The Employment Effects of COVID-19

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Abstract

The spread of COVID-19, beginning in 2020 in the United States, has had a widespread economic impact on unemployment rates. This paper aims to investigate the relationship between the spread of the disease and growing unemployment, taking into account geographic location and resulting spatial effects. A fixed effects panel regression model was employed with month and county fixed effects to estimate the impact of COVID-19 on state and county level unemployment rates. In North Carolina, when regression coefficients are scaled for mean cases and deaths, we find that a multiple regression including border county cases and county cases increases the unemployment rate prediction by 0.08 percentage points over a simple regression with only county cases. Similarly, conducting a multiple regression with border county deaths and county deaths increases the unemployment rate prediction by 0.11 percentage points over a simple regression with only county deaths. Our findings reinforce the importance of regional policy in mitigating spatial spillover effects of the pandemic.

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Introduction

Beginning in the United States in 2020, the outbreak of the novel coronavirus (SARS-CoV-2 or COVID-19) has led to mass disruptions in employment and economic development. The rapid spread of the disease has made it unique and especially dangerous. Two months after the first confirmed case, the number of cases in the United States topped 100,000. One week later, the number of cases reached 200,000 (Harcourt et al., 2020). This spread has left severe economic effects. Government imposed quarantine measures in response to public health risks sharply decreased economic activity in the earliest months of the pandemic. As a result, unemployment rose sharply following the onset of lockdown protocols, rising to 14.7%, the highest rate of national unemployment since December 1940 (U.S. Bureau of Labor Statistics, 2020). Although cases continue to see upticks around the country, some employment recovery has occurred because of state re-openings, but the difficulty of both reopening and containing spread has stilted the process in many areas. This suggests that long term employment recovery is likely to be uneven from state to state and even county to county, as varying regional policy impacts both consumer demand and worker willingness to rejoin the workforce. As shown by economic indicators, lockdowns have created marked drops in productivity and consumption. We aim to give more attention to the regional macroeconomic impact that the pandemic has had, specifically on individual county labor markets. Furthermore, researchers have closely followed swings in both infection and unemployment rates in hopes of predicting the movement of the pandemic and the resulting economic impact it will leave in its wake. Although the causal link between the pandemic and resulting unemployment is clear, variation on a smaller regional scale has not been investigated as thoroughly, and may not be obvious given the differences around the country in state policy, population density, and other local factors. We contribute to the literature by disaggregating the data and studying county level effects in greater detail. Moreover, we investigate the role that border effects play on a county's unemployment rates. While the state of affairs in an individual county may dictate its residents' preferences regarding reopening, these effects radiate out in a regional span. Decisions made by actors in a particular county may be based not only on the situation within their county but by the state of the pandemic in the surrounding counties, which may generate uneven economic impact and infection rates based on proximity. These border effects have the power to influence household, firm, and government level decisions. In this paper, we use regression models with region and month fixed effects to illuminate the relative impact of county level pandemic related variables, including border county measures, on county unemployment. Greater understanding of these spatial effects allows policy makers to tailor solutions to specific regions, resulting in more effective policy that better accomplishes its goal. In the first section, we overview the current body of literature surrounding pandemic outcomes on the economy, as well as spatial effects. We then describe the regression models used and pertinent results in the second section, and conclude with our findings, which suggest that the addition of border effects is beneficial to the analysis of the pandemic's impact on the unemployment rate.

Prior Literature

There have been several studies that look at the relationship between measures of economic productivity and health outcomes. In particular, a 2015 study based in China found that a 1% increase in the unemployment rate was associated with a 6.8% increase in mortality in the long run (Wang, 2015). Investigating this relationship from the opposite direction will illuminate health and mortality impacts on unemployment rates, and is especially pertinent during a pandemic.

Prior to the pandemic, the countrywide unemployment rate remained stable and low. Since March 2018, the national unemployment rate had stayed at or below 4% (U.S. Bureau of Labor Statistics, 2020) until the pandemic. This can be explained in part by rising job vacancies and increased consumption driving demand for goods up, and thus increasing labor demand within companies (Petrosky-Nadeau & Valletta, 2019). This increased labor demand has resulted in lower unemployment rates, as new job openings allow more members in the labor force to become employed. In January 2020, the unemployment rate in the U.S. was 3.6%, the lowest rate seen in almost 50 years (U.S. Bureau of Labor Statistics, 2020).

