THE EFFECT OF RESTRICTIONS AT THE US/MEXICO BORDER ON EMPLOYMENT OUTCOMES

Thesis by Alexander MacDonald Imhof
University of Colorado Economics Honors Program

Abstract

In March of 2020, the United States instituted new restrictions on the US/Mexico border that severely limited travel. This policy made it very hard for Mexican consumers to cross the border and engage in economic activities. This paper asks how the border restrictions affected US employment outcomes in the period after the closure, based on pre-existing vulnerability defined by ratio of foreign to domestic population. I estimate this effect using a difference-in-differences strategy and an event study accounting for the effects of the COVID-19 pandemic utilizing a created term of vulnerability in the interaction. I found evidence that the closure affected counties with a higher vulnerability more than those with low vulnerability after the closure relative to before.

Advisor: Francisca Antman, Department of Economics

Defense Committee: Francisca Antman, Department of Economics, Brian Cadena, Department of Economics, Adrian Shin, Department of Political Science

1.0 INTRODUCTION

Consumer-focused industries situated on the domestic side of an international border often serve foreign patrons. The interdependence between these groups is disrupted when border restrictions are tightened, and can yield adverse welfare outcomes for individuals that depend on the ability to cross. I observe this relationship at the US/Mexico border, where approximately 950,000 individuals cross the border daily to work, make purchases, go to school, and engage in numerous other economic activities (US Customs and Border Protection, 2021). The US/Mexico border region should be of special interest for several reasons. California and Texas possess both the largest populations and state economies respectively, with very economically significant areas located adjacent to the border. Additionally, Texas and Arizona are also in both the top 10 fastest growing state economies and top 10 fastest growing populations (BEA, 2018). In total, an estimated 19.1 million Americans live along the southern border, and the overall population growth since 2012 has increased by 4.5%, which is larger than the national average of 4.2% (US Census 2020). In March 2020, as a response to the COVID-19 pandemic, the United States implemented a policy for all ports of entry on the US/Mexico border limiting non-essential travel. The implications of these restrictions on employment and general economic welfare in the counties along the southern border would be of great interest to national and state policymakers, and add to the growing amount of research concerning border economics.

In this analysis I ask how employment outcomes responded to the March 2020 border restrictions in counties with various ratios of foreign population to domestic population, based on their reliance on the foreign population of consumers. In Mexico, the equivalent of a US County jurisdiction is a Municipio. Adding clarification to this measurement, a ratio with a numerator of

Mexican municipio population and denominator of US county population. It can be expected these outcomes will vary, since some counties may be more reliant on Mexican consumers. Employment decreased abruptly after March of 2020 in both the US/Mexico border region and nationally, for reasons related to the COVID-19 pandemic. I isolate the effect of the border restrictions by examining whether individuals in counties that depended more heavily on foreign consumers were affected differently than those that did not, indicating a difference in the effect of the border closure and that of national trends for employment outcomes. To quantify this dependence, I create a measurement of vulnerability to the closure, discussed later on.

Using data from the Current Population Survey, I have constructed several difference-in-differences regressions, to estimate the effect of the closure over time. I compare individuals living in eight counties at the US/Mexico border before and after the implementation of border restrictions to see how implementing border restrictions affects employment outcomes. In other words, my difference-in-differences method uses the border restrictions as a treatment, with the vulnerability index measuring treatment intensity, and employment results as the outcome. The interaction between vulnerability to border closure and binary variable denoting if the observation is post-border-closure serves as the primary independent variable. I have several important outcome variables: whether someone is employed, whether someone is participating in the labor force, and the log of their hourly wage.

Existing research has often focused on regions with free flows across land borders such as the European Union, which is not true along the US/Mexico border where the ability of individuals to cross the border in a timely fashion is more variable. In this analysis, I examine this less static border situation, where economic integration is happening in different counties at different rates. I also differ from most similar papers since my analysis focuses on the effects of border restriction rather than relaxation. Lastly, because the effects of COVID-19 were so profound in both the border-region and internationally, I add a unique dimension to the analysis of labor dynamics at the border by using very recent data on the pandemic. I make sure to control for Covid-19 case rates and death rates to assure that the pandemic is not driving results. My project may contribute to existing research on the subject of border integration and barriers by focusing specifically on how tightening rather than relaxing the US/Mexico border has affected welfare outcomes, specifically unemployment.

