

Demography and Labor Economy During COVID-19: How Fluctuations In Workforce Age Distribution Impacted GDP Per Capita

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ABSTRACT

In the United States alone, the COVID-19 pandemic was responsible for over 1.2 million deaths and 18 million layoffs, significantly reshaping the demography and productivity of the labor force. These changes triggered a sharp contraction in economic activity, where such effects could be observed in supply chains, consumer demand, and ultimately GDP per capita. In this article, I run two linear regressions to test how 1) the share of individuals employed and 2) the per capita death rate by age bracket impacts GDP per capita. Specifically, I compare the relative coefficients of younger age groups with older age groups, highlighting how people's income and consumption trends fluctuate as they age. My coefficients reveal that within the employed population, 65-100 year olds generally contribute the most to the GDP measure, while 55-64 year olds contribute the least. However, when accounting for both the employed and unemployed population, I find that 25-34 year olds contribute the most to the economy, while 55-64 year olds again contribute the least. Therefore, these results suggest that the economic impact of COVID-19 was exacerbated because the 25-34 and 65-100 age groups, which had the highest economic productivity, experienced the highest levels of job loss and premature retirements during the pandemic.

Keywords: COVID-19, Heterogeneity, GDP Per Capita

1. INTRODUCTION

COVID-19 (SARS-CoV-2), a global pandemic that first emerged in December 2019, has negatively impacted public health and economic systems worldwide. While animals such as bats were understood to be the initial hosts of the SARS-CoV-2 virus, this respiratory disease quickly spread to humans, disproportionately placing dense regions and under-resourced communities at risk for disease outbreaks (Velavan & Meyer 2020). Over a matter of months, the pandemic scaled in magnitude due to the virus' highly contagious nature, leading to early projections that the number of COVID-19 cases would nearly double every week (Velavan & Meyer 2020). As of 2025, COVID-19 related deaths have totaled over 1.2 million in the United States alone, temporarily causing average life expectancy to decrease by 2.94 years (Center for Disease Control and Prevention) (Goldstein & Lee, 2020). Accordingly, with some workers spending fewer years within the labor force than anticipated due to fatal or debilitating COVID-19 complications, this change in life expectancy likely reduced the overall capacity of the labor force. Moreover, due to the disruptions of supply chains across the world, the pandemic triggered a sharp contraction in economic activity, causing over 18 million Americans to be laid off by April 2020 (Bureau of Labor Statistics).

However, not all industries experienced the same magnitude of economic disruption. For example, while healthcare and manufacturing industries experienced little change in employment during the COVID-19 recession, many service and hospitality sectors including the travel industry experienced a rapid decline in consumer demand. This was largely due to the nation-wide lock-down orders, which caused many workers to be laid off and businesses to shut



down. At the same time, older populations were more susceptible to contracting the virus compared to all other age groups, with people over the age of 50 accounting for roughly 53.6% of all reported cases as of 2020 (Shi, Yu, et al. 2020). Consequently, because the older population not only experienced high mortality rates but also more quickly transitioned to retirement, the labor force lost a substantial number of older workers during the height of the pandemic, evidently hurting overall economic output. Accordingly, the combination of COVID-19 deaths and disruptions in the labor force caused rapid decline in economic health, as indicated by the United States' nominal gross domestic product which declined by almost 500 billion dollars in just the first two quarters of 2020 (Federal Reserve Economic Data).

While existing research on heterogeneity in unemployment trends provides valuable insights into the correlation between COVID-19 and GDP decline, there is limited research on how specific age groups contribute to GDP. Filling in this gap is especially important when understanding the economic effects of COVID-19 deaths and layoffs, which have been observed to disproportionately affect certain age groups. Currently, Viscusi's VSL (value of a statistical life) estimates and other similar models have been used by the federal government to attach quantitative values to the hypothetical number of lives saved by public or private measures (Goldstein & Lee, 2020). In *Demographic perspectives on the mortality of COVID-19 and other epidemics*, Goldstein and Lee applied two of Viscusi's estimates to COVID-19 deaths, where they either assigned 10 million dollars to each life saved or half a million dollars to each year of life saved. In comparing both methods, they found that avoiding 1.75 million deaths or the loss of 20.5 million years could be valued at anywhere from 10.2 to 17.5 trillion dollars. However, despite the wide range of this projection, Viscusi's estimates don't always align with other existing models, with some economists projecting values as low as 2.6 trillion dollars per 20.5 million years saved (Goldstein & Lee, 2020). This discrepancy demonstrates the complexity of assigning a single universal value to statistical lives, where age distribution is not accounted for within the model. Furthermore, in his paper *The heterogeneity of the value of statistical life: Introduction and overview*, Viscusi explores how people's income tend to rise and fall over their lifetime, causing an inverted U-shaped relationship between age and the value of a statistical life. However, this VSL model primarily grounds its estimates in consumption patterns rather than income, which may run the risk of underestimating the economic contributions of older age groups, specifically those who are actively participating in the labor force.

My research aims to build upon existing VSL models by designing and analyzing two regression models that examine how different age groups in the labor force contribute to GDP per capita in different capacities. Specifically, I investigate both the yearly percent share of each age group as well as the per capita all-cause deaths, comparing the coefficients of younger age groups with older age groups. After running my first regression—which focused on the percent share of age groups—the coefficients revealed that workers aged 65 and older contribute the most to GDP per capita, meaning that they are likely the most skilled and productive workers in the labor force. In addition, the coefficients also revealed that workers aged 55-64 contribute the least to cumulative GDP per capita, likely capturing the immediate effect of short term retirees. Accordingly, the results from my first regression reveal that the economic output of workers doesn't necessarily rise with age or even follow an inverted U-shaped curve, but rather fluctuates over the course of one's life. Subsequently, the coefficients of my second regression—which focused on the per capita deaths of each age basket—revealed that while a percent increase in per capita deaths belonging to the 25-34 age bracket would have the most

detrimental effects on the economy, a percent increase in the 55-64 age bracket would have the least. My findings demonstrate that there are notable differences between the economic contributions of different age groups, suggesting that accounting for age distribution in VSL models could strengthen their accuracy, thus helping policymakers better allocate resources during public health crises.