Quickly following the onset of the pandemic in the United States, stay-at-home orders caused most non-essential business to come to a halt, decreasing employment, work hours, and labor force participation (Béland et al., 2020). Even as restrictions gradually lift, areas with higher infection rates appear to be taking a slower path to labor market recovery (Federal Reserve Bank of St. Louis, 2020). Because regional factors such as local industry, population density, and local policy are highly relevant in determining the impact of COVID-19 on unemployment, it is essential that impacts on a regional scale are investigated in order to best tailor policy to both economic and public health improvement.

Regional factors play a significant role in a population's labor market characteristics (Smith & Glauber, 2013) and health outcomes, including mortality rates (Sparks & Sparks, 2009), and will certainly do so in the case of an infectious disease. Mobility across regions can proliferate the spread of infection, further exacerbating any potential risks for those living in a region such as socioeconomic status, access to health and resources, as well as employment

(Jarynowski et al., 2020). During the pandemic, spatial factors have become especially relevant with the onset of governmental policy at both the state and local levels creating large scale effects on employment in the area (Devaraj & Patel, 2020). Stay-in-place orders, as well as reopening restrictions and legal limits on gathering, have worked to decrease the spread of the disease while greatly dampening economic activity. Although these policies are often enacted at the state level, actual outcomes may be better measured on the county level, as bordering counties in different states show similar responses to social and economic factors despite differences in state policy (Arindrajit et al., 2010). In the case of the coronavirus pandemic, state level policy may create disparate outcomes for counties based on the state they are housed in rather than their immediate surrounding region (Lyu & Wehby, 2020). However, the labor market impacts of COVID-19 are twofold, with supply side factors such as supply chain disruption reducing the ability of firms to provide goods and services, while demand side factors such as individual risk aversion reduce consumer demand. Paired with lockdown orders affecting both parties, the resulting loss in economic activity cannot be traced to a single policy (Forsythe et al., 2020). Given the variety of factors influencing labor market outcomes, spatial analysis and further investigation of local effects is necessary. Research suggests the usefulness of county data, as it provides a relatively homogeneous sphere of activity and interaction for a population, but remains a relevant political and social unit (Thiede & Monnat, 2016). This emerging body of work begins to characterize the relationship between pandemic variables and unemployment rates, and suggests the importance of regional factors and influences. These spatial factors merit further investigation, as they are crucial to the determination of state and local policy moving forward as we work to combat pandemic related harms.

Data

The data for unemployment rates, including adjusted unemployment rates, comes from the Bureau of Labor Statistics. These were collected on a county by county and state by state basis in order to facilitate analysis at different geographic scales. Two datasets were compiled with the most current data at the time of writing, with one beginning in November 2019 and including data until June 2020, and the other with additional preliminary data from July 2020.

COVID-19 case information was also obtained on a county by county and state by state basis from the CDC's online reporting data source, USA Facts. End of month cumulative cases, deaths, and test counts were used. County and state level unemployment data were collected from the Bureau of Labor Statistics. End of month cumulative testing data on a state by state basis were obtained from The Atlantic's COVID Tracking Project.

COVID-19 tracking data for case and death counts were not available corresponding to all available unemployment data, leading to the removal of US territory data including Puerto Rico, Guam, Virgin Islands, American Samoa, and Northern Mariana. Case reporting was not widely available concerning United States cases of COVID-19 before January 2020, and the relative inactivity of the pandemic allowed for the assumption of zero cases and deaths until data was made available for these metrics starting in January. Reliable test tracking on a state by state basis became available in March, restricting statewide testing analysis on unemployment statistics to the months of March-June.

The data samples used begin in November 2019 to establish baseline conditions pre-pandemic. The state level data sample included a total of 408 observations, split equally between observations before and after the onset of the pandemic. County level data included 25,128 observations, with 12,564 observations before March 2020 and an equal amount during the pandemic thus far. In North Carolina, the total of 800 observations were also split equally between data from before the pandemic and data during the pandemic.

Measuring the economic impact of COVID-19 is complex for various reasons. Most notable among these is the rapidly changing state of the pandemic and that we are still living in it. We can make attempts to mitigate these problems by looking at a snapshot in time (Ataguba, 2020). For that reason, this paper focuses on COVID-19 cases up until June 30, 2020. Because of the continuously emerging quality of the data, not all adjustments that will be made are reflected in the information used.