2.0 LITERATURE

It is common for research concerning international borders to examine the effects of economic integration on trade and welfare in neighboring countries. In such literature that deals with trade flows across borders, the effect of borders are often determined with gravity and general equilibrium models, which are considered poor at measuring welfare (Anderson and van Wincoop, 2001). This paper combines modeling with an econometric analysis to show that the benefits of economic integration have incredible potential, even in countries with existing trade relationships. Their findings also indicate that poor trade policies at borders can carry great costs, more than would be assumed from models. My own research contributes to these findings by specifically looking at trade flows from a consumer perspective, showing how when borders are relaxed, consumers enhance economic integration by purchasing goods and services from the other side of the border. My analysis may provide some answers to why models fail to capture the full extent of the consequences of tight borders, as the losses from physically crossing a border are hard to quantify.

A similar paper examines specifically the free movement of individuals and income, finding that countries with different productivity levels suffer massive efficiency losses by maintaining border barriers (Kennan, 2012). The losses that are quantified in this paper show specifically how variables such as welfare could be increased in the long run if barriers are removed gradually. This literature indicates that even if borders are relaxed, there are few substantial effects to the real wage in countries that individuals are going to, not harming employment as much as implied by popular rhetoric. My own findings assist these conclusions by further examining the relationship between open borders and domestic wages, with specific emphasis on how foreign spending in a border area actually supports domestic employment outcomes.

This paper is followed by specific literature that examines the long term effects of free movement across borders (Kennan, 2017), using the European Union as a case study. This analysis more robustly concluded that relaxing borders does not depress wages, and that allowing people to work in EU countries different from their home country provided massive gains in welfare. It is suggested that the EU is living proof of how a relatively open borders regime maximizes capital allocation among countries. My own analysis examines a separate but similar case, where rather than a long run effect on keeping borders relaxed, I examine the short run effects when a border is heavily restricted. Much like in his earlier analysis, my findings hope to show the domestic costs in closing borders, especially when regions are integrated or undergoing integration.

Klein and Ventura (2007) investigate the consequences of the misallocation of the global labor force, caused in part by border policies. Their findings indicate that allocating global labor would significantly increase output. Output primarily increases because of the movement of labor from areas of lower total factor productivity to areas where it is higher. My research hopes to examine the inverse relationship of how movement of consumers can similarly affect output.

Another paper, (Hanson 1996) examines how the interconnectedness of various border pairs of cities on the US/Mexico border is causing economic activity to move to the border region. Hanson finds that city pairs that are relatively integrated spur economic activity on the US side and increase the capital strength of the border region relative to others. My findings would contribute to this research, adding a new layer to analyzing the effect of integration by measuring how severing integrated counties can hurt welfare in the border region.

Similar works by the same author looks at how integration on the US/Mexican border has differed from that of the US/Canada border (Hanson 1998, Feenstra and Hanson 1995). One very relevant finding this paper reveals is that employment outcomes in US border cities were strongly correlated with export production in the adjacent Mexican cities. This result is important since it broadly shows how US employment responds when Mexican goods at the border are not purchased by domestic consumers. My contribution specifically looks at this relationship, and hopes to determine that border access is a hidden variable in Hanson's study of why employment outcomes rise.

Other studies looking at policy effects on the border region exist (Peach, Adkisson, 2000), looking at a variety of welfare and economic outcomes at the border in the wake of NAFTA. Key findings of this paper indicate that NAFTA caused a significant amount of resources and activity to move to the border region from elsewhere in the United States, and that most labor market effects in the US were small and industry specific. This research is important as it examines how a shift in trade policy (albeit on a grander scale) affects the border region. My findings would specify how movement of individuals at the border may have tied into this general trend of increased activity, on why the border closure hurt the region.

Additional literature specifically examines and proposes causes for why national borders substantially reduce trade flows. Important to us is the result that the substitutability of goods at the border is a large reason for why the border effect is great. My own findings contribute to these results by showing how the greater the US reliance at the border selling highly elastic products, the greater the effect of closing the border to foreign patrons should be.

It is also important to consider the broad effects of COVID-19 on labor markets, considering the confounding nature of the pandemic on any study. Analyses (Borjas and Cassidy 2020) show that while the first months of the COVID-19 pandemic hurt labor outcomes overall, immigrants to the US were particularly hurt. The authors theorize this was a result of remote jobs that became common during the pandemic being less accessible to immigrants. My own research does not look at industry or work-habit changes, though implicit conclusions from my findings would reinforce the results of this paper as many of the counties in my analysis have high immigrant populations.

