SOCIAL CONNECTION IN TIMES OF ECONOMIC CRISIS: COVID-19 AND UNEMPLOYMENT

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ABSTRACT

This project examines the effect that social capital, mainly economic connectedness (EC), has on the economic response to the COVID-19 pandemic. For the purposes of this study, the effect that the COVID-19 pandemic had on unemployment levels across the United States was examined separately by ZIP code and county. Using a difference-in-differences framework, this project analyzes how economic connectedness is correlated with changes in unemployment at the ZIP code level. A second regression model builds on the previous by adding COVID-19 case rates at the county level. Results from the difference-in-differences analysis suggest that high EC ZIP codes show slight increases in unemployment as a result of COVID in the post period. However, the next regression model, directly incorporating COVID cases in the analysis, provided an interaction coefficient between case rates and EC. The outcome shows that areas of high EC were able to mitigate the effect that COVID exposure had on unemployment compared to areas of low EC, when higher case rates led to increases in unemployment overall. This implies that EC plays a role in managing the negative effects of the pandemic. Policy makers should explore developments that mix socio-economic classes to improve economic outcomes and strengthen communities.

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1 Introduction

The COVID-19 pandemic was a global health crisis that led to a recession in the United States, disrupting everyday life for all. The shutdowns of nearly all nonessential businesses brought the U.S. economy and most social activity to a halt. As the economy shut down, unemployment shot up to 14.8%, an unprecedented high, affecting millions regardless of industry or demographic group (Falk et. al, 2021). The past couple of years have seen a major recovery from the peak rates of unemployment seen in early 2020. By 2022, most parts of the U.S. saw their unemployment rates return to pre-pandemic levels according to the U.S. Bureau of Labor Statistics (via FRED). Since COVID-19 led to major economic downturns and reductions in social interactions, its recovery can reveal valuable insights about the relationship between both changes in behavior.

The purpose of this project is to analyze differences in economic outcomes and explore how social capital plays a role in economic recovery. Emerging research has shown that social connections and socio-economic mixing can be beneficial to one's economic mobility in local communities. This is most likely due to increased access to job opportunities, networks, and resources for lower socio-economic individuals through friendships with people of higher socio-economic status (SES) (Schmutte, 2015). Improvements in socio-economic mixing can be made, since people of similar economic classes naturally tend to isolate themselves within their own group, a concept known as homophily (Avin et. al, 2020). Socio-economic mixing in an area can determine how communities fare during major recessions and public health emergencies. With COVID-19 as the main focus, changes in unemployment will be examined through the lens of economic connectedness (EC): an index that measures how connected people of high and low socio-economic status are in an area (Chetty et. al, 2022A).

A difference-in-differences (DiD) analysis is used to first approach this question. With high EC as the treatment and low EC as the control variables, the change in unemployment was observed across the 2018-2022 time period on a ZIP code level. Although high EC areas have lower overall unemployment than low EC areas (-1.033%), high EC areas actually see a slight increase in unemployment in the post period (0.061%), whereas the low EC ZIP codes saw decreases (-0.607%) on average. Other unknown factors could be at play that are obscuring the impact of EC across the events of the pandemic. Moving ahead, a second regression with interaction terms between COVID case rates and the high EC dummy variable directly incorporates COVID exposure into the analysis. Where COVID cases increase unemployment rates (0.037%), areas of high EC see reductions to a similar degree (-0.038%). The results show that, at a county-level, areas of high EC were able to mitigate the effect that case rates had on unemployment on average. Therefore, the negative impact that COVID exposure had on the unemployment in an area could be lessened by increasing social connections between people of different socio-economic classes.

The results could provide insight on what characteristics make areas more resilient to health risks and major social changes. Reducing segregation between individuals of opposing SES can be a goal for policymakers to build better municipalities. COVID-19 has undoubtedly changed the geographic mobility of workers and consumption patterns, accelerating shifts in social behavior from new technology (Akan et al. 2024, Walton, 2020). In times of increasing gentrification and social isolation, policies that push for redistribution in urban development should be made to reduce income inequality and improve economic mobility to strengthen communities. The conclusions in this project provide reinforcement that higher socio-economic mixing can lead to better economic outcomes.

2 Literature Review

The labor market dynamics during the U.S. recovery from COVID-19 have been shaped by several key factors, with significant differences across industries, geographic regions, and demographic groups. Initially, the pandemic caused a sharp spike in unemployment, but as the economy reopened and stimulus measures took effect, employment levels quickly rebounded, reaching pre-pandemic levels in many sectors (Edwards, 2022). However, there were noticeable differences in certain areas. Post-pandemic data from the USDA showed varying effects to employment levels by poverty and metropolitan status. Although areas of urban counties responded worse to the employment shock at the beginning of the pandemic than rural counties, areas of persistent poverty, whether they were of urban or rural status, saw slower and worse recoveries in unemployment rates than those of non-persistent poverty (Sanders, 2023). The higher levels of unemployment could be attributed to which local industries were considered essential and stayed open or closed due to reduced demand. Clearly, COVID-19 caused a major disruption to the U.S. labor market as a whole, but the recovery has not been equal for everyone.