Descriptive statistics help to characterize both the pandemic and movement within the labor market. Because the pandemic became active and widespread in the United States in March, related variables are described from March to June in order to provide the most relevant context, and prevent averages from being skewed by low values in the first half of the time frame.

Table 1.1: Descriptive Statistics, Pandemic Variables

	March 2020 – June 2020		
	Mean	Maximum	Standard Deviation
State			
Monthly Cases	27,686.11	393,496	54010.77
Monthly Deaths	1,434.368	31,625	3,805.251
Monthly Tests	276,201.7	4,167,139	521,687
County			
Monthly Cases	446.335	103,529	2,809.253
Monthly Deaths	23.283	7,103	200.521
NC County			
Monthly Cases	259.59	11,170	746.915
Border Cases	1,673.405	15,712	2,543.482
Monthly Deaths	6.485	146	14.426
Border Deaths	41.795	265	53.592

Table 1.2: Descriptive Statistics, Unemployment Rate

	November 2019 – February 2020			March 2020 – June 2020		
	Mean	Maximum	Std. Dev	Mean	Maximum	Std. Dev
Monthly State UR%	3.55	6.1	0.846	10.127	30.1	4.977
Monthly County UR%	4.136	21.2	1.842	9.016	41	4.772
Monthly NC County UR%	4.147	14.4	1.254	9.053	24.1	3.752

COVID-19 cases and deaths on a state and county level basis exhibited a pattern consistent with exponentially increasing cases throughout the United States. Unemployment rates by county and state prior to pandemic related changes were close to 4%, but rose to a county level and state level maximum of 41% and 30.1%, respectively. Within North Carolina, unemployment rates were comparable to county level averages, with a mean of 4.147% prior to the pandemic and a mean of 9.053% during it.

Effect of Statewide Cases on Statewide Unemployment Rate

Both in the case of lockdowns and re-openings, state policymakers have led the way in the administration of COVID-19 public health measures. The lack of a unified federal policy regarding containment measures suggests that a state level breakdown may be a useful starting point in the spatial analysis of the pandemic's effects on unemployment. The use of a fixed effect regression model allowed us to control for invariant factors within months, as well as invariant factors within states. Specifically, the fixed effect for each month captured variables unique to that particular month, such as seasonal economic activity, while the fixed effect for each state captured variables unique to the state, including important metrics such as population and industrial and political makeup. These effects are unlikely to shift significantly over the time frame of analysis.

The regression model with fixed effects and robust standard errors for state by state data can be described as follows:

$$UR_{i,t}{}^{s} \;=\; \alpha_i + \alpha_t + \beta C_{i,t}{}^{s} + \; \varepsilon_{i,t} \tag{1}$$

Here, $UR_{i,t}{}^{s}$ represents the U3 unemployment rate in a particular state at time t. α_i is a state fixed effect, and α_t is a month fixed effect. The coefficient β describes the change in the unemployment rate for each unit change in $C_{i,t}{}^{s}$, which represents cases in a particular state and month.

Table 2. State Regression Results

Monthly UR%	(1)	(2)	(3)
State Cases	$1.72 * 10^{-5}$*** ($3.51*10^{-6}$)		
State Deaths		$2.54*10^{-4}$*** (0.000)	
State Tests			$1.79*10^{-6}$*** ($2.72*10^{-7}$)
Observations	408	408	408
R-squared	0.864	0.866	0.864

Robust standard errors are reported in parentheses. All regressions include state and month fixed effects.

***p<0.01, **p<0.05, *p<0.1

Column 1 of Table 2 quantifies the impact of each additional case in a state on its unemployment rate. This coefficient is best understood in the context of mean cases after the onset of the pandemic, 27,686, which predict an increase in the unemployment rate of approximately 0.48 percentage points. At the maximum statewide case count, 393,496, the model predicts an increase in the unemployment rate of 6.77 percentage points. It is important to consider that many states had reached a number of cases at or greater than the mean value early in the progression of the pandemic, and the number of cases in most states continues to increase at the time of writing. As a result, future data points are highly likely to show higher maximum values, and thus higher impacts on unemployment rate. Using a statewide average close to 4% prior to the pandemic, this would suggest an increase to 11% unemployment, meaning that the unemployment rate more than doubled.

