analysis. This results in a new set of regression; Equation 2. This equation is given below;

$Y \quad = \omega D_{demo(i)} + \theta D_{2020M3} + \delta D_{2020M4} + D_{demo(i)} + \gamma D_{m(t)} + D_{demo(i)} + \rho D_{occ(\quad)} + \beta D_{2020M4} + D_{occ(\quad)} + \alpha D_{y(t)} + \epsilon$ **Equation 2**

There are several differences between Equation 1 and Equation 2. The first difference is the base data for the regression. In Equation 1, the regression is run using group-level demographic data. In Equation 2, the regression is run using individual-level data. This pools all demographic groups together. The dependent variable shows all individuals that transitioned out of employment. A dummy variable is used to represent April 2020, which controls for year and group effects. The coefficient of interest differential values in exit rates within different demographic groups. The regression still allows for seasonal differences in employment patterns.

The second difference is the introduction of occupation and industry-fixed effects. These factors have interacted directly with the April 2020 indicator. These effects control for the expected variations in exit rates across occupations and industries. Differences in job loss per occupation are also controlled. Demographic group differences are explained by pre-displacements within occupations in the period under analysis. The estimate of the coefficient shows the differential exit rates within occupations and within job groups.

For better illustration, the coefficients in Equation 2 are plotted in Figure 5, 6, 7, and 8 at a 95% confidence interval. The graphs first show the baseline differentials in different demographic groups. This differential is indicated using the blue bars. The occupation effects and industry effects are then introduced. These are represented by red and orange bars, respectively. The green bars show the effects in occupation and industries with the highest effects. The y-axis is the unemployment rate. The coefficients are assessed with respect to the primary groups; men, whites, graduates, age, and graduates. The coefficients are further summarized in Table 4.

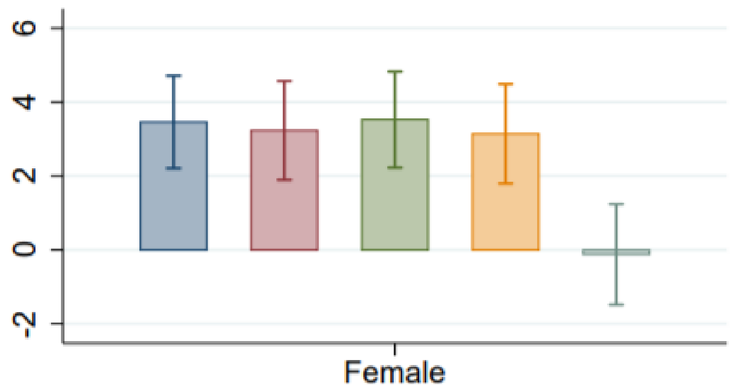

Figure 5. Controlled pandemic effects on female employment rates

Figure 5 shows the effect of the pandemic on female unemployment rates. Notably, the rates in April show a higher effect of the pandemic on female employment compared to men's employment. However, the gap disappears when detailed occupation and industry data are controlled. This is examined by comparing the baseline differential and the group bars in the graph. It can therefore be concluded that the exit of women from employment is primarily because of their types of jobs. Figure 6 shows the impact of the pandemic across different demographic groups. Differences in employment rate are higher in Hispanics compared to Black and Caucasians.