The recession caused by the pandemic was uniquely spurred on by health risks that necessitated social isolation. Research on job loss disparities in the early pandemic reveal various impacts across demographic groups and education levels that differ from other financial crises. Undoubtedly, nonessential jobs that required face-to-face interaction saw the greatest decline in labor supply than jobs that could be delivered remotely, disproportionately affecting those who identified as women, hispanic, or black (Guerrieri et. al, 2020). Unlike previous recessions, less job losses were experienced by under-educated workers in essential businesses, but higher-educated workers were in industries most protected in the early pandemic, normally associated with the least physical contact, higher incomes, and higher job security (Montenovo et. al, 2022). Nonetheless, gaps in employment remain after sorting by occupation and the reallocation of workers is costly. This hints at pre-existing disparities within the labor market that contributed to inequitable exposure to health and unemployment risks across the population.

Due to COVID-19's unprecedented effect on social interaction, a possible explanation for the differences in response to the employment shock could be social connections. The relationship between social capital and economic outcomes is an emerging area of interdisciplinary study. Previous economic research discusses measurements of social capital and their relationships with economic outcomes. Using SafeGraph phone data, Chetty et. al (2022A) observes a relationship between economic connectedness, or friendships across socio-economic lines, and upwards economic mobility. Using similar methods in another work, it is clear that policy changes should be made to increase exposure across social classes, but friendship bias or class segregation persists (Chetty et. al, 2022B). This is likely due to a concept called homophily. Defined by Avin et. al (2020), homophily is the tendency for people to bond with others of the same social group, like nationality, gender, or background. This plays a role in how people of similar socio-economic backgrounds tend to isolate with each other, for example, the "rich get richer" phenomenon. The isolation of socio-economic classes is not ideal for economic outcomes and researchers have been able to identify where this happens. Related work by Massenkoff and Wilmers (2023) measures where the most inter-class mixing is observed in daily activities utilizing similar phone data. Class segregation can be found in most areas, public or private, but it is the upper class, or "the rich", who are the most isolated in urban and suburban areas as a result of residential segregation, and the most inter-class mixing is found in casual chain restaurants (Massenkoff & Wilmers, 2023). Analyzing where individuals naturally distribute themselves can guide policymakers in encouraging integration across income groups. This socioeconomic mixing can have beneficial employment outcomes.

With millions trying to find work after the start of the pandemic, labor market disparities could be bridged through networking. Job search outcomes are highly dependent on local labor markets, where social connections play a crucial role in obtaining employment opportunities. Schmutte's study on job referral networks shows that workers are disproportionately likely to find employment with their neighbors, and have greater chances of obtaining higher-wage jobs if their neighbors work in higher-wage firms (2015). Workers without strong networks may face limited opportunities, so improving access to job information for under-networked workers could help reduce wage inequality (Schmutte, 2015). The strength of local networks play a role in an area's economic connectedness and labor market recovery.

Additionally, preserving job matches through short-term crises is optimal in the long run and proves intrinsic value in worker-firm relationships. Reductions in the misallocation of workers and productivity were observed when Danish furlough policy, allowing for fewer lay-offs, positively impacted growth and sales (Bennedsen et. al, 2023). This led to a speedier pandemic recovery compared to the United States. There is clearly economic value in workplace social connections that improve labor market outcomes by minimizing reallocation of firms and workers. In times of uncertainty, policies that maintain these beneficial relationships can lessen the negative impacts of economic downturns.

Looking into relationships that were established before the pandemic and post-pandemic economic outcomes could give more insight into the relationship between two disciplines. Places with higher economic connectedness may see stronger recoveries from impacts on the labor market due to better networked and protected workers following the pandemic's inception. The following analysis and discussion in this paper will directly explore the relationship between economic connectedness and unemployment rates in the aftermath of the COVID-19 recession.

3 Data

The economic and demographic data come from the United States Census Bureau's American Community Survey (ACS) 5-Year Estimates (via data.census.gov, U.S. Census Bureau, 2022). Different metrics were compiled from the DP02: Selected Social Characteristics in the United States, DP03: Selected Economic Characteristics, and DP05: ACS Demographic and Housing Estimates. The variables of interest include unemployment, age, gender, income, education level, and race. Data was collected by ZIP code from 2018 to 2022, such that every ZIP code has an observation for each year.

Social capital statistics were sourced from Raj Chetty's Opportunity Atlas: Social Capital Atlas (via socialcapital.org, Chetty et. al, 2022A). This project compiles and offers data on different social capital metrics, like economic connectedness, volunteer rate, and friending, by ZIP code or county for the year 2018. For the purposes of this project, the economic connectedness variable is used as the sole measure of social capital and was derived from atlas's ZIP code data. It was joined by ZIP code to the variables of interest from the ACS data.

Economic connectedness (EC) measures the extent to which people with low and high socio-economic status are friends with each other. For each ZIP code, it measures the average level of high SES friendships within the community, representing how many people of below-median SES are friends with people of above-median SES. The value is calculated as two times the share of high SES friends among low-SES individuals, averaged over all low SES individuals in the ZIP code (Chetty et. al, 2022A).

$$Economic\ Connectedness\ = \frac{\#\ of\ High\ SES\ Friends}{Total\ \#\ of\ Friends} \times 2$$

A ZIP code that has an EC value of 1 would represent an area where low SES people have an equal number of friendships between low SES and high SES individuals. This indicates that half of low SES individuals in that community have high SES friendships. An EC greater than 1 would indicate more high SES friendships, and lower than 1 would indicate less high SES friendships among low SES people in the community. An EC of 0 would imply no connection between people above and below the median SES or pure homophily. Mean EC is slightly lower than 1, suggesting that ZIP codes see less than equal SES mixing on average. Figure 1 and 2 are histograms to visualize the distribution of EC in the U.S. by ZIP code and county. Both are similar in shape and center, and are approximately normally distributed.