Measuring the severity of the spread of the pandemic and resulting economic impact may be better handled by the number of deaths reported by a state, as this outcome records the most severe cases. In order to investigate this possibility, the model utilizing statewide effect of pandemic related deaths on the unemployment rate was developed and can be represented as follows, where variables remain the same as in equation 1, with the exception of ${D_{i,t}}^{s}$, which represents statewide deaths in a particular state and month.

$$ {UR_{i,t}}^{s} = \alpha_i + \alpha_t + \beta {D_{i,t}}^{s} + \varepsilon_{i,t} \qquad (2) $$

Column 2 of Table 2 shows that each death had more than ten times the effect on the unemployment rate as each case, but given the lower number of deaths relative to cases, this impact on the unemployment rate is comparable to that of cases. In particular, 1,434 mean deaths during the pandemic correspond to an increase in the unemployment rate by 0.36 percentage points. At its maximum, a state death count of 31,625 predicts an increase in the unemployment rate of 8.05 percentage points. Greater death counts may indicate the severity of the spread of COVID-19 in certain areas, and may lead to greater caution taken either by the state itself or individual citizens within it. As a result, self-isolation and subsequent lack of consumer spending may lead to greater joblessness and higher unemployment rates, potentially explaining the size of relative effects. However, the smaller number of deaths by state balances out the magnitude of the coefficient.

An additional variable that may represent the reach and severity of the pandemic is testing. The model relating statewide test counts with unemployment rate uses the variable ${T_{i,t}}^{s}$ to represent the number of tests administered in a particular state and month, with all other variables unchanged from Equation 1:

$$ {UR_{i,t}}^{s} = \alpha_i + \alpha_t + \beta {T_{i,t}}^{s} + \varepsilon_{i,t} \qquad (3) $$

Column 3 of Table 2 quantifies the impact of each test on the unemployment rate. The mean number of tests conducted, 276,202, would correspond to an increase in the unemployment rate of 0.49 percentage points, and the maximum number of tests, 4,167,139, corresponds to an increase in unemployment of 7.46 percentage points. Although tests are conducted broadly and are rarely found to be majority positive at any region size, the economic impact on the unemployment rate predicted by the model utilizing tests was not starkly different from those using cases and deaths, which may initially appear to be better measures of severity.

Statewide cases, deaths, and tests had a statistically significant effect on the state level unemployment rate at the 99% level, and the R-squared value across all models was approximately 0.86. In economic terms, the scale of unemployment changes caused by these three pandemic variables are very similar, suggesting that all three may be used as metrics to gauge the severity of the pandemic. While coefficients are not equal in magnitude, the corresponding case, death, and test counts appear to balance out these differences in practical terms.

Effect of County Cases on County Level Unemployment Rate

State level policy may inform general decisions made by a state's residents, but local political climate and circumstances are likely to vary within states, and mobility is more common in a smaller physical radius. Given the relevance of counties as spatial and political units, local analysis provides a closer look at regional pandemic impacts on unemployment rates. Narrowing in on the county level, a similar regression model with fixed effects and robust standard errors was used to estimate the effect of county pandemic variables on the unemployment rate in that county. This model is characterized as follows:

$$UR_{i,t}{}^{c} = \alpha_i + \alpha_t + \beta C_{i,t}{}^{c} + \varepsilon_{i,t} \tag{4}$$

In this model, $UR_{i,t}{}^{c}$ represents the U3 unemployment rate in a particular county and month. The county and month fixed effects are represented by α_i and α_t, respectively. The coefficient β describes the change in the unemployment rate for each unit change in $C_{i,t}{}^{c}$, which represents cases in a particular county and month. Given state results, we can expect county impacts on unemployment rates to follow a similar pattern in terms of the relative effect of additional cases and deaths. If both cases and deaths tend to be similar representatives of the severity of the pandemic and related economic impact, this should hold at a smaller regional level as well.

Table 3. County Regression Results

Monthly UR%	(1)	(2)
County Cases	$2.36 * 10^{-4}$***	
	$(2.28 * 10^{-6})$	
County Deaths		0.00323***
		$(2.61 * 10^{-4})$
Observations	25,128	25,128
R-squared	0.791	0.791

Robust standard errors are reported in parentheses.
All regressions include state and month fixed effects.