Similarly, women have seen a larger drop in employment outcomes (Albanesi and Kim 2021) despite being usually more resistant to recessions than men. Because the pandemic-induced recession has lowered the demand for services, and increased the need for available and affordable childcare, the rate of women that are unemployed or have exited the labor force is greater than typical recessions. Utilizing a similar dataset from the CPS and an event study method, the authors discern that more women worked in 'high contact' jobs than men, and because of the aforementioned reasons, saw lower employment outcomes. Contributing to these findings, my analysis is very similar by examining the same general time frame but testing a different characteristic and hypothesizing a different but related cause, being the border closure.

Finally, a last paper examines the effect of the COVID-19 pandemic on labor markets more broadly. A last piece of literature specifically examines and proposes causes for why national borders substantially reduce trade flows. Important to us is the result that the substitutability of goods at the border is a large reason for why the border effect is great. My own findings contribute to these results by showing how the greater the US reliance at the border selling products with higher rates of substitution, the greater the effect of closing the border to foreign patrons should be. Also using the CPS, the authors discuss the unique nature of the collapse, different from many past recessions that can be observed. Among the notable features was the rapid nature of the collapse, and again showed the severity of the loss in employment outcomes for people in high contact non-remotable jobs like service work. General demographic features were also consistent, with more education indicating an individual was less likely to leave work, and saw a gender disparity akin to that described in the above paper. Among race identifiers, those identifying as white were more likely to stay at work than those identifying as Hispanic, and those two groups were both more likely to stay at work than those identifying as black. I attempt to build on these conclusions by hypothesizing the border closure as a confounding factor in the COVID-19 recession, and showing that it had an adjoining effect on employment outcomes for individuals.

3.0 DATA

3.1 Data and descriptive statistics

This analysis hopes to understand the effect of border restrictions on employment outcomes in areas close to the US/Mexico border. Most of my variables are provided by the Current Population Survey, a survey in the United States that collects demographic information, employment data, income, and other statistics. The CPS collects monthly data in a reported county, from over 65,000 households across the country. My sample contains monthly individual measurements from March of 2015 to November of 2021 (When the border reopened), in 8 counties along the US southern border. From IPUMS, only 45% of households reside in a county that can be identified, which accounts for why only 8 of the 22 counties along the border are used in my sample. Because the CPS is a smaller survey, IPUMS has disclosed it is possible that some counties with smaller populations may be entirely missing from a specific extract of data. Among the 8 counties, 1 is in California, 2 are in Arizona, 1 is in New Mexico, and 4 are in Texas. Individuals in my sample are all over the age of 18, the age when one should have completed secondary education. Outside of San Diego county, all counties in the dataset reflect less than 25% of individuals having college degrees, so I have set my age boundaries from 18 to 65, the age of retirement.

My dependent variables are employment outcomes, which take the form of EMPLOYED, INLAB, and log(HOURWAGE). EMPLOYED characterizes one's employment status built from the categorical variable EMPSTAT, with a certain set of numbers indicating whether or not a respondent is employed, unemployed, or not in the labor force with information on the activity or condition of respondents in any category (e.g. being a new worker, being at school). I make this variable binary by assigning any respondent that is employed a '1', and '0' otherwise. This new created variable is EMPLOYED. The CPS characterizes being in the labor force as either being at work, or seeking work. INLAB is a binary variable created from LABFORCE indicating whether or not a respondent claimed they were part of the labor force in the previous week. I assign those participating in the labor force a '1' and '0' otherwise. HOURWAGE is a variable given by the CPS, assigning a reported hourly wage to a respondent. This variable only captures workers that receive an hourly wage, excluding those paid in lump sums and others. The CPS does not adjust this wage for inflation, however they do include inflation tables which I use for adjustment. With log(HOURWAGE), I include the supporting variable EARNWT in my analysis which is a binary variable that tells if a respondent answered any earnings questions from IPUMS, helpful in letting me properly select my sample. It is such that we only include a respondent when EARNWT is equal to 1.

Among my time periods of interest, **Figure 1** illustrates the monthly change in means for employment outcomes for the counties divided into HIGH and LOW, where HIGH denotes a county being above the median vulnerability score and vice versa for LOW. In March of 2015, 93.6% of people in the labor force in the 8 counties responded as being employed, consistent with the national unemployment rate at that time of 5.4% . In April of 2020, one month after my period of interest, the mean of those respondents had shifted down to 85.9%, the lowest mean of my sample. By November of 2021, when the restrictions were ended, the mean for employment outcomes among those in the labor force had climbed back to 94.4%. Among those respondents, around 56.4% participated in the labor force in March of 2015, with only 48.3% of respondents participating in April of 2020. In November of 2021, this statistic climbed back up to 57.8% of respondents. Each of these estimates come directly from my sample. Means for changes in the amount of people participating in the labor force can be found in **Figure 2**.