Figure 1: Histogram of ZIP Code EC

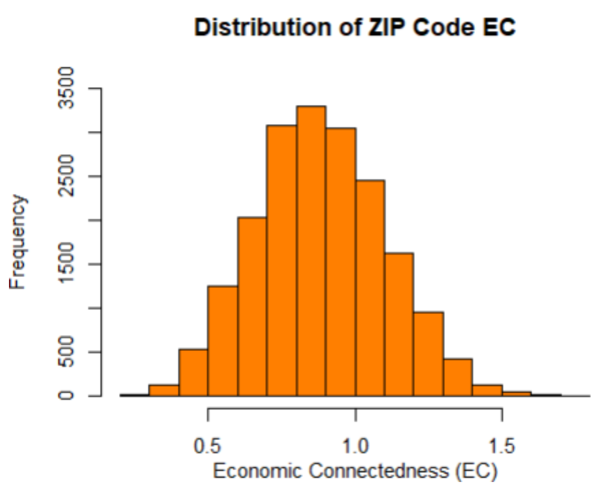
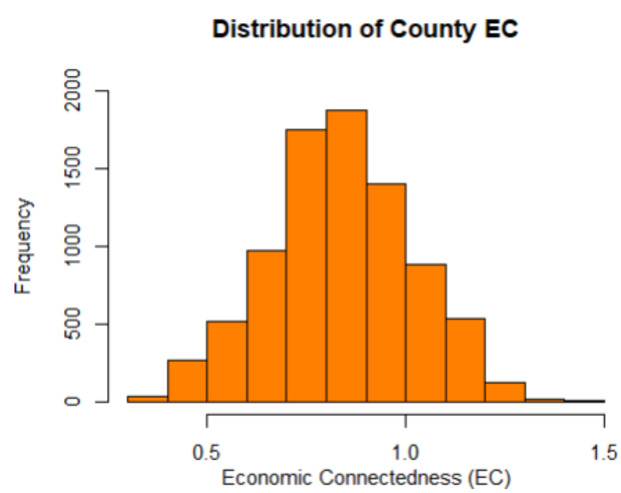


Figure 2: Histogram of County EC



In order to directly analyze the pandemic's role in the labor market, data on COVID-19 infections and cases was also obtained. The COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University collected and reported the daily spread of COVID-19 globally (via GitHub, Dong, et. al, 2020). Cases and deaths were aggregated for each U.S. county from 2020 until mid-2023. Since only county estimates were available, merging this data with the data from the U.S. Census required the economic connectedness, unemployment, and other variables of interest had to be averaged for each county based on the ZIP code-level data.

4 Methods

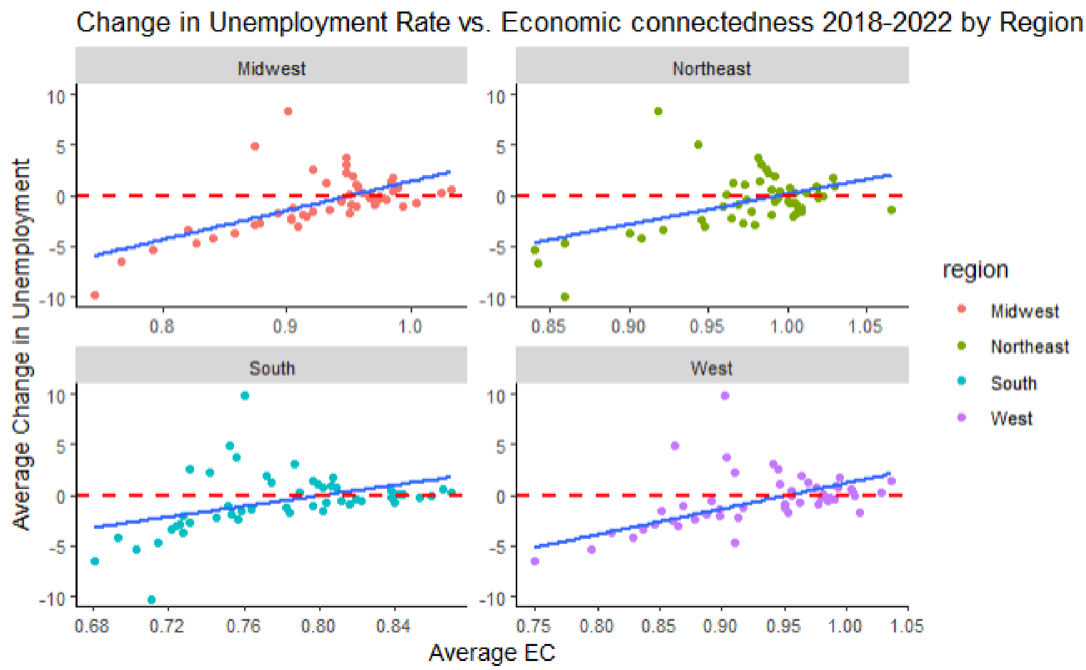
4.1 Data Exploration

Two datasets were compiled for the analyses using different parts of the collected data sets above. One dataset has information on a ZIP code-level from 2018 to 2022 and the other only consists of county-level data from 2020 to 2022. The latter includes information on the infection rates of COVID-19 in U.S. counties.