2. RELATED LITERATURE

In this section, I examine and analyze existing research on the COVID-19 pandemic and its effects on public health, socio-economic inequality, and personal consumption expenditures.

2.1 COVID-19 COMPARED TO HIV/AIDS AND ALL-CAUSE MORTALITY

While COVID-19 is in many ways similar to the HIV/AIDS epidemic, the rapid spike in mortality makes the pandemic unique. With an estimated three deaths per every thousand people, COVID-19 mortalities in the United States were projected to reach roughly 200,000 before the fall of 2020, less than a year after the pandemic was first reported (Goldstein & Lee, 2020). On the other hand, the HIV/AIDS epidemic stretched over decades, with the infection accounting for roughly 11.7 million deaths globally and over 15% of all adult male mortalities at the epidemic's peak (Curran, Jaffe, et al. 1988) (Schwartländer, Bernhard, et al. 1999). Given these statistics, while the total mortality due to HIV/AIDS was higher than COVID-19, COVID-19 displayed more fatal transmission rates as the pandemic spiked over a period of months rather than decades. In the paper, *What Will Be the Impact of Covid-19 in the US? Rough Estimates of Disease Scenarios*, Atkeson grapples with the unique timing and severity of the COVID-19 pandemic, creating a SIR model that forecasted the 12-18 month progression of the pandemic from an economics viewpoint. In his model, he measured the transmission rates between the population that is susceptible to the disease, infected with the disease, and recovered from the disease—using these three indexes to predict potential labor shortages and public health challenges that may arise from the transmission rate and severity of COVID-19. Atkeson's results revealed that so long as the pandemic persisted, there would be short-term economic consequences due to reductions in labor activity, regardless of whether or not pandemic mitigation efforts—such as social distancing requirements—were implemented. On one hand, he identified that given the rapid transmission of COVID-19, implementing mitigation efforts would likely lead to job loss and reduced work time. However, on the other hand, not implementing these mitigation efforts would likely cause an increase in COVID-19 mortalities, which would also be consequential to the economy. Accordingly, Atkeson's findings are indicative of how COVID-19's contagious nature amplified its effects on labor forces around the world.

In addition to having higher transmission rates, COVID-19 also disproportionately affects the older population, even more so than all-cause mortality. Like many other causes of death, COVID-19 mortality is positively associated with age, with older age groups being more susceptible to the disease (Sasson 2021). More specifically, the World Health Organization and US CDC classified individuals 65 years and older as a “vulnerable group,” advising stricter social isolation practices among older individuals (CDC 2020). While the relationship between COVID-19 mortality and age tends to slightly fluctuate across countries with different public health regulations, COVID-19 overall reflects the Gompertz Law, where the rate of mortality exponentially increases with age (Kirkwood 1825). Thus, COVID-19 mortality is similar to that of all-cause mortality, where a majority of deaths are attributable to the older population. However,

as Goldstein and Lee's research note, in the United States, individuals 70 years and older make up 70% of all COVID-19 deaths while making up 64% of all-cause mortality deaths (Goldstein & Lee, 2020). This finding suggests that COVID-19 is even more fatal to the older population than all-cause mortality, highlighting the pronounced relationship between age and the fatality of contracting COVID-19.

Accordingly, the rapid outbreak COVID-19 challenged healthcare and economic systems globally, leading to abrupt and detrimental changes in the labor force. Since the older population was disproportionately affected by COVID-19, many older workers were not only contracting fatal cases of the virus, but also retiring at a quicker rate due to health concerns and the inconvenience of working remotely. Consequently, by the second quarter of 2020, participation in the labor force fell by almost 3%, as reflected by the 4.2 million individuals who had left their jobs semi-permanently or permanently (Faria-e-Castro 2021). This meant that the number of retirements during the COVID-19 pandemic exceeded initial projections by almost 2.4 million, causing drastic changes to the demography and capacity of the labor force. Similarly to COVID-19 deaths, retirements predominantly occurred within the older population, indicating that the decline in older workers was far higher than any other age group during the COVID-19 pandemic.

2.2 OPTIMISM AND CONSUMPTION PATTERNS

Due to the uncertainty and pessimism surrounding the COVID-19 pandemic, various forms of consumption underwent notable changes, affecting the economy as a whole. During the recession, the US government issued a total of 931 billion dollars of stimulus to over 165 million Americans, attempting to relieve the financial stress of the pandemic while also boosting gross domestic product (Government Accountability Office 2022). However, as revealed by Corbion et al., 85% of recipients planned to primarily save their stimulus checks or use them to pay off existing debt, while only 15% of recipients were primarily planning to spend their checks on actual durable or non-durable goods. Moreover, compared to previous recessions such as the financial crisis of 2008, the average marginal propensity to consume was notably lower during the COVID-19 recession, likely due to factors such as the absence of in-person consumption and the reduced need for durable transportation such as cars (Corbion et al. 2020). At the same time, the pandemic also triggered temporary hoarding behavior among consumers, where the fear of potential shortages caused people around the world to buy an excess of non-durable goods such as toilet paper, produce, and masks (Cambefort 2020). In the long-run however, COVID-19 nevertheless reduced consumption, introducing anti-consumption trends where people opted for a more simplistic lifestyle that was less dependent on physical goods and services (Cambefort 2020). One specific example of this change was the decline of travel in 2020 due to the perceived risk of the pandemic as well as government issued lockdowns (Rahman et al. 2021). More broadly, it was also concluded that COVID-19 had increased risk perception and aversion among both consumers and businesses, both of which contributed to declines in gross domestic product around the world.