The primary explanatory variable is a constructed measurement of how vulnerable to the implementation of border restrictions a US county is, interacted with a binary term denoting whether the observation took place before or after a certain time *t*. Each county in my sample is associated with a set of Mexican municipios. Municipios are matched with a US county if the two jurisdictions share a port of entry along the US southern border. With this association in mind, I take population statistics from the United States 2020 Census for county data, and the Censo de Población y Vivienda 2020 for municipio data. I create a ratio of vulnerability for each county, putting the population of all associated municipios above the population of the associated county. To this end, counties with a relatively larger population across the border are more vulnerable to the effect of border closure. Among the vulnerability ratios, the average is 1.77, with a maximum of 6.88 and a minimum of 0.013. **Table 1** gives a summary of VBC across the counties. The binary variable that is interacted with vulnerability is POSTMARCH2020, assigned a '1' if it occurred after that month when the closure went into effect, or '0' otherwise. I have chosen to include multiple "post" dates, since it is likely that some effects of the border closure may have been delayed months after the restrictions were put in place.

The most important controls I will use in this analysis are those dealing with the impacts of the COVID-19 pandemic. Among the most important events going on at the border during the time of my study are the COVID-19 pandemic and the closure at the border. By controlling for COVID, I will be able to make strong conclusions about the economic impacts of the border closure. The controls I find especially relevant are found in an ongoing county - month dataset, provided by The New York Times, which are cases and deaths. I have included these in the data being used as CASE and DEATH. Both CASE and DEATH are variables that are assigned the total cases and total deaths in a given county. Because IPUMS provides monthly data, I aggregate the total cases and deaths that occurred in that month and county when creating a value for CASE and DEATH.

Included also is a string of other individual controls from IPUMS, which are RACE, AGE, NCHILD, MARST, CITIZEN, and SEX. I modify these variables by taking the indicators in RACE and creating binary terms for identifying as white, black, hispanic, and asian. These become WHITE, BLACK, HISPAN, and ASIAN respectively. Number of children remains the same variable, detailing a respondent's number of children. MARST is broken up into three binary variables, denoting if a respondent is single, married, or divorced. Citizen is a binary variable dictating if a respondent is a US citizen, and '0' otherwise. From SEX I make the control MALE, which is a 1 if the respondent is male and '0' otherwise.

Any differences across location and time are captured by the county and time fixed effects in terms of the regression models. The county fixed effects are created normally by allowing for each county to exist as a binary variable with '1' indicating the designated county and '0' otherwise, and time fixed effects as a binary variable for each month with '1' indicating the designated month and '0' otherwise. These controls are chosen to minimize the effect of individual characteristics on employment outcomes.

3.2 Description of Regressions

The specification I use in my analysis is

$$\textbf{(1)} \qquad \boldsymbol{y_{ict} = \alpha + \beta_3(POSTMARCH2020_t \times VBC_c) + \mu_c + \delta_t + X_{ict}\beta + \varepsilon_{ict}}$$

Where y_{ict} represents the outcome for a given individual in county (c) at time (t), $POSTMARCH2020_t$ is an indicator for whether the border closure was in place at time (t) and

VBC_c is my constructed measurement of how vulnerable a county (c) is to implementation of the restrictions, based on reasons described above. X_{ict} is set of individual controls, including the age, race, sex, marital status, citizenship status, and number of children, of a respondent that are described in the above section. Included in X_{ict} are the COVID-19 controls mentioned. It is such that μ_c represents a county fixed effect, while δ_t represents a month-year fixed effect for month (t), and ε_{ict} is the error term. As another measure of robustness, I run the same regressions excluding the two major VBC outliers, Doña Ana county and Pima county from a portion of the analysis. I do this because all of the other Vulnerability ratios cluster close to 1, though Doña Ana county has an incredibly high ratio of 6.88 and Pima county has an incredibly low ratio of 0.013. By excluding these outliers, I will be able to see the results in the main analysis in which I include all of the counties.