Table 1 presents the summary statistics for the observed ZIP codes from 2018-2022. There are almost 20,000 ZIP codes observed across the five year period. All of the variables, other than income, age, and economic connectedness (EC), represent a proportion in the ZIP code observation. Education is measured as the proportion of the ZIP code's population above the age of twenty-five with a bachelor's degree. Gender and race are the proportions of the ZIP code that identify as male or white respectively.

First, the relationship between economic connectedness and unemployment were observed through a binned scatter plot visualization in Figure 3. Each plot is faceted by region in the U.S. Across the country, places with lower EC saw larger decreases in unemployment between 2018-2022 than places with higher EC. In areas of high EC, unemployment slightly increased over the time period. Interestingly the South saw a slightly flatter relationship than the other regions, however, the trend is still similar to the rest of the nation. Further analysis could be conducted on the American South based on its historical economic underperformance compared to the rest of the country in future studies.

Figure 3: Binned Scatterplots of Unemployment and EC, faceted by region



Overall, changes in unemployment decreased or got close to 0 as the average EC increased. It was expected that places of higher EC would have lower unemployment levels after COVID-19's impact, assuming that places of higher EC had more resilient economies, but the figures show otherwise. Possibly, places of higher EC are also places with high social interaction and labor supplies with more jobs that require face-to-face contact. As a result, those areas would see greater job losses compared to areas with lower EC. It's also plausible that areas of low EC felt a greater shock in response to COVID-19, therefore, showed a more substantial recovery than areas of high EC that were not impacted as hard. This will be further investigated in later discussion.

Table 2 reports summary statistics at the county level, emphasizing the relationship between unemployment and COVID case rate. It includes observations of about 2,800 counties in the U.S. in each year from 2020-2022. Each variable represents a proportion of the population in a county except for income, age, EC, confirmed COVID cases, and COVID related deaths. The education, race, and gender variables are measured similarly as the ZIP code statistics. The confirmed COVID cases and COVID related deaths were aggregated and recalculated to count the number of incidents in each county per year. The case and death rates are the numbers of each incident in a county divided by the population of the specific county.

One may assume that higher EC leads to higher social interactions which could increase exposure to COVID-19 and infection. Figure 4 displays the relationship between average case rate and EC by county, suggesting an inverse relationship. As average EC increased, average case rates actually show a clear decreasing trend. This can be attributed to places of high EC having more resources between those of low EC, allowing for lesser spread of COVID-19. These could be better public health education, higher distribution of preventive care measures, and greater access to medical intervention in higher EC areas. Stronger EC could be correlated with better public health infrastructure and lower infection rates.

Figure 4: Binned Scatterplot of Average Economic Connectedness and COVID Case Rates

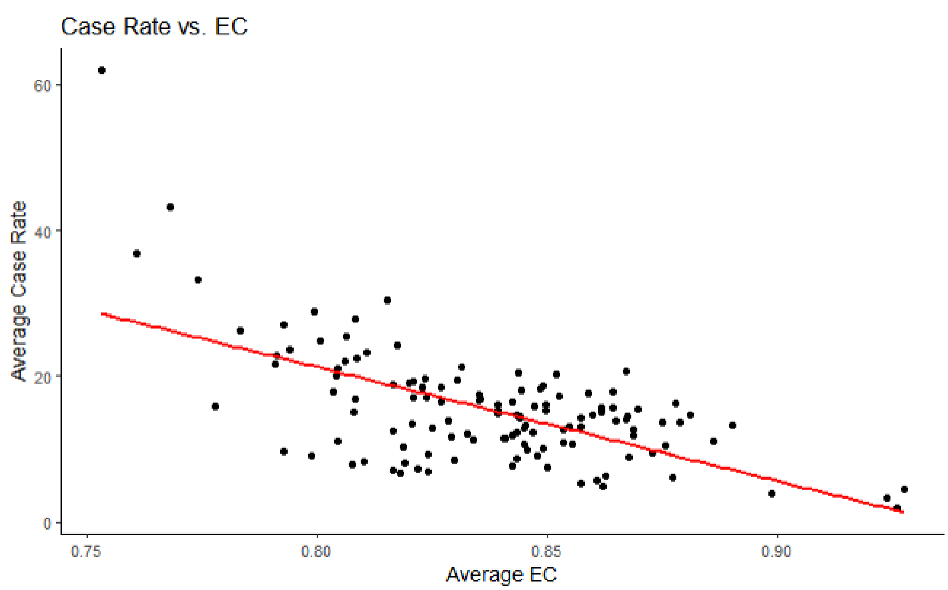
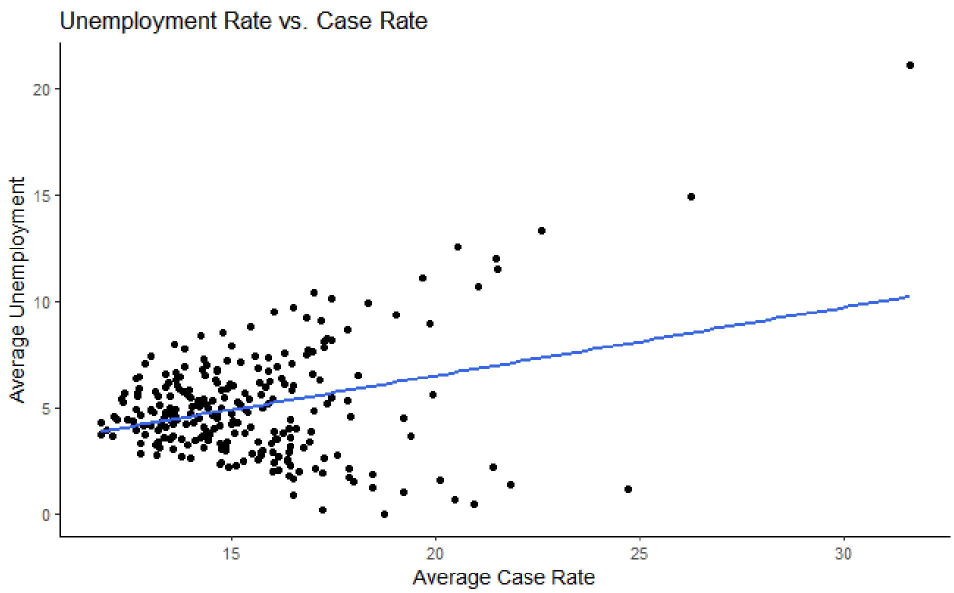