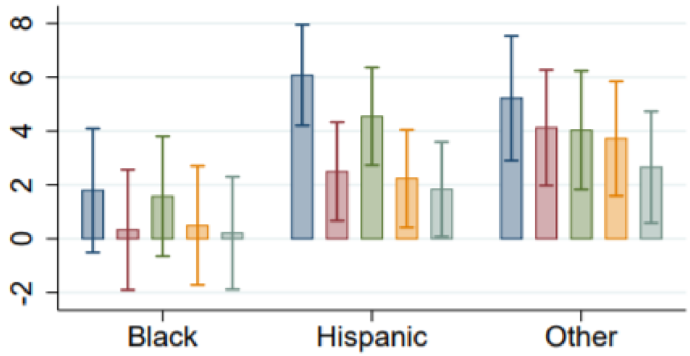

Figure 6. Controlled effects of the pandemic across demographic groups

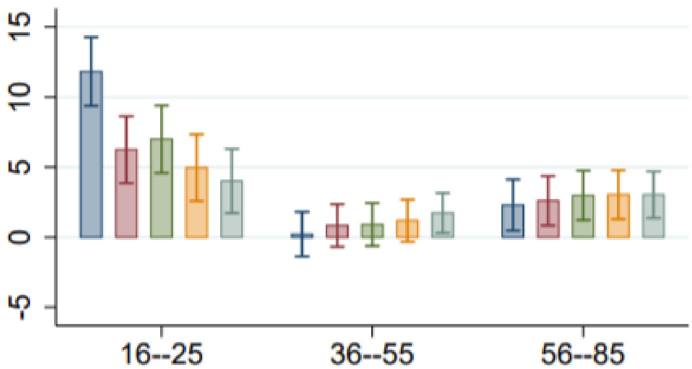

Figure 7. Controlled effects of the pandemic across age groups

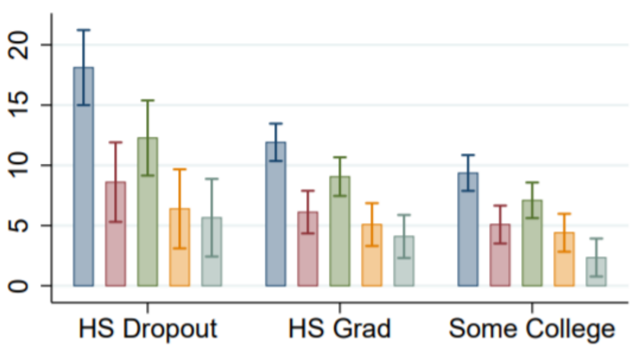

Figure 8. Controlled effects of the pandemic across education levels

Age differences in the pandemic are examined in Figure 7. This is done by examining the difference in the bars. Exit rates in employees aged 25 are higher compared to those between the ages of 26 to 35 years. After implementing occupation and industry controls, this difference is significantly reduced. Exit rates in the 56 years and above category are higher than all other groups. The rate does not change after implementing industry and occupation controls. This shows that narrowly defined job categories were responsible for the rise in exit rates in the 56 years and above age group.

The last Figure, Figure 8, shows variations in exit rates as per the level of education. Notably, individuals without high school qualifications had high exit rates compared to other categories. After controlling for industry and occupation effects, the exit rates in this category are slightly reduced. This trend is similar to employees with only high school and college degrees. After controlling for occupation and industry effects, the exit rates were significantly reduced. Table 5 gives a detailed summary of the above analysis. Although the variation in employment rates is explained by hiring patterns across industries and occupations, it does not give a conclusive explanation for variation across gender.

All in all, it is evident that the impact of the pandemic is different across race, age, and gender. The analysis in this section is further visualized in Figure 9, 10, 11, and 12. The Figures show the variations in employment share within specific occupations in the Feb-April 2020 period. These variations would not have been present if the shocks were only driven by internal occupation-related effects.

Education Impacts of Covid-19 Pandemic

As illustrated above, the education spending impacts of previous recessions have been widely documented. Labor shocks caused by recessions seem to reduce the ability of households to invest in education. This is according to the OECD (OECD, 2020). Similar responses to education spending in recessions and labor shocks have been reported in past recessions.

Recessions increase the financial burden, which forces them to cut spending on education or reduce spending on other necessities in order to afford education. In the U.S., households are a significant component of education spending. It was expected that any labor shocks would start reducing education spending. Although the majority of researchers in education finance focus on government spending on education, the current research specifically analyzes household spending.

As illustrated above, there is a high likelihood that reduced education spending will be witnessed in specific demographic groups associated with low income and disproportionate labor shock impacts. The effects of labor shock on spending may also vary depending on whether labor shocks have income or substitution effects. In this context, the effect of the shock on time and money will be assessed. This is whether the shock creates less time or less money. Similarly, the effects of labor shocks on education spending also depend on the perception of households of education. Some households may perceive education as a tool for overcoming labor shocks. In high-income households, labor shocks may result in increased graduate school applications. In other households, education spending may increase because of the need for private tutoring and additional learning materials. However, it is more likely that reduced education spending will be witnessed in low-income households.