The second strategy I use is devised as follows. Vulnerabilities are separated into categories of high and low, based on whether they fall above or below the median VBC score. So I will have that exactly half of the sample is in each category. It is worth noting that by breaking up VBC into groups of high and low, I have the highly vulnerable group as three counties from Texas and one from New Mexico, and the Low group constitutes one county from California, two from Arizona, and one from Texas. To cut down on the number of intervals, I separate the time frame from June of 2018 to September of 2021 into thirteen time periods of three months to each. The period immediately preceding both the border closure and the pandemic is January through March of 2020, and serves as the reference period of 0. I thus compare the employment outcomes between counties that varied in vulnerability during the period after the border closure. See the following regression:

$$\textbf{(2)} \quad y_{ict} = \sum\nolimits^{6}_{k=-6,\, k\neq 0} j(High_c \, x \, Period_{kt}) + \sum\nolimits^{6}_{k=-6,\, k\neq 0} k(Low_c \, x \, Period_{kt}) + \mu_c + \delta_t + X_{ct}\beta + \varepsilon_{ct}$$

In this regression my dependent variable is employment outcomes in county c at time t. This will include EMPSTAT, LABFORCE, and log(HOURWAGE). I have explanatory variables $HighVBC_c \, x \, Period_{kt}$ and $LowVBC_c \, x \, Period_{kt}$ which represent the interaction between the vulnerability to border closure in county c and the dummy variable post, where intervals for *Period* are divided by month, of which there are 6 for which the border restrictions were in place, and 6 that occurred before. This regression includes county fixed effects, controlling for geographic location, infrastructure, or other county trends. I include these controls to prevent correlation between vulnerability and employment outcomes from undesired sources. This regression also includes time fixed effects, allowing my analysis to separate out national economic trends such as those of the pandemic.

4.0 RESULTS

4.1 First Specification

I first examine the specification without controls in **Table 2**, adding three groups of controls; first being the individual controls, and then each of the two fixed effects, one at a time. For all four regressions, I include the COVID controls, as I hope to isolate the effect of the border closure from that of the pandemic in each column. Overall, I find that for my first specification, when regressed on Employment Outcomes, I find that more vulnerable counties are predicted to see a more negative effect for employment outcomes before the border was closed rather than after. This coefficient estimate is around -0.007 in the most robust regression, though the standard error remains fairly large relative to the coefficient. I see very little change between my terms of interest in columns 2, 3, and 4, however the significance level rises between columns 1 and 2. So because statistical significance increases and I see only around a thousanths place worth of change between the four columns, the results are strong under the addition of new controls. I find that in each column, my controls for covid are always significant at the highest level, and that being married negatively affects employment outcomes. I also find there is an economically significant positive effect if one is male, single, or divorced, whilst the effect of identifying as Mexican, or being an immigrant have a significantly negative effect.

Interpreting these results, I find that raising vulnerability to border closure in a county by a single unit is predicted that employment outcomes will decrease by approximately 0.7 percentage points more after the border closed than before. This supports the VBC measurement as an indicator for vulnerability, seeing that counties were in fact worse off after the border closure than they were before.

For robustness, I remove Yuma county, AZ, and Dona Ana county, NM. These counties both had a very outlying vulnerability ratio, whilst the others all clustered around 1. The term VBC:March 2020 still represents the difference in the effects of varying VBC ratios before and after the border closure, with the removal of the aforementioned counties. In **Table 5**, I use only counties with a VBC measurement between 0.5 and 2. Here, the coefficient of interest is -0.052 in the most complete regression, which is much more than when the outlying counties are included. I do remove almost 30,000 observations and find that even though the counties are of relatively similar size, removing both yields a much stronger negative effect for the remaining counties. It appears the effect that the very low VBC county had on my sample was much stronger than that of the very high VBC county. This could be because the employment outcomes in the high VBC outcomes were better than expected; removing it from the regression enhanced the negative effects. Moreso, the effect from the low VBC county may have been much greater than the effect of the high VBC county, despite the similar sizes of Yuma and Doña Ana county. The effects of my controls stay mostly the same, both in effect and significance.

There are similar results in **Table 3**. with a slightly larger effect for the vulnerability of border closure upon labor force participation. I create this table akin to the first table, starting with just my term of interest and the COVID controls. From there, I add the various controls that were described for **Table 2**. This effect of VBC*POSTMARCH2020 is around -0.8 percentage points, indicating that more people are leaving the labor force after the pandemic than before. Like with the above results for employment, this result is anecdotally expected; closure of the border deprives US border economies of patrons and thus has an adverse effect on employment outcomes as a whole. Noticeably different from employment, identifying as white is now significant. This coefficient is negative, and thus indicates being white means one was more likely to drop from the labor force. Most other effects make sense anecdotally, with being male having a positive effect of 1.2% effect on labor force participation.