***p<0.01, **p<0.05, *p<0.1

Column 1 in Table 3 shows the percentage point increase in county unemployment rate for each additional case. To scale, the mean number of cases by county during the pandemic, 446, is associated with an increase in the unemployment rate of 0.11 percentage points. The maximum number of cases by county, 103,529, predicts a percentage point increase in the unemployment rate of 24.39. This increase to the county average unemployment rate of 6.57 represents a final rate of 30.96.

Countywide death tolls were also used to predict the unemployment rate in that county with the following model, where variables remain the same as in equation 4, with the exception of ${D_{i,t}}^c$, which represents the number of deaths in a county and month.

$$ {UR_{i,t}}^c = \alpha_i + \alpha_t + \beta {D_{i,t}}^c + \varepsilon_{i,t} \quad (5) $$

The mean number of deaths by county during the pandemic, 23, is associated with an increase in the unemployment rate of 0.07 percentage points given the results in Column 2 of Table 3, while the maximum number of deaths by county, 7,103, is associated with a 22.96 percentage point increase.

Both coefficients were statistically significant at the 99% level, with an R-squared value of about 0.79 across models. Unlike state level analysis, the maximum number of deaths in a county predicted a smaller increase in the unemployment rate, further providing evidence to support the idea that both cases and deaths may serve as equivalent metrics of pandemic severity. In addition, mean case and death counts predict very low shifts in the unemployment rate for that county. At the maximum values of these variables thus far, however, the predicted impact is much greater than that observed for states. This may be partially explained by the greater variation in county data, as many counties have seen few cases and even fewer deaths. In those areas, initial onset of the pandemic may have created less comparative unrest and economic upheaval, while heavily populated regions, or those with economies largely dependent on service related industries, may have seen sharp spikes in unemployment.

Effect of County Border Cases on County Unemployment Rate

Economic outcomes within a county are certainly based on factors within that county, but are also affected by thoroughfare and surrounding circumstances. Due to smaller physical size and ease of mobility between counties, neighboring areas' futures are often linked. Higher case and death figures may become less relevant to local unemployment as they move further away in physical distance, so it is likely that within-county variables will predict larger shifts in the unemployment rate when compared with external county variables. However, cross-county travel and potential infectious spread are likely to play a role as well, meaning border county cases and deaths will likely be associated with an increase in unemployment rates and potentially lead to higher total prediction values.

In order to investigate these effects in greater detail in North Carolina, we first employed a simple regression model with county and month fixed effects and robust standard errors in order to set up comparison to border effects, as follows:

$$UR_{i,t}{}^{NC} = \alpha_i + \alpha_t + \beta C_{i,t}{}^{NC} + \varepsilon_{i,t} \quad (6)$$

$UR_{i,t}{}^{NC}$ is equal to the U3 unemployment rate in a particular month and North Carolina county. As in the previous models, α_1 and α_2 represent the fixed effects of county and month, respectively. Coefficient $\boldsymbol{\beta_1}$ represents the change in unemployment rate for one county for every unit change in its monthly cases.

The following model for deaths within North Carolina counties was set up identically to Equation 6, with the sole exception of variable $D_{i,t}{}^{NC}$, now representing deaths rather than cases.

$$UR_{i,t}{}^{NC} = \alpha_i + \alpha_t + \beta D_{i,t}{}^{NC} + \varepsilon_{i,t} \quad (7)$$

Table 4. Bordering Regression Results

Monthly UR%	(1)	(2)	(3)	(4)
County Cases	$3.09 * 10^{-4}$***		$2.63 * 10^{-4}$***	
	($9.9*10^{-5}$)		($8.24*10^{-5}$)	
County Border Cases			$5.76*10^{-5}$**	
			($2.61 *10^{-5}$)	
County Deaths		0.024***		0.021***
		(0.004)		(0.004)
County Border Deaths				0.003**
				(0.001)
Observations	800	800	800	800
R-squared	0.890	0.891	0.890	0.891

Robust standard errors are reported in parentheses. All regressions include state and month fixed effects.