2.3 INDUSTRY AND RACIAL DISPARITIES

While the COVID-19 pandemic affected every part of the economy to some extent, certain industries such as leisure and hospitality experienced the most detrimental changes, including job loss and a reallocation shock which made economic recovery especially difficult (Aaronson

2021). These challenges are largely attributable to the social restrictions such as lockdowns and social distancing which drastically decreased the demand for in-person services. Thus, many restaurants and hospitality businesses found themselves shutting down entirely or having to employ stricter health regulations (Gursoy & Chi 2020). Even when business reopened after COVID-19 subsided, the process of bringing back customers happened slowly due to persisting safety concerns (Gursoy & Chi 2020). Moreover, Barrero et al. found that COVID-19 caused the labor force to shrink in size overall, with approximately 3 new hires for every 10 layoffs. In addition, the reallocation shock and high mortality rates of COVID-19 were believed to have long-term consequences as well, with projections that 42% of layoffs would lead to permanent job loss (Barrero et al. 2020). However, other industries such as the manufacturing sector recovered relatively quickly despite temporary supply chain disruptions (Aaronson 2021). Within industries that experienced notable economic damage and reallocation shocks, Hispanic and non-White workers were more likely to be laid off than their White counterparts, often because of their overrepresentation in industries that experienced the most detrimental declines in consumer demand (Cortes et al. 2022). In other cases however, structural racism also played a significant role in employment cuts, causing people of color to be disproportionately affected by COVID-19 even when working in predominantly White industries. These racial disparities in job displacement were inevitably prevalent during the COVID-19 pandemic, exacerbating the socio-economic inequalities between White and non-White workers (Gemelas et al. 2021).

2.4 UNEMPLOYMENT RATES AND JOB OPENINGS

Despite the unprecedented record of over 20 million US job losses during the COVID-19 recession, the unemployment rate still remained relatively low, increasing by only 2% (Coibion et al. 2020). As a result, even when job vacancies reached over 11.4 million by the end of 2021, only a fraction of these openings were actually filled by new workers—thus sending conflicting signals regarding the state of the economy (Penn & Nezamis 2022).

First, many unemployed workers might have experienced the phenomenon of “discouraged workers,” when people temporarily disengage from job searches due to pessimism and a lack of motivation in response to the state of the recession. This phenomenon is explored in *Labor Markets During the Covid-19 Crisis: A Preliminary View*, in which Coibion details its effects on the unemployment rate and employment-to-population ratio. Because individuals must be actively seeking employment in order to be considered as “unemployed” in this index, the US unemployment rate remained relatively constant, despite the overall 7.5% decline in employment-to-population ratio (Coibion et al. 2020). This implies that there was not only an unmet demand for labor within US industries, but also a decline in job market competition—compromising the overall skill level of hired workers. Moreover, labor shortages due to the COVID-19 recession can also be attributable to declines in productivity and output, thus causing the United States’ gross domestic product to fall by almost 500 billion dollars.

Secondly, many older workers, both employed and recently laid-off, chose to retire earlier, causing an overall decline in labor force participation. Specifically, by the end of 2020, almost 1.3 million individuals over the age of 55 who had been recently laid-off chose to permanently retire, as opposed to seeking new employment—thus causing the employment to population ratio to fall by 2.2 percentage points within the age sector (Davis 2021). Moreover, within the older population, quicker transitions to retirement occurred the most among those working high-contact or part-time jobs, meaning that most of them had either belonged to the highest or lowest earning sector. Consequently, the rise of permanent retirements among the older

population caused an increase in job vacancies that couldn't be immediately filled by younger workers, primarily due to their lack of qualifications or overall discouragement.

3. METHODOLOGY AND REGRESSION DESIGN

In order to measure how different age groups in the labor force contribute to the health of the economy, I have designed two linear regression models, answering the question: “how did demographic changes during the COVID-19 recession impact the health of the US economy as measured by GDP per capita?” In both regressions, I quantify the health of the economy as gross domestic product per capita, making it my dependent variable and regression output. Then, because both of my regressions focus on individual economic contributions, I group my data into age brackets starting from age 16 (the average legal working age), going up by increments of roughly 10 years from there. In doing so, I created the following six age brackets: 16-24, 25-34, 35-44, 45-54, 55-64, 65-100.

In both regressions, I held my control variables constant, attempting to eliminate the influence of any extraneous variables that could interfere with identifying an unbiased casual relationship between GDP per capita and my treatment variables. First, I set year (B1) as a continuous control variable in order to track the generalized growth of GDP per capita over time. In addition, I take a difference-in-differences regression approach by setting Covid Year (B2) as a binary indicator variable, using 0 (no) and 1 (yes) to identify if the regressed year is 2020—the year of the COVID-19 recession. In doing so, I isolate the discrepancy in GDP per capita that occurred specifically because of the recession, denoting that the significant decline in economic output is inconsistent with the overall trends of previous years. Finally, I also set unemployment rate (B8) and savings rate (B9) as control variables in both regressions, accounting for the influence of exogenous consumption and labor trends that could have also been attributable to changes in GDP per capita—particularly during recession years such as 2008-2009 and 2020.

$$\begin{aligned} \text{GDPperCapita} = & \beta_0 + \beta_1 \text{Year} + \beta_2 \text{CovidYear} + \beta_3 \text{ShareofAges16-24} + \beta_4 \text{ShareofAges25-} \\ & 34 + \beta_5 \text{ShareofAges35-44} + \beta_6 \text{ShareofAges45-54} + \beta_7 \text{ShareofAges55-64} + \\ & \beta_8 \text{UnemploymentRate} + \beta_9 \text{SavingsRate} + \epsilon \end{aligned} \quad (1)$$

In my first regression model, I examined how workers between the age of 16 and 64 contribute to GDP per capita in comparison to workers aged 65 to 100. In order to do so, I set my treatment variables (B3-7) as the percent share of US workers aged 16-24, 25-34, 35-44, 45-54, and 55-64—ranging from the year 2000 to 2023 which gives me 24 observations. Then, I set the age bracket “65-100” as a dummy variable by omitting it from my regression equation entirely—thus meaning that coefficients B3-7 will all be relative to the coefficient of my omitted variable “share of ages 65-100.”

$$\begin{aligned} \text{GDPperCapita} = & \beta_0 + \beta_1 \text{Year} + \beta_2 \text{CovidYear} + \beta_3 \text{PerCapitaDeaths16-24} + \\ & \beta_4 \text{PerCapitaDeaths25-34} + \beta_5 \text{PerCapitaDeaths35-44} + \beta_6 \text{PerCapitaDeaths45-} \\ & 54 + \beta_7 \text{PerCapitaDeaths55-64} + \beta_8 \text{UnemploymentRate} + \beta_9 \text{SavingsRate} + \epsilon \end{aligned} \quad (2)$$

Then, in my second regression model, I align each age basket with the per capita deaths of the total population (employed and non-employed), allowing me to identify a coefficient for each one. Similarly to the first regression, I have also set the “65-100” age bracket as an omitted dummy variable, meaning that coefficients B3-7 will all be relative to the coefficient of “per capita deaths 65-100.” It is important to note that for this regression, I could only find raw-count population data from the years 2000 and 2007 to 2023, meaning that this regression is being computed with 18 observations instead of 24.