The first two months of the COVID-19 pandemic saw an incredible drop in labor force participation (BLS 2022) down from approximately 63% to 60%, with this number back up to 61% after the first two months and climbing slowly after that. Oddly, my own data for labor force participation does not follow this trend. In **Figure 2**, labor force participation declines generally after the onset of the pandemic, with a greater rise in the months following than seen in national trends. This is likely due to the nature of my sample size, but also could be the result of a hidden variable such as industries at the border. It could be possible that the border economy bounced back or suffered less during the pandemic because of such bias, which could reflect why labor force outcomes differ wildly from what is seen at national levels.

I do the same as I did above for Employment in **Table 6**, removing the two counties with outlying VBC ratios. Like above, removing these counties has increased the difference in effects, indicating the relative importance of these counties in making inferences about the border. Unlike in **Table 3**, this result grows to be significant at the 0.05 level. I see again that removing a number of observations does drastically change my result and that additional controls may be necessary to refine the analysis with the exclusion of certain observations. In theory, the difference in the effect of VBC before and after border closure for the different counties should grow with a more diverse sample, so it is possible that I once again have either overestimated the effects of the very high VBC county, or the success of the low VBC county was much greater than that of other low VBC counties and shifted the ‘weight’ of the effect to the high VBC counties.

Moving to **Table 4**. Below, I regress against log(HOURWAGE), the logarithm of hourly wages. Here, I find the effect was such that wages declined by 4.3% more after the border closure than before. As I would expect, wages in my plot of means follows the trend of sharply declining after March of 2020, recovering, and growing at a seemingly slower rate. Standard errors are lower, and this result is more significant than either of my two other outcome variables. The effect of the closure was likely more pronounced in a change of hourly wages considering people were paid less to work during the pandemic, and jobs such as hospitality and service, suffered wage growth nationally (BLS 2022). Among my controls, identifying as Asian became significant, as other controls remained relatively unchanging in both the strength and direction of their impact.

I apply the same exclusion in **Table 7**, examining the difference in the effects on the logged hourly wages. As in the other two tables created from the exclusion of two counties, I find that the coefficient has grown much larger and has increased in significance. The term of interest remains negative throughout all four columns, though the difference in the effects is diminished with addition of each set of controls. As a result of the strong difference in the effect from subtracting observation, additional controls could explain why some effect in the two counties has changed the interaction term to such a degree, aside from the explanations I have provided above for the previous tables where counties are excluded. Identifying as black has become more significant with the new sample, as the excluded counties were predominantly white and hispanic.

4.2 Second Specification

In the event study portion of the analysis, I have compiled the coefficients for each employment outcome variable. For ease of viewing, the coefficients have been plotted in the first panels of **Figure 4, 5, and 6**. Beside them, the difference between the Low and High estimates has also been plotted. Beginning with **Figure 4,** the coefficients differ wildly from period to period, and the difference in the effects both before and after are the most noticeable. This large preexisting difference for being employed does not help my parallel trends assumption, though I do see parallel trends in the "before border closure" period for my other two variables. While not graphed, the confidence intervals for each coefficient are large throughout, which may account for the great difference in **Figure 4.** I interpret each coefficient as the observed counties experiencing the coefficient's worth of change more than the control counties *t* periods after treatment relative to before.

Moving to the results from **Figure 5 and 6**, the difference in effects was large in the before period, however these effects converged after the border closed. I have decent evidence to believe that had the border not closed, the effects seen before would have continued during the 'post' period. In general for labor force participation, the two counties follow similar trends relative to before, with the High VBC counties initially seeing greater labor force participation than the Low VBC counties (though still negative), with a slower recovery in the later periods of the study. While not entirely consistent with the hypothesis that highly vulnerable counties would be affected more harshly, it is logical that counties with a higher vulnerability ratio would end up seeing a slower recovery from the negative effects of the border and that they would be having lower employment outcomes initially because of this lower vulnerability status. This is addressed in the conclusion section more broadly, but the difference seen in the before period, and the seeming convergence in the after period may be a result of industries more commonly located in either group of counties, or national economic trends not accounted for in this analysis. The results of the event study are still consistent with the results of the first specification however, since outside of the few periods immediately after the border closed, Higher VBC counties were associated with a more negative effect than the reference group, moreso than the Lower VBC counties.