Data Analysis and Discussion

To get a complete understanding of the impact of labor shocks on household spending, the current study examines spending data from the BLS. Specifically, the data is obtained from consumer expenditure surveys which aggregate data on income, expenditures, and the demography of U.S. consumers. Pre-pandemic and post-pandemic spending data on households are analyzed. Changes in spending between the years 2018 and 2020 are analyzed. All 14 major categories of spending are analyzed. These categories are presented in Table 4 below.

Spending Category	2018-2019 % Changes	2019-2020 % Changes
Total Changes	3	-2.7
Food General	3.1	-10.4
Food at home	4	6.4
Food from home	1.9	-32.6
Beverage (Alcoholic)	-0.7	-17.4
Housing Expenditure	2.9	3.5
Apparel and services Expenditure	0.9	-23.8
Transportation Expenditure	10.1	-8.5
Gasoline, other fuels, and motor oil Expenditure	-0.7	-25.1
Public and other transportation Expenditure	-4.5	-66.3
Healthcare Expenditure	4.5	-0.3
Medical services Expenditure	8.3	-12.2
Medical supplies Expenditure	12.8	-12.4
Entertainment Expenditure	-4.2	-5.8
Fees and admissions Expenditure	14.9	-51.7
Personal care products and services Expenditure	2.3	-17.8
Reading Expenditure	-14.8	23.9
Education Expenditure	2.6	-11.9
Tobacco products and smoking supplies Expenditure	-7.8	-1.6
Miscellaneous Expenditure	-9.5	0.9
Cash contributions Expenditure	5.7	14.4
Personal insurance and pensions Expenditure	-1.8	1.1

Table 4. Pre-pandemic and post-pandemic changes in expenditure

Notably, the onset of the pandemic led to reduced spending in most of the spending categories. Spending on entertainment, retail outlets, and transportation was reduced. Work from home restrictions and business closures further reduced spending. From 2018 and 2019, average spending among households increased by 3%. In a similar period, household spending reduced by 2.7%. These changes can be illustrated in Figure 17 below.