When constructing my datasets, I extracted annual demographic, population, economic, and public health data from IPUMS, Census Bureau, Federal Reserve Economic Data (FRED), and Human Mortality Database (HMD), respectively. This data can be found in Table 1 in the Appendix. To find the coefficients for my treatment and control variables, I used the software Gretl—an econometrics software that is able to run linear regressions and time-series analyses.

4. RESULTS

In this section, I interpret the coefficients that Gretl computed for each term in my two regressions, analyzing their implications in the context of labor economics and individual output.

4.1 SHARE OF AGE SECTORS

*How Do the Percent Share of Workers Belonging to Different Age Sectors
Impact Gross Domestic Product Per Capita?*

Table I

Linear Regression of the Annual Percent Share of Workers, 2000-2023

| | P-value | I1 |
|---------------------|--------------|--------------|
| Constant | 7.93e-07 *** | -5.20442e+06 |
| Year | 2.15e-08 *** | 2778.91 |
| Covid Year | 0.1956 | -939.541 |
| Share of Ages 16-24 | 0.2156 | -2506.49 |
| Share of Ages 25-34 | 0.0067 *** | -5726.77 |
| Share of Ages 35-44 | 0.3239 | -1865.62 |
| Share of Ages 45-54 | 0.2232 | -1633.36 |
| Share of Ages 55-64 | 0.0082 *** | -6179.60 |
| Savings Rate | 0.0754 * | -195.045 |
| Unemployment Rate | 0.4581 | -80.9802 |

Figure 1: Coefficients for Share of Age Sectors, 2000-2023

Summary Statistics – Share of Age Sectors

| | Obs | Mean |
|----------------------|-----|-------|
| Share of Ages 16-24 | 24 | 0.146 |
| Share of Ages 25-34 | 24 | 0.221 |
| Share of Ages 35-44 | 24 | 0.225 |
| Share of Ages 45-54 | 24 | 0.216 |
| Share of Ages 55-64 | 24 | 0.145 |
| Share of Ages 65-100 | 24 | 0.047 |

Figure 2: Summary Statistics – Share of Age Sectors

As visualized in *Figure 1*, the negative coefficients for each “share_of_age” variable that range from 15-64 indicate that a one percent increase in the share of individuals aged 65-100, who are employed, will increase GDP per capita by the highest amount compared to any other age group. Given that the omitted group from the regression analysis is the “share of age 65-100,” this means that this bracket is the most productive in contributing to the growth in GDP per capita—given that estimates for all other age bracket provides a lower relative growth to GDP per capita when compared to the 65 to 100 year old employed workers. Then, by observing the coefficient of the treatment variable “share of ages 45-54,” we know that a percent increase in the share of employed individuals belonging to this age group increases GDP per capita by only 1633.36 dollars less than a percent increase in the 65-100 age group—the smallest difference among any age group listed as treatment variable. Thus, it can be interpreted that 45-54 year olds are the second most influential age group on GDP per capita. From there, the same intuition can be applied to rank all age baskets of the employed population from most to least influential, giving us the following order: 65-100, 45-54, 35-44, 15-24, 25-34, 55-64.

My continuous variable “year” has a coefficient of 2778.91, meaning that each additional year can be attributable to an increase in GDP per capita of 2778.91 dollars. This coefficient is likely attributable to the United States’ growing productivity along with the inflation, which has occurred at an average annual rate of 3.3% over the past century. Then, my indicator variable “Covid year” has a coefficient of -939.541, meaning that during a Covid recession year, GDP per capita will deviate below its projected value by 939.541 dollars. “Savings rate” has a coefficient of -195.045, meaning that a percent increase in savings rate will cause GDP per capita to decline by 195.045 dollars. Finally, “unemployment rate” has a coefficient of -80.9802, meaning that a percent increase in unemployment will cause GDP per capita to decline by 80.9802 dollars.

4.2 PER CAPITA DEATHS

How Do the Per Capita Deaths of Different Age Sectors Impact Gross Domestic Product Per Capita?

Table II
Linear Regression of Annual Per Capita Deaths, 2000; 2007-2023

| | P-value | III |
|-------------------------|------------|----------------|
| Constant | 0.0004 *** | -6.87281e+06 |
| Year | 0.0003 *** | 3428.73 |
| Covid Year | 0.8840 | -875.404 |
| Per Capita Deaths 16-24 | 0.1743 | 0.0593812e+07 |
| Per Capita Deaths 25-34 | 0.0072 *** | -0.0719499e+07 |
| Per Capita Deaths 35-44 | 0.5008 | 0.0115233e+07 |
| Per Capita Deaths 45-54 | 0.7780 | -0.0193181e+06 |
| Per Capita Deaths 55-64 | 0.1770 | 0.0667539e+06 |
| Savings Rate | 0.5442 | -484.999 |
| Unemployment Rate | 0.7021 | -248.424 |

Figure 3: Coefficients for Per Capita Deaths, 2000; 2007-2023

Summary Statistics – Per Capita Deaths

| | Obs | Mean |
|----------------------|-----|-------|
| Share of Ages 16-24 | 18 | 0.168 |
| Share of Ages 25-34 | 18 | 0.17 |
| Share of Ages 35-44 | 18 | 0.164 |
| Share of Ages 45-54 | 18 | 0.167 |
| Share of Ages 55-64 | 18 | 0.151 |
| Share of Ages 65-100 | 18 | 0.18 |