***p<0.01, **p<0.05, *p<0.1

In Columns 1 and 2 of Table 4, it is shown that coefficients in North Carolina are similar in magnitude to those seen between counties around the United States. We then expanded on Equation 6 to incorporate border cases with a multiple regression model with county and month fixed effects and robust standard errors. This model was set up as follows:

$$UR_{i,t}{}^{NC} = \alpha_i + \alpha_t + \beta_1 C_{i,t}{}^{NC} + \beta_2 BC_{i,t}{}^{NC} + \varepsilon_{i,t} \tag{8}$$

Most variables remain the same as in Equations 6 and 7, with the exception of β_2, which represents the change in unemployment rate for that county with every unit change in the sum of all cases in border counties, represented by $BC_{i,t}{}^{NC}$.

Because North Carolina's county mean and maximum number of cases and deaths are lower than the mean and maximum values among counties throughout the United States, coefficients of similar magnitude will create smaller practical effects when scaled compared to those seen for countrywide county level data. Column 3 of Table 4 reports the impacts on unemployment rate of both county cases and county border cases. As expected, the magnitude of impact on unemployment rates of each additional case or death within one county is higher than the impact of each additional case or death in a border county. Given the mean number of cases during the pandemic in North Carolina counties, approximately 260, the model predicts the unemployment rate within that county should increase by 0.068 percentage points. The maximum predicted impact on the unemployment rate is an increase of 2.94 percentage points, at 11,170 cases. As for the average of border cases, column 3 in Table 4 predicts a 0.096 percentage point increase in the unemployment rate, with a maximum increase of 0.905 at 15,712 border cases. Adding border cases may not have greatly modified the coefficients on within-county cases, but it does affect overall unemployment predictions. These predicted effects are modestly larger than those predicted by the model that utilizes only North Carolina county cases to estimate the unemployment rate. In total, the simple regression model predicted an increase in the unemployment rate by 0.08 percentage points for mean cases, while the multiple regression model predicted an increase of 0.164 percentage points. For maximum cases, the simple regression model predicted an increase of 3.45 percentage points, while the multiple regression model predicted an increase of 3.85.

The multiple regression model using both within county deaths and border county deaths is written as follows, with variable definitions unchanged from Equation 8 except ${D_{i,t}}^{NC}$ and ${BD_{i,t}}^{NC}$, which represent death counts and border death counts in a particular county and month, respectively.

$$ {UR_{i,t}}^{NC} = \alpha_i + \alpha_t + \beta_1 {D_{i,t}}^{NC} + \beta_2 {BD_{i,t}}^{NC} + \varepsilon_{i,t} \tag{9} $$

To ensure that border cases and deaths did not exhibit multicollinearity with cases and deaths, the weak relationships between these variables were verified by a variance inflation factor below five, which indicates that cases and deaths within a county do not have a collinear relationship with border county cases and border county deaths.

Per the results in column 4 of Table 4, the mean number of deaths and border deaths both individually predict an increase in the unemployment rate of 0.126 percentage points. The predicted effect using maximum deaths and maximum border deaths is an increase in the unemployment rate of 3.07 and 0.795 percentage points, respectively. In total, the simple regression model predicted an increase in the unemployment rate by 0.144 percentage points for mean deaths, while the multiple regression model predicted an increase of 0.252 percentage points. For the maximum death count, the simple regression model predicted an increase of 3.504 percentage points, while the multiple regression model predicted an increase of 3.865.

Each coefficient was statistically significant at the 95% level, with an R-squared value of approximately 0.89 for both models.

Examining an individual county illustrates the predictive accuracy of the model and provides further context for the effects to scale. In Orange county, for example, the unemployment rate in January before the beginning of the pandemic was 3.2%. By the end of June, Orange county reported 669 cases, and border counties reported a total of 5,986 cases. The model predicts an increase in the unemployment rate of 0.521 percentage points, to about 3.721%. Similarly, Orange county reported 41 total deaths within the county in June, and border counties reported a total of 143 deaths. The model predicts an increase in the unemployment rate of 1.29 percentage points, to 4.49%. The actual unemployment rate at the end of June, 5.9%, was underestimated by the model, but fell closer to the rate predicted by the number of deaths and border deaths. Because the multiple regression model consistently predicts a higher level of unemployment than the simple regression model, it begins to close the underestimation gap. Taking border cases into account seems to increase the accuracy of the prediction.