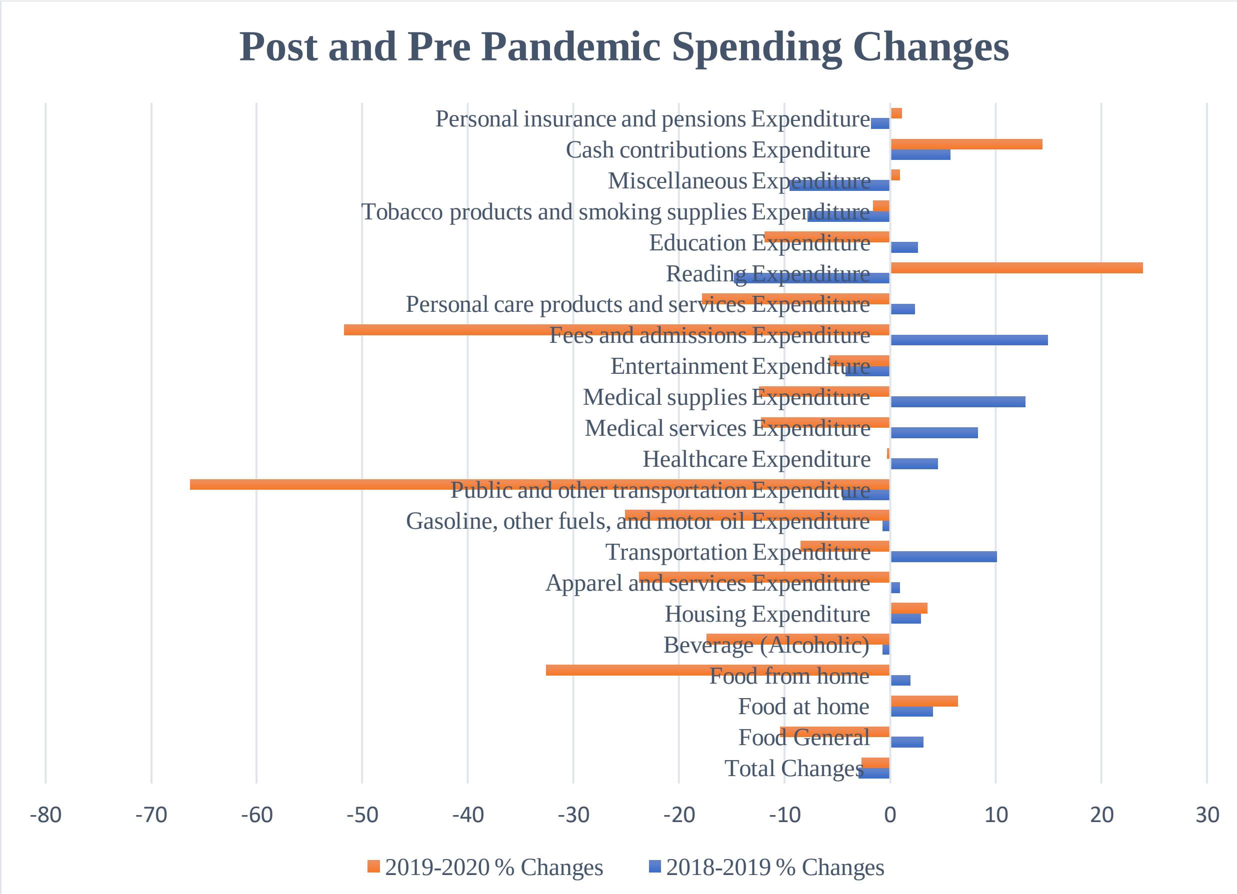

Figure 17. Post and pre pandemic spending changes

From the data, it can be seen that the labor shocks in spending were distributed across all spending categories. From the data, 9 out of 14 categories reported a drop in spending. Notably, households reduced education spending by 11.9%. It can therefore be concluded that labor shocks had a notable impact on education spending.

Conclusion

As illustrated above, the labor effects of the pandemic have affected almost every industry in the U.S. economy. The pandemic has, however, had differentiated impacts across job types, industry, age, and demographic groupings. The current study shows that the pandemic has exacerbated demographic inequalities that already existed in the economy. Notably, there is a disproportionate impact on employees in low-paying industries and occupations. This is because high employment rates have been higher in low-paying occupations compared to high-paying occupations. Consistent with the analysis given by Dingel and Neiman (2020), differences in employment effects illustrate the heterogenous effects of jobs that accommodate work-from-home arrangements.

Most importantly, it is clear that the disproportionate impact of these groups is made worse by the industry affiliations. After controlling for industry and occupation affiliations, the study shows that demographic groups like Hispanics and Blacks still suffered the highest effect compared to their Caucasian counterparts. This is a critical issue for policymakers in both public and private spheres. Special attention needs to be placed on disadvantaged groups during recessions. These groups suffer the highest economic impact.

In terms of the labor shock's effect on education, it is clear that labor shocks/employment losses have had a negative effect on household spending on education. Consistent with the analysis of the distributional effects of labor shocks, reduced education spending is likely to have an unequal effect on households. Households with well-paying jobs are likely to experience reduced effects compared to households with low-paying occupations. If the pandemic continues, inequality caused by labor shocks and other existing inequalities are likely to interact and create bigger gaps in socio-economic status.

References

Abay, K. A., Tafere, K., & Woldemichael, A. (2020). Winners and losers from COVID-19: Global evidence from Google Search. *World Bank Policy Research Working Paper*, (9268).

Acemoglu, D. & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics,* volume 4 (pp. 1043– 1171). Elsevier.

Adian, I., Doumbia, D., Gregory, N., Ragoussis, A., Reddy, A., & Timmis, J. (2020). *Small and Medium Enterprises in the Pandemic: Impact, Responses and the Role of Development Finance*. The World Bank.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., ... & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics*, *191*, 104274.

Alon, T., Kim, M., Lagakos, D., & VanVuren, M. (2020). *How should policy responses to the COVID-19 pandemic iidiffer in the developing world?* (No. w27273). National Bureau of Economic Research.

Apedo-Amah, M. C., Avdiu, B., Cirera, X., Cruz, M., Davies, E., Grover, A., ... & Tran, T. T. (2020). Unmasking the Impact of COVID-19 on Businesses.