Figure 4: Summary Statistics – Share of Age Sectors

As visualized by *Figure 3*, a percent increase in the per capita deaths of the 25-34 age bracket will have the most detrimental effects on the economy, indicated by the coefficient -0.0719499e+07. This means that compared to the omitted group “per capita deaths 65-100,” a

percent increase in per capita deaths will lead GDP per capita to fall by $0.0719499e+07$ dollars more. Moreover, since the coefficient is the smallest among any age bracket, it is implied that one percent of the raw count population of the 25-34 age group contributes more to GDP per capita than one percent of any other age group. On the other hand, applying the same intuition, we can conclude that a percent increase in per capita deaths of the 55-64 age bracket will have the least impact on the economy because of its positive coefficient $0.0667539e+06$. This means that compared to the 65-100 age bracket, a percent increase in per capita deaths of the 55-64 age bracket will cause GDP per capita to fall by $0.0667539e+06$ dollars less. Thus when we order each age bracket from being the most to least influential on GDP per capita, we derive the following order: 25-34, 45-54, 65-100, 35-44, 16-24, 55-64.

My continuous variable “year” has a coefficient of 3428.73, meaning that each additional year can be attributable to an increase in GDP per capita of 3428.73 dollars. Then, my indicator variable “Covid year” has a coefficient of -875.404, meaning that during a Covid recession year, GDP per capita will deviate below its projected value by 875.404 dollars. “Savings rate” has a coefficient of -484.999, meaning that a percent increase in savings rate will cause GDP per capita to decline by 484.999 dollars. Finally, “unemployment rate” has a coefficient of -248.424, meaning that a percent increase in unemployment will cause GDP per capita to decline by 248.424 dollars. It is important to note that while I am using the same control variables across both regressions, the coefficients are slightly different for each one—likely because there are certain exogenous variables that my regressions don’t completely account for. With that being said, the coefficients still accurately represent more general casualties, with consistent positive and negative correlations along with minimal variation between values. For example, while the “Year” coefficient for my second regression is not completely identical to the “Year” coefficient of my previous regression, they are both significantly positive with a relative difference (absolute difference/reference value) of only 0.2338—denoting that GDP per capita is expected to rise by several thousand dollars with each additional year.

5. DISCUSSION

The results from the first regression—share of workers—seem to be capturing the immediate effects of the increased cost of living over the past few decades. Typically, between the ages of 62 to 65, many workers will reduce the time they spend working, transitioning to part-time jobs where they can spend more time taking care of family and other personal responsibilities. Resultantly, while these workers are still considered as active members of the labor force, the collective income of the employed 55-64 age bracket declines significantly, meaning that each additional percent share of the “55-64” age bracket is less significant and therefore contributes the least to GDP per capita. However, due to the rise in consumer price index and overall cost of living, some retired individuals—typically between the age of 65 and 100—have found that they can no longer sustain themselves comfortably, thus prompting them to re-enter the labor force. Accordingly, given this phenomenon of short-term retirements, it makes sense that these older workers are not only the most skilled, but also the most productive workers, meaning that their economic output will be inherently higher. Moreover, the employed elderly population likely also contributes to the economy through their higher consumption trends, primarily due to their expensive medical bills and the cost of providing for their grandchildren.

The results from the second regression—per capita deaths—seem to reflect not only the employment demography of each sector, but also raw-count population and consumption trends, causing slightly different results from the first regression. Demographically, 25-34 year

olds make up the largest sector of the total population, hence why a percent increase in per capita deaths is the most detrimental to the economy compared to any other age group. Specifically, it makes sense that the younger population as a whole is contributing more to the economy since they might be paying off larger expenses such as student debt, rent, and cars which all count towards consumption. This trend continues for 35-44 year olds, who are the second most influential age bracket on GDP per capita. Similarly to 25-34 year olds, 35-44 year olds are likely also paying off large expenses such as real estate, given that the average first-time homebuyer is 38 years old (CNBC). In contrast, while individuals aged between 55 and 64 don't necessarily make up the smallest share of the total population, a significant portion of this demographic is made up of part-time workers and short-term retirees, meaning that their average income level is likely relatively low compared to other age sectors. Moreover, among the 55-64 year old population, there is also a notable decline in consumption, specifically in regards to durable goods such as housing. Accordingly, the combination of their lower employment rates and reduced spending habits can explain why a percent increase in deaths per capita in the 55-64 age bracket will have the least impact on GDP per capita compared to any other age bracket.

6. LIMITATIONS

It is important to note that both regression models have potential limitations and sources of bias. First, while I account for exogenous variables such as savings rate, unemployment rate, and year—my regressions don't capture the effects of two key variables: intergenerational mobility and the economic disparities between sub-communities. Since the dependent variable of both regressions is quantified by GDP per capita, I am measuring the average level of personal output which primarily consists of income and consumption. However, by not accounting for intergenerational mobility, my regressions likely don't capture the economic effects of inheritance, which is often passed down through generations in the form of monetary or durable assets. Capturing fluctuations in inheritance trends over time is especially important since its effects can often determine whether or not someone needs to allocate their money to substantial assets such as real estate, drastically shaping their consumption and economic output. Moreover, it is also important to note that because my dependent variable GDP per capita merely represents the average economic output of the entire US population, it can also over-generalize trends that are unique to specific demographics, offering a slightly skewed representation of the average consumer. For instance, the inclusion of outliers, specifically billionaires, will drastically drive up the average GDP per capita, despite representing a very small share of the actual US population. Thus, using an output metric that excludes outliers in this case would likely give us a better sense of the overall income and consumption trends of the average person. Likewise, there are also notable socio-economic disparities between states, communities, and even people that GDP per capita can't fully capture. Being able to break down the US population into more specific subgroups would help strengthen the accuracy of my results, particularly in scenarios where major economic changes are occurring within specific demographics.