Overall, the data shows that a lack of virus containment in surrounding areas is related to greater economic damage within a county unit, although less so than lack of containment within the county itself. High levels of mobility between counties may explain the importance of containment in a larger regional area in alleviating growing unemployment. The size of these spillover effects illustrates the importance of regional and even state level policy, in that county units, if able to safely contain the spread of COVID-19, have the potential to support recovery in neighboring counties.

Conclusion

In this paper, we analyzed the effect of various pandemic related variables on unemployment rates at the state level, countrywide county level, and county level within North Carolina. We used fixed effects panel regression models with data ranging from November 2019 to June 2020. At both the state and county levels, we find that deaths and cases are comparable predictors of unemployment rate changes, and may be equivalent indicators of pandemic severity. We focused on the spatial effects on North Carolina county unemployment rates created by cases and deaths in border counties, finding that multiple regression models utilizing border sums consistently increase unemployment rate predictions and raise predictive accuracy. The multiple regression model with cases and border cases predicts an unemployment rate that is 0.08 percentage points higher than the simple regression model scaled for mean cases, and 0.4 percentage points higher scaled for maximum cases. The multiple regression model with deaths and border deaths predicts an unemployment rate that is 0.11 percentage points higher than the simple regression model scaled for mean deaths, and 0.365 percentage points higher scaled for maximum deaths. These results point to the relevance of geographic location to pandemic spread, and suggest the importance of containment measures in regional units. In line with previous findings, each county's policy and resulting crowd dynamics, including mobility, are associated with their bordering county's infection rates and unemployment rates, highlighting the importance of unified regional policy. Reducing spillover effects and containing the spread of COVID-19 may be associated with positive economic outcomes not only for a particular local area, but communities surrounding it as well.

To further this work, a wider dataset including county level information for every state in the United States would be beneficial. Around the world, spatial units comparable to counties may also provide crucial insight into the differences among global regions in virus containment, mobility based spread, and resulting economic impact. As the pandemic continues to spread around the United States, time series modeling with a longer panel of data may provide additional insight into the economic impact of a “wave” and recovery times for reopening states. In addition, as cases mount, nonlinear effects may be observed if additional cases create diminishing economic impacts. Finally, event studies evaluating the impact of local and state policy decisions can help account for unprecedented unemployment rates and provide a greater basis for effective policy that helps a community and its neighbors move toward a healthy and economically productive future.

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APPENDIX A: Descriptive Statistics with Preliminary Data

Table 1.3: Descriptive Statistics, U.S. Counties

November 2019 – July 2020 (p)			
	Mean	Maximum	Standard Deviation
Monthly Cases	357.3122	188481	2889.633
Monthly Deaths	15.711	7247	165.626
Monthly UR%	6.729	41	4.268

Table 1.4: Descriptive Statistics, North Carolina

November 2019 – July 2020 (p)			
	Mean	Maximum	Standard Deviation
Monthly Cases	251.091	20502	1016.74
Bordering Cases	1637.371	29462	3733.978
Monthly Deaths	5.018	199	15.052
Bordering Deaths	32.95	392	62.868
Monthly UR%	6.816	24.1	3.595

APPENDIX B: Regression Results With Preliminary Data

Table 5: County Regression Results, Nov 2019 – July 2020 (p)

Monthly UR%	(1)	(2)
County Cases	$1.57 * 10^{-4}$ *** ($2.26*10^{-6}$)	
County Deaths		0.00323*** ($2.05 * 10^{-4}$)
Observations	28,268	28,268
R-squared	0.784	0.786

Robust standard errors are reported in parentheses.
All regressions include state and month fixed effects.

***p<0.01, **p<0.05, *p<0.1

Table 6: Bordering Case Regression Results, Nov 2019 – July 2020 (p)

Monthly UR%	(1)	(2)
County Cases	$1.52 * 10^{-4}$ *** ($4.73*10^{-5}$)	
County Border Cases	$3.30*10^{-5}$ ** ($1.37 * 10^{-6}$)	
County Deaths		0.017*** (0.003)
County Border Deaths		0.003*** (0.001)
Observations	900	900
R-squared	0.886	0.888

Robust standard errors are reported in parentheses. All regressions include state and month fixed effects.

***p<0.01, **p<0.05, *p<0.1