Figure 5 is another binned scatter plot that displays the relationship between average case rate and average unemployment by county. The average unemployment rate seems to diverge as the average case rate increases, showing some heteroskedasticity. This could indicate that areas with higher average case rates experienced more variable unemployment outcomes. However, the overall positive trend line suggests that higher rates of COVID-19 infections led to higher rates of unemployment. More job losses are likely a result of greater lockdowns and business closures. Still, the divergence in the data suggests that there are more unknown factors at play.

Figure 5: Binned Scatterplot of Average Unemployment and COVID Case Rates



The next two sections will delve into the two regression models used in this project. Using these methods, the variables that have the most significant impact on unemployment can be identified and quantify the effects of economic connectedness. The regression models can help determine the direction and strength of the relationships between unemployment and COVID or economic connectedness, providing insight into a possible causal relationship.

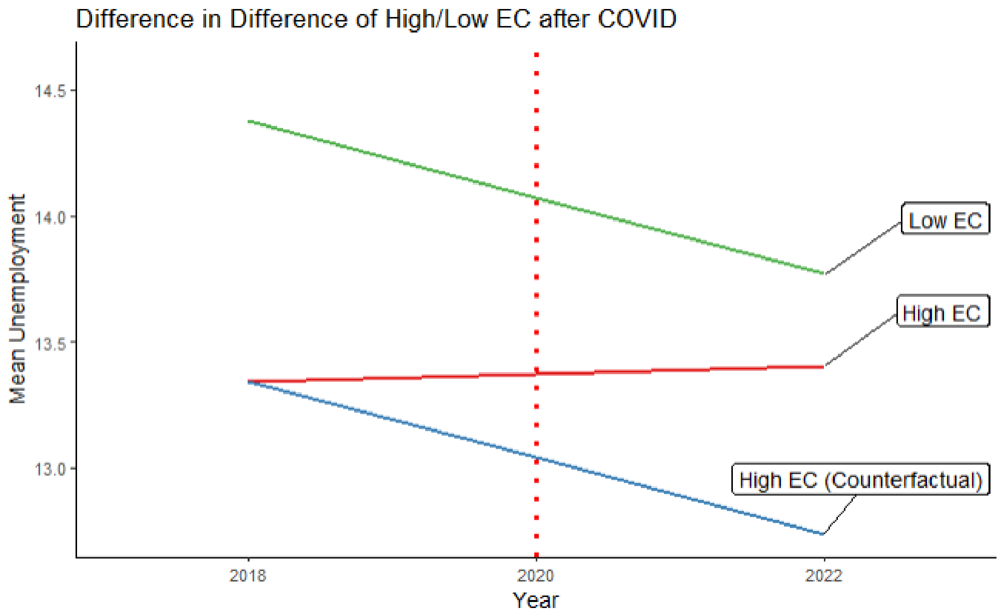
4.2 Difference-in-Differences (DiD)

To estimate the effects of economic connectedness and COVID cases on unemployment, a difference-in-differences (DiD) analysis was conducted. This utilized the ACS data combined with the social capital data by ZIP code from 2018 to 2022. For the purposes of this analysis, areas of high EC were considered to be the treatment group, with areas of low EC as the control group. The pre and post period were separated by the year 2020, which represents the start of the pandemic.

$$Unemployment_{i,t} = \beta_0 + \beta_1 * HighEC_i + \beta_2 * Post_t + \beta_3 * HighEC_i * Post_t + \gamma_t + \alpha_i + \beta_{i,t} * X_{i,t} + \varepsilon_i$$

Common covariates and demographic characteristics of each ZIP code were also added as control variables and are represented by $X_{i,t}$. The term ε_i represents the error. Time and state fixed effects were also added, represented by γ_t and α_i respectively . In this regression, if the value of the interaction coefficient is negative, it would indicate that the areas of high EC would have their unemployment diverge from the counterfactual and be lower in the post period. That would allow conclusions to be drawn that higher EC areas are able to see decreased unemployment rates after major economic shocks. Figure 6 helps us visualize the changes over the time period.