Azevedo, J. P., Hasan, A., Goldemberg, D., Geven, K., & Iqbal, S. A. (2021). Simulating the potential impacts of COVID-19 school closures on schooling and learning outcomes: A set of global estimates. *The World Bank Research Observer*, *36*(1), 1-40.

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, *117*(30), 17656-17666.

Bachas, P., Brockmeyer, A., & Semelet, C. (2020). The Impact of COVID-19 on Formal Firms.

Barbieri Góes, M. C., & Gallo, E. (2021). Infection is the cycle: unemployment, output and economic policies in the COVID-19 pandemic. *Review of Political Economy*, *33*(3), 377-393.

Béland, L. P., Brodeur, A., & Wright, T. (2020). The short-term economic consequences of Covid-19: exposure to disease, remote work and government response.

BLS (2020). The Employment Situation- April 2020. Technical report, Bureau of Labor Statistics. https://data.bls.gov/timeseries/LNS14000000

Brodeur, A., Gray, D., Islam, A., & Bhuiyan, S. (2021). A literature review of the economics of COVID-19. *Journal of Economic Surveys*, *35*(4), 1007-1044.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., & The Opportunity Insights Team. (2020). *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data* (pp. 1-109). Cambridge, MA: National Bureau of Economic Research.

Chen, Z. (2020). COVID-19: a revelation–a reply to Ian Mitroff. *Technological forecasting and social change*, *156*, 120072.

Cowger, T. L., Davis, B. A., Etkins, O. S., Makofane, K., Lawrence, J. A., Bassett, M. T., & Krieger, N. (2020). Comparison of weighted and unweighted population data to assess inequities in coronavirus disease 2019 deaths by race/ethnicity reported by the US Centers for Disease Control and Prevention. *JAMA network open*, *3*(7), e2016933-e2016933.

Cox, N., Ganong, P., Noel, P., Vavra, J., Wong, A., Farrell, D., ... & Deadman, E. (2020). Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data. *Brookings Papers on Economic Activity*, *2020*(2), 35-82.

Dang, H. A., Huynh, T. L. D., & Nguyen, M. H. (2020). Does the Covid-19 pandemic disproportionately affect the poor? Evidence from a six-country survey.

Decerf, B., Ferreira, F. H., Mahler, D. G., & Sterck, O. (2021). Lives and livelihoods: estimates of the global mortality and poverty effects of the Covid-19 pandemic. *World Development*, *146*, 105561.

Demirgüç-Kunt, A., Lokshin, M., & Torre, I. (2020). The sooner, the better: The early economic impact of non-pharmaceutical interventions during the COVID-19 pandemic. *World Bank Policy Research Working Paper*, (9257).

Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home?. *Journal of Public Economics*, *189*, 104235.

Dreger, C., & Gros, D. (2021). Lockdowns and the US unemployment crisis1. *Covid Economics,* 165.

Elsby, M. W. L., Michaels, R., & Solon, G. (2009). The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics*, 1(1), 84–110.

Fairlie, Robert W. 2020a. "The Impact of COVID-19 on Small Business Owners: Evidence of Early-Stage Losses from the April 2020 Current Population Survey." IZA Discussion Paper No. 13311.

Falk, G. (2020). *Unemployment Rates During the COVID-19 Pandemic:* Congressional Research Service.

Fujita, S. & Ramey, G. (2009). The cyclicality of separation and job finding rates. *International Economic Review*, 50(2), 415–430.

Forsythe, E. (2020). Labor market flows and the Covid-19 economy. *Available at SSRN 3586074*.

Garrote Sanchez, D., Gomez Parra, N., Ozden, C., Rijkers, B., Viollaz, M., & Winkler, H. (2020). Who on earth can work from home?

Gezici, A., & Ozay, O. (2020). How race and gender shape COVID-19 unemployment probability. *Available at SSRN 3675022*.

Gupta, A., Zhu, H., Doan, M. K., Michuda, A., & Majumder, B. (2021). Economic impacts of the COVID− 19 lockdown in a remittance-dependent region. *American Journal of Agricultural Economics*, *103*(2), 466-485.

Gottlieb, C., Grobovšek, J., Poschke, M., & Saltiel, F. (2021). Working from home in developing countries. *European Economic Review*, *133*, 103679.

Hoynes, H., Miller, D. L., & Schaller, J. (2012). Who suffers during recessions?. *Journal of Economic perspectives*, *26*(3), 27-48.