Secondly, due to limitations in available data, the employed population data that I used in my first regression is from the IPUMS American Community Survey. This means that the data is based on a representative sample of the US population as opposed to the raw count numbers, making the data more prone to minor inaccuracies. Likewise, also due to data availability, my second regression only has 18 observations, which could have slightly compromised the

accuracy of my coefficients. Thus, future research could better address these regression limitations by incorporating additional control variables, limiting the use of representative data (as opposed to raw-count data), and regressing a wider range of observations for more comprehensive results.

7. MECHANISMS

In order to better understand the causal relationship between public health crises and economic downturns, future areas of research should explore the influence of political spheres, level of education, and accessibility of contraception. As demonstrated by the historical trends of the United States, there is a notable correlation between the political party of the president and the health of the economy. For instance, according to the Joint Economic Committee, the US economy has consistently performed better under Democratic presidents due to their prioritization of the middle-class—hence why only 1 out of 11 US recessions had begun under Democratic governance (Joint Economic Committee). Similarly, people's education level also plays a critical role in determining the trajectory of their career and participation in the labor force. For instance, higher degrees of education have been positively associated with income and consumption, meaning that as the average level of education fluctuates, so will GDP per capita (Bureau of Labor Statistics). In parallel, federal policies that determine the accessibility of birth control and abortion also drastically impact the economy, influencing fertility rates and population growth around the world. Understanding this relationship is especially important in the present day, where the downward trend in US birth rates is projected to compromise the capacity of the labor force in the long-run, thus increasing the demand for immigration as a means to make up for lost economic productivity. Similarly, higher education levels among women have also been associated with lower birth rates, meaning that as the overall level of education increases in the long-term, we can expect the population to decrease as the demand for birth control increases. Finally, research also suggests that when a Republican president is in office, there may be a negative correlation with birth rates and population, due to healthcare and social welfare policies along with the prioritization of the upper class, who tend to have smaller household sizes.

8. CONCLUSION

In this paper, I analysed two linear regression in order to estimate the effect of various age demographic groups on the health of the US economy, as quantified by nominal GDP per capita. My findings reveal that within the employed population, 55-64 year olds generally contribute the least to the GDP measure, due to increased transitions to part-time work and changing family responsibilities. On the other hand, my coefficients suggest that within the employed population, 65-100 year olds generally contribute the most to the GDP per capita measure, likely due to their higher skill sets and productivity relative to other age groups. Accordingly, this estimate captures the effects of the increased cost of living over the past few decades, where recently retired individuals will re-enter the labor force in order to comfortably sustain their lifestyle.

In contrast, I find that within the raw population (employed and unemployed), 55-64 year olds also contribute the least to the GDP measure, due to the rise in short-term retirements, where workers will temporarily leave their jobs under the assumption that their social security and savings will cover their cost of living. On the other hand, I find that 25-34 year olds contribute the

most to the GDP per capita measure, which is likely attributable to their higher consumption of non-durable goods such as real estate and transportation.

The COVID-19 pandemic significantly shaped employment trends in the United States, driving up retirement rates while prompting companies to lay off younger employees with less work experience—both of which compromised the health of the economy. This issue is highlighted by the outcomes of my two regressions, where the 65-100 and 25-34 age brackets are both indicated as key contributors to GDP per capita. Thus, my findings suggest that economically, public health resources should be prioritized to young adults and the elderly population, as their participation in the labor force is likely the most critical to promoting quicker economic recovery during recessions and public health crises. Finally, my findings also demonstrate the importance of factoring in employment status and age when assigning short-term quantitative values to statistical lives, adjusting for the ever-changing employment patterns and work sentiment of the US labor force.

9. APPENDIX

TABLE 1: Economic and Demographic Data Compiled (FRED; HMD; IPUMS; Census Bureau)

| Year | GDP Per Capita | Savings Rate | Unemployment Rate | Percent of Workforce (Ages 16-24) | Per Capita Deaths (Ages 16-24) | Percent of Workforce (Ages 25-34) | Per Capita Deaths (Ages 25-34) |
|------|----------------|--------------|-------------------|-----------------------------------|--------------------------------|-----------------------------------|--------------------------------|
| 2000 | 36298 | 4.3 | 4 | 16.06% | 0.0008 | 22.51% | 0.0010 |
| 2001 | 37100 | 4.7 | 4.7 | 15.36% | Not Used | 22.65% | Not Used |
| 2002 | 37954 | 5.6 | 5.8 | 15.29% | Not Used | 22.39% | Not Used |
| 2003 | 39419 | 5.2 | 6 | 15.15% | Not Used | 22.16% | Not Used |
| 2004 | 41658 | 4.7 | 5.5 | 15.18% | Not Used | 21.86% | Not Used |
| 2005 | 44051 | 2.3 | 5.1 | 15.12% | Not Used | 21.63% | Not Used |
| 2006 | 46233 | 2.8 | 4.6 | 15.54% | Not Used | 21.39% | Not Used |
| 2007 | 47975 | 2.5 | 4.6 | 15.29% | 0.0008 | 21.30% | 0.0011 |
| 2008 | 48499 | 4.1 | 5.8 | 15.16% | 0.0008 | 21.32% | 0.0011 |
| 2009 | 47123 | 5.7 | 9.3 | 14.76% | 0.0007 | 21.80% | 0.0011 |



| | | | | | | | |
|------|-------|------|-----|--------|--------|--------|--------|
| 2010 | 48569 | 5.9 | 9.6 | 14.45% | 0.0007 | 21.43% | 0.0011 |
| 2011 | 49951 | 6.6 | 8.9 | 14.43% | 0.0007 | 21.59% | 0.0011 |
| 2012 | 51644 | 7.9 | 8.1 | 14.52% | 0.0007 | 21.73% | 0.0011 |
| 2013 | 53234 | 5 | 7.4 | 14.59% | 0.0007 | 21.83% | 0.0011 |
| 2014 | 55093 | 5.5 | 6.2 | 14.50% | 0.0007 | 22.09% | 0.0012 |
| 2015 | 56796 | 5.9 | 5.3 | 14.34% | 0.0007 | 22.25% | 0.0013 |
| 2016 | 57930 | 5.4 | 4.9 | 14.26% | 0.0008 | 22.40% | 0.0014 |
| 2017 | 60000 | 5.8 | 4.4 | 14.02% | 0.0008 | 22.54% | 0.0014 |
| 2018 | 62824 | 6.4 | 3.9 | 13.84% | 0.0007 | 22.72% | 0.0014 |
| 2019 | 65170 | 7.3 | 3.7 | 13.82% | 0.0007 | 22.78% | 0.0014 |
| 2020 | 64350 | 15.1 | 8.1 | 13.33% | 0.0009 | 23.01% | 0.0017 |
| 2021 | 71218 | 10.9 | 5.4 | 13.56% | 0.0010 | 22.24% | 0.0019 |
| 2022 | 77775 | 3 | 3.6 | 14.11% | 0.0008 | 22.24% | 0.0016 |
| 2023 | 82220 | 4.7 | 3.6 | 13.75% | 0.0007 | 22.19% | 0.0014 |