Figure 6: Difference-in-Differences Graph between High/Low EC, 2018-2022



As seen in the figure above, if low EC and high EC areas were to follow similar trends in unemployment, both groups would see a decrease in unemployment after the inception of the pandemic. The actual change in high EC areas did diverge from the counterfactual, but in the opposite direction. High EC areas saw increased unemployment rates after COVID-19, bringing their mean unemployment rate closer to the mean unemployment in low EC areas. Thus, high EC areas saw slightly higher unemployment rates in the post period, even though unemployment rates returned to pre-pandemic levels nationwide.

These trends in unemployment are quantified in the difference-in-differences analysis (Table 3), where many of the variables show statistical significance. Of the covariates, age, income, education, and race each had significant effects in unemployment. ZIP codes with higher proportions of Bachelor's degree educations had lower unemployment rates, and higher proportions of white individuals had lower unemployment rates than non-white during the pandemic. Also, areas of higher income had decreased unemployment, whereas higher median age slightly increased unemployment. Gender did not have a significant effect. The adjusted R^2

value of the regression is 0.308 which indicates at about 31% of the variability in unemployment is captured by this model.

Each column in the table represents a sequential adding of variables to better capture the significance of the main result. The first column represents the raw correlation between EC and unemployment. The second column is the difference-in-differences coefficient without any added controls. The third column shows the previous two coefficients with the added covariates and fixed effects in order to reduce omitted variable bias in the final difference-in-differences coefficient.

Notably, the post period coefficient resulted in a negative value suggesting that unemployment decreased by an average of 0.607% in the post period for the low EC ZIP codes and the counterfactual. The high EC coefficient has a value of -1.033%, which means that high EC ZIP codes started with lower unemployment rates in the pre-period compared to low EC ZIP codes. However, the interaction term between high EC and the post period, the DiD coefficient, provided a positive result of 0.668%, indicating a slight uptick in unemployment in high EC areas when subtracted from the post period coefficient. High EC ZIP codes see unemployment rates increase by about 0.061% on average after COVID.

There doesn't seem to be evidence here to back up the idea that places of high EC fared better in terms of unemployment after the pandemic's inception. It's not immediately clear as to why higher EC did not contribute to lower levels of unemployment in the post-pandemic time period. In fact, ZIP codes of high EC fared worse in terms of changes in unemployment compared to low EC areas. To dive deeper, the next model will directly look at the effect that exposure to COVID-19 had on an area.

4.3 Model with COVID Case Rates

The final regression model consisted of using a dummy variable of economic connectedness to observe its interaction with COVID case rates. This model only looks at the post period since the COVID-19 repository only has observations after the start of the pandemic. It uses data from 2020 to 2022 across all available U.S. counties. In this model, the HighEC variable appears again but is used as a dummy variable, rather than a representation of treatment. Counties above the median in economic connectedness were assigned to the binary value of 1, whereas those below the median were assigned 0.

$$Unemployment_{i,t} = \beta_0 + \beta_1 * Case\_Rate_i + \beta_2 * HighEC_i + \beta_3 * Case\_Rate_i * HighEC_i + \gamma_t + \alpha_i + \beta_{i,t} * X_{i,t} + \varepsilon_i$$

Time and county fixed effects were added to the model as γ_t and α_i respectively. $X_{i,t}$ are demographic and labor-related controls and ε_i is the error term, similar to the previous model. The main coefficient of interest is β_3, the interaction between case rate and high EC. Given that case rate increases unemployment, as in β_1 is a positive value, a positive coefficient would suggest that high EC would add to the effect that case rate has on unemployment. On the other hand, a negative coefficient would demonstrate a reduction on the impact that case rate has on unemployment.

According to the results from the COVID regression model (Table 4), income, education, and race each had significant effects in unemployment. Counties with higher proportions of white individuals and higher proportions of educated individuals saw decreased unemployment rates on average. Higher incomes also led to decreased unemployment rates. A higher proportion of males in a county shows only slight significance in decreasing unemployment. In this model, age did not have a significant effect.

Similar to the previous DiD analysis, multiple models were created, adding variables in each iteration, to observe the development of the final interaction coefficient. The first and second columns display the high EC, case rate, and interaction terms before adding the covariates. The third column includes all the related controls, time fixed effects, and state fixed effects. Lastly, the fourth column includes all previous variables, but instead uses county fixed effects to show how the results change after capturing more granular differences in the data. With all the controls and fixed effects, the adjusted R^2 value of the model is about 0.557, which indicates that almost 60% of the variability in unemployment is captured. The predictability of this model is an improvement from the previous.