Last, a similar trend can be observed in **Figure 6** dealing with log(HOURWAGE) as seen in **Figure 5**. Higher and Lower VBC counties see vastly different effects, but then converge after the border is closed. Based on the means of Log(HOURWAGE) for this time, the counties observed similar trends both before and after the border was closed, though they were especially further apart in the period before. In this sense, what I see in the plot of coefficients is consistent with what I see in terms of means. Despite wages consistently rising in my table of means for both groups, VBC does prove to have a negative effect on hourly wage, but either this effect is not so strong as to greatly depress wages, or some omitted variable is at play.

5.0 CONCLUSION

This analysis comes to several general conclusions about the effects of the March 2020 border closure, though making these conclusions more detailed or robust is among its major shortcomings. I divide these shortcomings into those applying to data and methodology. Among the problems with my data, the CPS is only able to identify 8 counties on the Southern border. This is significantly less than the total number of counties on the border, and makes it so my sample only accounts for a fraction of the population that lives along the border. This is especially confounded when two of my given counties are outliers, and as I saw in my analysis in part 4.1, they have a large impact on the effect from the overall sample. There are also problems with my other dataset -- being the Covid-19 data from the New York Times. While this data is no doubt accurate, I likely lose some of the trends from the pandemic when I aggregate data to fit my monthly IPUMS data. I lack many controls that seem to skew my analysis and create very high standard errors, making it quite hard to make definitive conclusions. Among these would be a way to measure the industries in each county and the political and economic trends not covered by fixed effects. This is likely negatively correlated with all of our variables for employment outcomes. I would assume these would be vastly important, as most of my High VBC counties are found in Texas, which had a very different response to the pandemic than California or the other two states. Controls for someone's political party or how much they followed social distancing guidelines would be very insightful in seeing if my current analysis had very overt omitted variable bias. Moreover, the Covid-19 pandemic looms over this analysis, and although I controlled for cases and deaths, the economic, societal, and psychological effects of the pandemic are still being studied and likely have some unseen hand in my results. This could be the effects of polarization around mask mandates, supply chain disruptions, or having to leave work because of covid-related anxiety, or some other factors that I do not include in the analysis.

Still, I do provide evidence that VBC as a measure of integration does affect the behavior of employment outcomes in counties at the border differently after closure relative to before. All of my estimations in specification 1 were more or less consistent with each other and signaled that having a greater population in the United States during a closure event increased employment outcomes after the event occurred. Inversely, counties that had a lower domestic population did seem to do worse off. All of this is consistent with most models of border integration and supports the results from literature, especially that of Hanson, 1996. My event study had similar results but gave a more nuanced picture of how this effect differs; in both employment and labor force participation, the High counties saw an immediate positive spike in the period directly after the closure, indicating in the period they did much better than in the period immediately before the closure, but then saw the a similar decline to that of the Low counties, with a much slower recovery. In general for both groups, the border closure seemed to depress the log of hourly wages.

This analysis would have twofold policy implications, being answers to the questions "how should border counties react to border closure?" and "was closing the border in March 2020 good for employment outcomes in US border counties?". The answer to the latter question seems more concretely, no, closing the border does not seem to help domestic workers, at least in the long run. I cannot predict what would have happened if the border was not closed, but I have shown closing the border in March 2020 did affect employment outcomes in a worse way than it did before the closure. The second question is broad, and takes a more reactionary stance to the issue of raising employment after the border is closed. Even though almost all the counties did see negative effects in periods after the closure, counties with larger domestic populations compared to populations across the border did better overall. State and local lawmakers could thus incentivize more population growth along the border, or look to enhance some of the controls that seemed to positively affect employment outcomes.

Table 1.

COUNTY	Municipios bordering (with crossing)	County Population	Municipio Population	VBC
San Diego, CA	1	3,298,634	1,922,523	0.5828
Yuma, AZ	1	213,787	199,021	0.9309
Pima, AZ	1	1,047,279	13,627	0.01301
Doña Ana, NM	1	219,561	1,512,450	6.8885
El Paso, TX	1	865,657	1,516,687	1.7520
Cameron, TX	1	423,163	541,979	1.2807
Webb, TX	2	276,652	443,088	1.6016
Hidalgo, TX	2	774,769	852,928	1.1008

Figure 1.