TABLE 1 (Continued): Economic and Demographic Data Compiled (FRED; HMD; IPUMS; Census Bureau)

| Year | Percent of Workforce (Ages 35-44) | Per Capita Deaths (Ages 35-44) | Percent of Workforce (Ages 45-54) | Per Capita Deaths (Ages 45-54) | Percent of Workforce (Ages 55-64) | Per Capita Deaths (Ages 55-64) | Percent of Workforce (Ages 65-100) | Per Capita Deaths (Ages 65-100) |
|------|-----------------------------------|--------------------------------|-----------------------------------|--------------------------------|-----------------------------------|--------------------------------|------------------------------------|---------------------------------|
| 2000 | 26.51% | 0.0020 | 21.50% | 0.0043 | 10.07% | 0.0099 | 3.34% | 0.0514 |
| 200 | 26.19% | Not | 22.24% | Not Used | 10.48% | Not Used | 3.08% | Not Used |



| | | | | | | | | |
|-----|--------|----------|--------|----------|--------|----------|-------|----------|
| 1 | | Used | | | | | | |
| 200 | 25.63% | Not Used | 22.46% | Not Used | 11.04% | Not Used | 3.19% | Not Used |
| 200 | 25.05% | Not Used | 22.66% | Not Used | 11.65% | Not Used | 3.32% | Not Used |
| 200 | 24.63% | Not Used | 22.81% | Not Used | 12.11% | Not Used | 3.40% | Not Used |
| 200 | 24.22% | Not Used | 22.99% | Not Used | 12.59% | Not Used | 3.45% | Not Used |
| 200 | 23.75% | Not Used | 22.84% | Not Used | 12.93% | Not Used | 3.55% | Not Used |
| 200 | 23.34% | 0.0019 | 23.07% | 0.0043 | 13.34% | 0.0089 | 3.67% | 0.0487 |
| 200 | 22.74% | 0.0018 | 23.06% | 0.0043 | 13.88% | 0.0089 | 3.85% | 0.0490 |
| 200 | 22.16% | 0.0018 | 23.04% | 0.0043 | 14.29% | 0.0088 | 3.94% | 0.0468 |
| 201 | 21.79% | 0.0018 | 23.14% | 0.0042 | 15.05% | 0.0088 | 4.13% | 0.0467 |
| 201 | 21.49% | 0.0018 | 22.79% | 0.0042 | 15.47% | 0.0087 | 4.23% | 0.0470 |
| 201 | 21.27% | 0.0018 | 22.34% | 0.0042 | 15.57% | 0.0087 | 4.56% | 0.0445 |
| 201 | 21.04% | 0.0018 | 21.89% | 0.0042 | 15.84% | 0.0088 | 4.81% | 0.0435 |
| 201 | 20.93% | 0.0018 | 21.56% | 0.0042 | 15.99% | 0.0089 | 4.94% | 0.0425 |
| 201 | 20.81% | 0.0019 | 21.30% | 0.0042 | 16.20% | 0.0089 | 5.09% | 0.0423 |
| 201 | 20.64% | 0.0020 | 21.04% | 0.0042 | 16.34% | 0.0090 | 5.32% | 0.0410 |
| 201 | 20.68% | 0.0021 | 20.69% | 0.0042 | 16.55% | 0.0092 | 5.52% | 0.0406 |
| 201 | 20.84% | 0.0021 | 20.29% | 0.0041 | 16.56% | 0.0092 | 5.74% | 0.0397 |
| 201 | 20.90% | 0.0021 | 19.83% | 0.0041 | 16.66% | 0.0092 | 6.01% | 0.0389 |
| 202 | 21.21% | 0.0027 | 19.61% | 0.0050 | 16.72% | 0.0107 | 6.12% | 0.0449 |



| | | | | | | | | |
|------|--------|--------|--------|--------|--------|--------|-------|--------|
| 0 | | | | | | | | |
| 2021 | 21.57% | 0.0031 | 19.65% | 0.0056 | 16.81% | 0.0116 | 6.18% | 0.0442 |
| 2022 | 21.59% | 0.0024 | 19.42% | 0.0047 | 16.33% | 0.0105 | 6.31% | 0.0407 |
| 2023 | 21.88% | 0.0021 | 19.34% | 0.0040 | 16.26% | 0.0091 | 6.58% | 0.0380 |