More importantly, the case rate variable had an overall positive effect on unemployment. Each additional increase in COVID case rates tends to increase unemployment levels by about 0.037% on average. On the other hand, counties with high EC tend to see lower rates of unemployment by about 0.563% compared to low EC counties. What is most compelling is that the case rate coefficient is equal in magnitude and opposite in value compared to the interaction between case rate and EC, which is about -0.038% on average. This suggests that areas of high economic connectedness are able to diminish the effect that COVID exposures had on unemployment. High EC counties can absorb the shock that COVID cases had on unemployment rates. Areas with greater high SES connections among low SES individuals could better withstand the impact that health risks pose on an economic outcome.

5 Discussion

5.1 Assumptions and Limitations

Each regression was conducted under common assumptions like linearity, independence, homoscedasticity, and normality of residuals. The difference-in-difference analysis was performed under the assumption of parallel trends. This would mean that the two groups, high EC and low EC, would see changes in unemployment of a similar amount over time without the treatment. That is, if COVID-19 did not happen, the differences in unemployment between both groups would be constant over the time period. Although controls were added to each model, omitted variable bias is still present since it would not be possible nor reasonable to account for every variable that impacts unemployment in a single analysis. Robustness checks could also be performed to ensure validity and reliability of results.

Unfortunately, accessible data on COVID case rates was only available by county. It would have been more insightful if the data was also broken down into the ZIP code-level. This would allow the second analysis to better investigate the interaction with more granularity. Direct access and funding for the phone data, as used in previous literature, could also contribute to developing more accurate results. If there was more time and accessible data, further analysis could be done on additional demographic characteristics. The most noteworthy, as mentioned repeatedly in the literature review, would be education and poverty levels. These would likely produce significant results. Another interesting variable could be political affiliations, like majority red or blue counties, however, this may already be absorbed by county fixed effects.

It is also important to acknowledge that economic connectedness may not be the best representation of social capital in this context. There could be other unknown measures that would better capture the social connections that people have and how they relate to the economic characteristics of a community. Due to the abstract nature of human relationships, it is difficult to accurately measure and reliably quantify the relationships that people have with one another. For example, there are also other social capital indices in Chetty's work, like clustering and friendship bias, that could be explored in a similar context. These variables were prominent in previous research, but do not have as much of an impact on economic outcomes compared to the economic connectedness index which is why they were not included.

COVID-19 was both a recession and a public health emergency. It would be interesting to perform comparisons of the economic outcomes due to social capital in different contexts. Using the same methods as this paper, but side by side with previous recessions like the 2001 Dot-Com Bubble and the 2008 Global Financial Crisis, could help in better understanding how social capital historically affects unemployment in major economic downturns. It could also be insightful to use these same methods to analyze how other public health outbreaks fare in comparison although there are not many precedents that have caused an economic shutdown at a similar scale. This raises questions about how much infectious diseases affect the overall labor market.

5.2 Conclusion

The first difference-in-difference regression model did not provide evidence that higher EC would be able to lessen the impact on unemployment over the time period. The ZIP codes with lower EC saw decreases in unemployment, whereas high EC areas had slight increases in unemployment, moving opposite of the counterfactual. Many other socio-economic factors could be at play that could be obscuring the full picture. However, a more notable result is observable in the model that directly included COVID exposure.

The COVID regression model shows compelling evidence that areas of high EC were able to mitigate the impact that COVID-19 cases had on unemployment. This is to suggest that high social capital and mixing of socio-economic-classes can be more resistant to recession caused by a health epidemic. However, this is not to say that areas of high EC are more immune to health risks in general. It's plausible that more inter-class mixing leads to more social support systems and stronger labor market structures that result in easier recovery from the pandemic. On the other hand, areas with less social capital show worse recovery presumably due to greater isolation and limited opportunities.

The presence of high socio-economic mixing is linked with more opportunities and connections that could aid individuals in finding employment after the pandemic. As mentioned in previous research, networking undoubtedly plays an important role in job searches and local job markets, helping workers find higher paying jobs (Schmutte, 2015). Policies aimed towards expanding networks of high paying firms could increase economic connectedness and employment opportunities to those who are underserved. Also, preserving worker-firm relationships can reduce friction in the labor market (Bennedsen et. al, 2023). Efforts should be made to protect these social connections in order to improve economic recovery. Even through downturns and emergencies, there should be safeguards in place to preserve economic connectedness.

Recent times have seen an increase in gentrification, which further isolates socio-economic classes to their own in-group. Currently, bridging the ever-increasing gap between the wealthy and poor is a major concern in political spheres and has only been exacerbated by the pandemic's social isolation. Some economists argue that it's time to truly rethink our cities at a human-level. New migratory patterns of workers (Akan et al. 2024) and changes in consumption due to COVID-19 (Walton, 2020) are examples of how people today are becoming increasingly “footloose” due to the mobility of labor and online commerce (Schumacher & McKibben, 2010). If workers do not live in self-reliant communities, less social capital and interaction will be present, weakening economic connectedness. In order to create better environments for socioeconomic mixing, critical discussions around redistribution should be on the forefront, promoting economic sustainability, rather than strictly economic growth.