Huang, A., Makridis, C., Baker, M., Medeiros, M., & Guo, Z. (2020). Understanding the impact of COVID-19 intervention policies on the hospitality labor market. *International Journal of Hospitality Management*, *91*, 102660.

Hobbs, J. E. (2020). Food supply chains during the COVID-19 pandemic. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 68(2), 171-176.

Sampi Bravo, J. R. E., & Jooste, C. (2020). Nowcasting economic activity in times of COVID-19: An approximation from the Google Community Mobility Report. *World Bank Policy Research Working Paper*, (9247).

Sevilla, A., & Smith, S. (2020). Baby steps: the gender division of childcare during the COVID-19 pandemic. *Oxford Review of Economic Policy*, *36*(Supplement_1), S169-S186.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics,* 15(2), 127–148.

Hardy, B. L., & Logan, T. D. (2020). Racial economic inequality amid the COVID-19 crisis. *The Hamilton Project*.

Hatayama, M., Viollaz, M., & Winkler, H. (2020). Jobs' amenability to working from home: Evidence from skills surveys for 53 countries. *World Bank Policy Research Working Paper*, (9241).

Jackson, J. K. (2021). *Global economic effects of COVID-19*. Congressional Research Service.

Kahn, L. B., Lange, F., & Wiczer, D. G. (2020). Labor Demand in the time of COVID19: Evidence from vacancy postings and UI claims. Technical report, National Bureau of Economic Research.

Kong, E., & Prinz, D. (2020). Disentangling policy effects using proxy data: Which shutdown policies affected unemployment during the COVID-19 pandemic?. *Journal of Public Economics*, *189*, 104257.

Lee, S., Schmidt-Klau D., Verick, S., (2020) The Labour Market Impacts of the COVID-19: A Global Perspective Indian Society of Labour Economics 2020 link.springer.com/article/10.1007/s41027-020-00249-y

Le, L. H. V., Huynh, T. L. D., Weber, B. S., & Nguyen, B. K. Q. (2021). Different firm responses to the COVID-19 pandemic shocks: machine-learning evidence on the Vietnamese labor market. *International Journal of Emerging Markets*.

Madrian, B. C. & Lefgren, L. J. (1999). A Note on Longitudinally Matching Current Population Survey (CPS) Respondents. *NBER Working Paper No. t0247.*

Manuelli, R. and A. Seshadri (2014). Human Capital and Wealth of Nations . American Economic Review 104(9).

Maloney, W. F., & Taskin, T. (2020). Determinants of social distancing and economic activity during COVID-19: A global view. *World Bank Policy Research Working Paper*, (9242).

Montenovo, L., Jiang, X., Rojas, F. L., Schmutte, I. M., Simon, K. I., Weinberg, B. A., & Wing, C. (2020). *Determinants of disparities in covid-19 job losses* (No. w27132). National Bureau of Economic Research.

OECD (2020), *OECD Employment Outlook 2020: Worker Security and the COVID-19 Crisis*, OECD Publishing, Paris, https://dx.doi.org/10.1787/1686c758-en.

Open DOI

Psacharopoulos, G., Collis, V., Patrinos, H. A., & Vegas, E. (2020). Lost wages: The COVID-19 cost of school closures. *Available at SSRN 3682160*.

Pabilonia, S. W. (2014). Measuring Hours Worked by the Unincorporated Self-employed Using the CPS and ATUS. In *Presented International Association of Research in Income and Wealth General Conference. http://www. iariw. org/papers/2014/PabiloniaPaper. pdf*.

Reichelt, M., Makovi, K., & Sargsyan, A. (2021). The impact of COVID-19 on gender inequality in the labor market and gender-role attitudes. *European Societies*, *23*(sup1), S228-S245.

Rissman, E. (2006). The self-employment duration of younger men over the business cycle. *Economic perspectives*, *30*(3).

Rojas, M., Rodríguez, Y., Monsalve, D. M., Acosta-Ampudia, Y., Camacho, B., Gallo, J. E., ... & Anaya, J. M. (2020). Convalescent plasma in Covid-19: Possible mechanisms of action. *Autoimmunity reviews*, *19*(7), 102554.