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11. REFERENCES

1. Aaronson, Daniel, Riley Lewers, and Daniel G. Sullivan. "Labor reallocation during the Covid-19 pandemic." *Chicago Fed Letter* 455.10.21033 (2021).
2. Aizenman, Joshua, et al. *The political economy of the COVID-19 fiscal stimulus packages of 2020*. No. w29360. National Bureau of Economic Research, 2021.
3. Atkeson, Andrew. *What will be the economic impact of COVID-19 in the US? Rough estimates of disease scenarios*. No. w26867. National Bureau of Economic Research, 2020.
4. Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis. *COVID-19 is also a reallocation shock*. No. w27137. National Bureau of Economic Research, 2020.
5. Bartik, Alexander W., et al. *Measuring the labor market at the onset of the COVID-19 crisis*. No. w27613. National Bureau of Economic Research, 2020.
6. Berger, David, et al. "Stimulating durable purchases: Theory and evidence." (2018).
7. Cambefort, Marine. "How the COVID-19 pandemic is challenging consumption." *Markets, Globalization & Development Review* 5.1 (2020).
8. Ciotti, Marco, et al. "The COVID-19 pandemic." *Critical reviews in clinical laboratory sciences* 57.6 (2020): 365-388.
9. Clemente-Suárez, Vicente Javier, et al. "The impact of the COVID-19 pandemic on social, health, and economy." *Sustainability* 13.11 (2021): 6314.
10. Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. *Labor markets during the COVID-19 crisis: A preliminary view*. No. w27017. National Bureau of economic research, 2020.
11. Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. *How did US consumers use their stimulus payments?*. No. w27693. National Bureau of Economic Research, 2020.
12. Cortes, Guido Matias, and Eliza Forsythe. "Heterogeneous labor market impacts of the COVID-19 pandemic." *ILR Review* 76.1 (2023): 30-55.
13. Curran, James W., et al. "Epidemiology of HIV infection and AIDS in the United States." *Science* 239.4840 (1988): 610-616.

14. Davahli, Mohammad Reza, et al. "The hospitality industry in the face of the COVID-19 pandemic: Current topics and research methods." *International journal of environmental research and public health* 17.20 (2020): 7366.
15. Davis, Owen. *Employment and retirement among older workers during the COVID-19 pandemic*. Schwartz Center for Economic Policy Analysis (SCEPA), Department of Economics, the New School for Social Research, 2021.
16. Deeks, Steven G., et al. "HIV infection." *Nature reviews Disease primers* 1.1 (2015): 1-22.
17. Elka Torpey, "Measuring the value of education," *Career Outlook*, U.S. Bureau of Labor Statistics, April 2018.
18. Faria-e-Castro, Miguel. "The COVID retirement boom." *Available at SSRN 3946093* (2021).
19. Gemelas, Jordan, et al. "Inequities in employment by race, ethnicity, and sector during COVID-19." *Journal of racial and ethnic health disparities* (2022): 1-6.
20. Goldstein, Joshua R., and Ronald D. Lee. "Demographic perspectives on the mortality of COVID-19 and other epidemics." *Proceedings of the National Academy of Sciences* 117.36 (2020): 22035-22041.
21. Gordon-Wilson, Sianne. "Consumption practices during the COVID-19 crisis." *International Journal of Consumer Studies* 46.2 (2022): 575-588.
22. Gursoy, Dogan, and Christina G. Chi. "Effects of COVID-19 pandemic on hospitality industry: review of the current situations and a research agenda." *Journal of Hospitality Marketing & Management* 29.5 (2020): 527-529.
23. Human Mortality Database. *Death Counts*, University of California, Berkeley, and Max Planck Institute for Demographic Research, 2025, www.mortality.org. Accessed 28 Mar. 2025.
24. IPUMS. *IPUMS USA*, University of Minnesota, 2025, www.ipums.org. Accessed 28 Mar. 2025.
25. Kirkwood, Thomas B L. "Deciphering death: a commentary on Gompertz (1825) 'On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies'." *Philosophical transactions of the Royal Society of London. Series B, Biological sciences* vol. 370,1666 (2015): 20140379. doi:10.1098/rstb.2014.0379.
26. Osuna, Victoria, and José Ignacio García Pérez. "Temporary layoffs, short-time work and COVID-19: the case of a dual labour market." *Applied economic analysis* 30.90 (2022): 248-262.
27. Parker, Jonathan A., et al. "Consumer spending and the economic stimulus payments of 2008." *American Economic Review* 103.6 (2013): 2530-2553.
28. Penn, Rick, and Eric Nezamis. "Job openings and quits reach record highs in 2021, layoffs and discharges fall to record lows." *Monthly Labor Review* (2022).
29. Rahman, Muhammad Khalilur, et al. "Effect of Covid-19 pandemic on tourist travel risk and management perceptions." *Plos one* 16.9 (2021): e0256486.
30. Roy, Shohini. "Economic impact of Covid-19 pandemic." *A preprint* 1 (2020): 29.
31. Sasson, Isaac. "Age and COVID-19 mortality." *Demographic Research* 44 (2021): 379-396.
32. Schwartländer, Bernhard, et al. "Country-specific estimates and models of HIV and AIDS: methods and limitations." *AIDS* 13.17 (1999): 2445-2458.



33. Shi, Yu, et al. "An overview of COVID-19." *Journal of Zhejiang University. Science. B* 21.5 (2020): 343.
34. Tauber, Kristen, and Willem Van Zandweghe. "Why has durable goods spending been so strong during the COVID-19 pandemic?." *Economic Commentary* 2021-16 (2021).
35. Tu, Yidong, Diwan Li, and Hai-Jiang Wang. "COVID-19-induced layoff, survivors' COVID-19-related stress and performance in hospitality industry: The moderating role of social support." *International journal of hospitality management* 95 (2021): 102912.
36. U.S. Bureau of Economic Analysis. *Gross Domestic Product per Capita* [A939RC0Q052SBEA]. Federal Reserve Bank of St. Louis, FRED, <https://fred.stlouisfed.org/series/A939RC0Q052SBEA>. Accessed 28 Mar. 2025.
37. U.S. Bureau of Economic Analysis. *Personal Saving Rate* [PSAVERT]. Federal Reserve Bank of St. Louis, FRED, <https://fred.stlouisfed.org/series/PSAVERT>. Accessed 28 Mar. 2025.
38. U.S. Bureau of Labor Statistics. *Unemployment Rate* [UNRATE]. Federal Reserve Bank of St. Louis, FRED, <https://fred.stlouisfed.org/series/UNRATE>. Accessed 28 Mar. 2025.
39. U.S. Census Bureau. *Age and Sex Composition in the United States*. U.S. Census Bureau, <https://www.census.gov/data.html>.
40. Velavan, Thirumalaisamy P., and Christian G. Meyer. "The COVID-19 epidemic." *Tropical medicine & international health* 25.3 (2020): 278.
41. Viscusi, W. Kip. "The heterogeneity of the value of statistical life: Introduction and overview." *Journal of Risk and Uncertainty* 40.1 (2010): 1-13.