Looking forward, policymakers should make efforts to foster socio-economic mixing within communities and across neighborhoods. Some options are redistributive zoning pratices, mixed-use developments, building parks, improving transit, civic engagement opportunities, supporting local small businesses, or offering diverse cultural programs and experiences. More research could be done to measure the impacts of modern urban development and their effects on social connection. Future research should make efforts to combine economics with other areas of study, like social structures and health impacts, to better understand human behavior. Hopefully, these results can contribute to discussions around sustainable economic development with greater human interaction in mind.

6 Appendix

6.1 ZIP Code-level Summary Statistics Table

Table 1: ZIP Code-level Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Income (1000's)	88.077	37.045	7.753	595.736
Unemployment	5.334	3.315	0	100
Education	28.737	16.519	0	100
Age	40.857	6.747	14.4	75.6
Gender (Male)	49.772	3.542	14.4	100
Race (White)	78.397	20.792	0	100
EC	0.883	0.219	0.235	1.708

(NOTE: Created in statistical software R. Unemployment, education, gender, and race represent a proportion in a ZIP code's observation. Income, age, and economic connectedness (EC) are summarized as values.)

6.2 County-level Summary Statistics Table

Table 2: County-level Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Income (1000's)	77.819	20.158	32.067	223.887
Unemployment	5.022	2.563	0	36
EC	0.837	0.18	0.334	1.427
Age	41.973	4.869	23.2	61.2
Gender (Male)	50.18	2.517	39.7	75.7
Education	22.684	9.503	3.767	78.338
Race (White)	82.496	15.73	1.675	99.9
Confirmed	11,355.04	41,022.39	29	1,935,154
Deaths	123.556	419.613	0	17,278
Case Rate	15.449	7.971	0.279	96.818
Death Rate	0.218	0.182	0	4.048

(NOTE: Created in statistical software R. Unemployment, education, gender, race, case rate, and death rate represent a proportion in a county's observation. Income, age, economic connectedness (EC), confirmed, and deaths are summarized as values.)

6.3 DiD Regression Table

Table 3: Difference-in-Differences of High EC on Unemployment Rate

	Dependent variable: Unemployment Rate		
	(1)	(2)	(3)
High EC	-2.238***	-2.558***	-1.033***
	(0.02)	(0.032)	(0.032)
Post	-0.289***	-0.555***	-0.607***
	(0.021)	(0.029)	(0.026)
Income (1000's)			-0.015***
			(0.0004)
Age			0.007***
			(0.002)
Gender (Male)			-0.0004
			(0.003)
Bachelor's			-0.024***
			(0.001)
Race (White)			-0.056***
			(0.001)
High EC:Post		0.532***	0.668***
		(0.041)	(0.036)
Constant	6.627***	6.787***	14.375***
	(0.019)	(0.023)	(0.225)
State Fixed effects	NO	NO	YES
Observations	94,869	94,869	94,685
R^2	0.116	0.117	0.309
Adjusted R^2	0.116	0.117	0.308
Residual Std. Error	3.117 (df = 94866)	3.115 (df = 94865)	2.695 (df = 94626)

(NOTE: Significance levels are interpreted as *p<0.1; **p<0.05; ***p<0.01. Created in statistical software R with *stargazer* package (Hlavac 2022). Column (1) represents the basic regression between EC, the post period, and unemployment. Column (2) includes the DiD coefficient of High EC and Post. Column (3) reiterates the previous two coefficients with all covariates and state fixed effects. This final model was used to determine the values of constant and coefficients β_0, β_1, β_2, and β_3. These were used to calculate the plot in Figure 6.

6.4 COVID Model Regression Table

Table 4: COVID Model: Regression of Case Rate on Unemployment

	Dependent variable: Unemployment Rate			
	(1)	(2)	(3)	(4)
Case Rate	0.031***	0.051***	0.032***	0.037***
	(0.004)	(0.004)	(0.004)	(0.004)
High EC		-0.814***	-0.084	-0.563***
		(0.113)	(0.113)	(0.116)
Income (1000's)			-0.033***	-0.017***
			(0.002)	(0.003)
Age			0.0001	0.006
			(0.005)	(0.007)
Gender (Male)			-0.022**	-0.027**
			(0.01)	(0.011)
Bachelor's			0.0002	-0.017***
			(0.004)	(0.005)
Race (White)			-0.058***	-0.047***
			(0.002)	(0.002)
Case Rate:High EC		-0.081***	-0.038***	-0.038***
		(0.007)	(0.006)	(0.006)
Constant	4.538***	5.221***	12.939***	12.261***
	(0.061)	(0.074)	(0.576)	(1.148)
Fixed effects	None	None	Year and State	Year and County
Observations	8,362	8,362	8,264	8,264
R2	0.009	0.184	0.372	0.66
Adjusted R2	0.009	0.184	0.368	0.577
Residual Std. Error	2.551 (df = 8360)	2.315 (df = 8358)	2.039 (df = 8206)	1.668 (df = 6635)

(NOTE: Significance levels are interpreted as *p<0.1; **p<0.05; ***p<0.01. Created in statistical software R with *stargazer* package (Hlavac 2022). Column (1) represents the basic regression between EC and unemployment. Column (2) includes the interaction term between Case Rate and High EC. Column (3) adds on covariates and year and state fixed effects. Column (4) includes county fixed effects instead of state.)

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