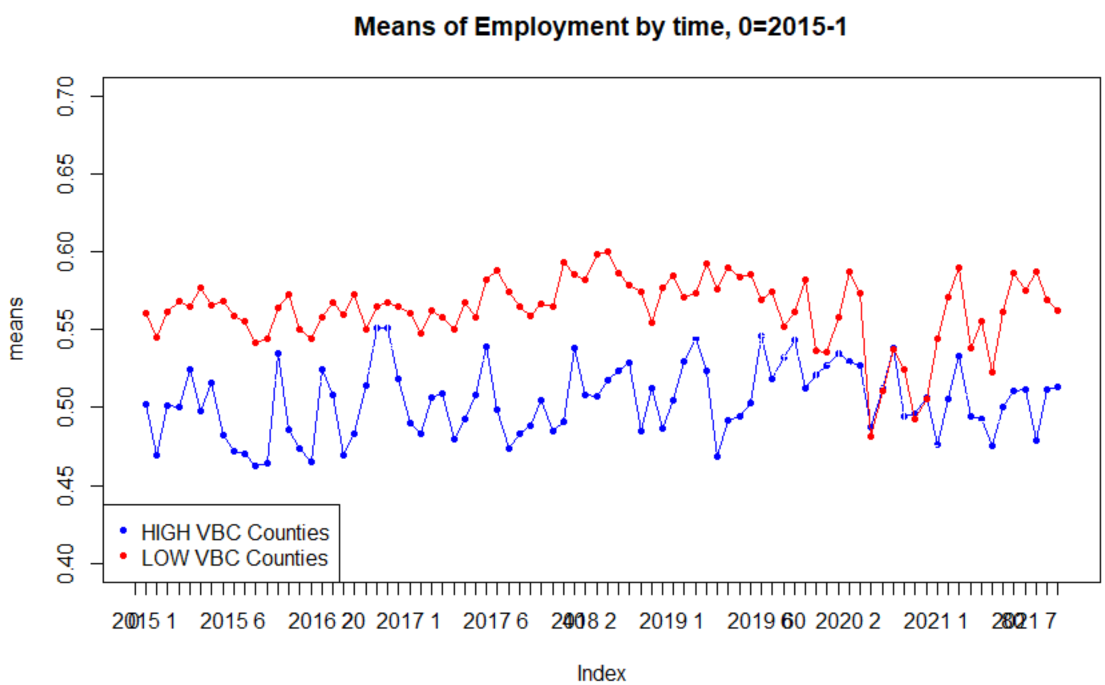


Figure 2.

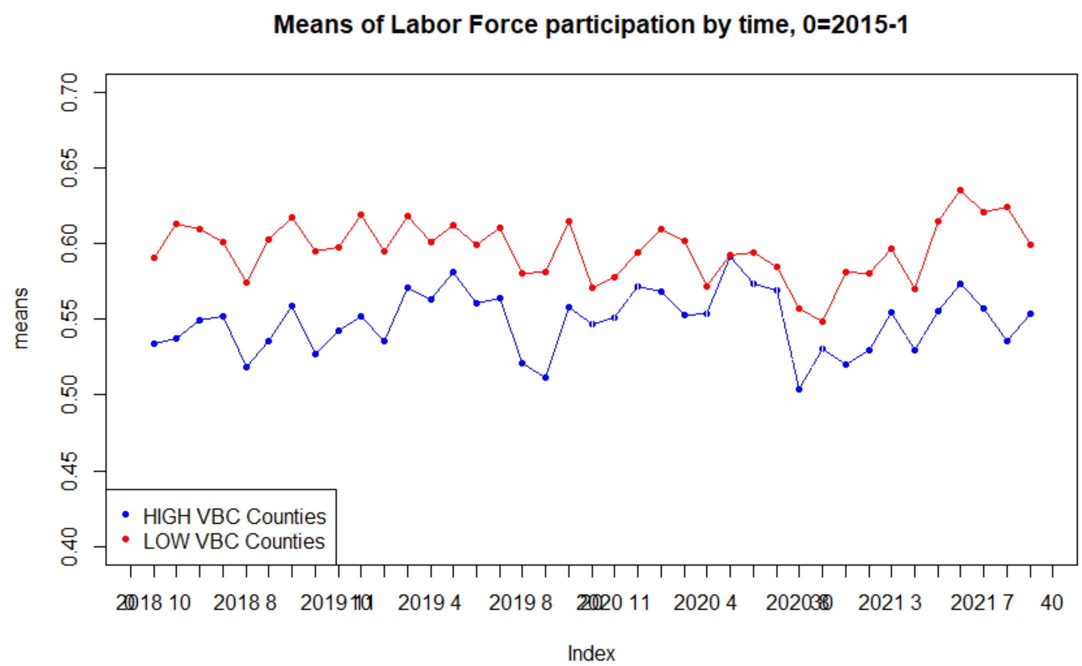


Figure 3.

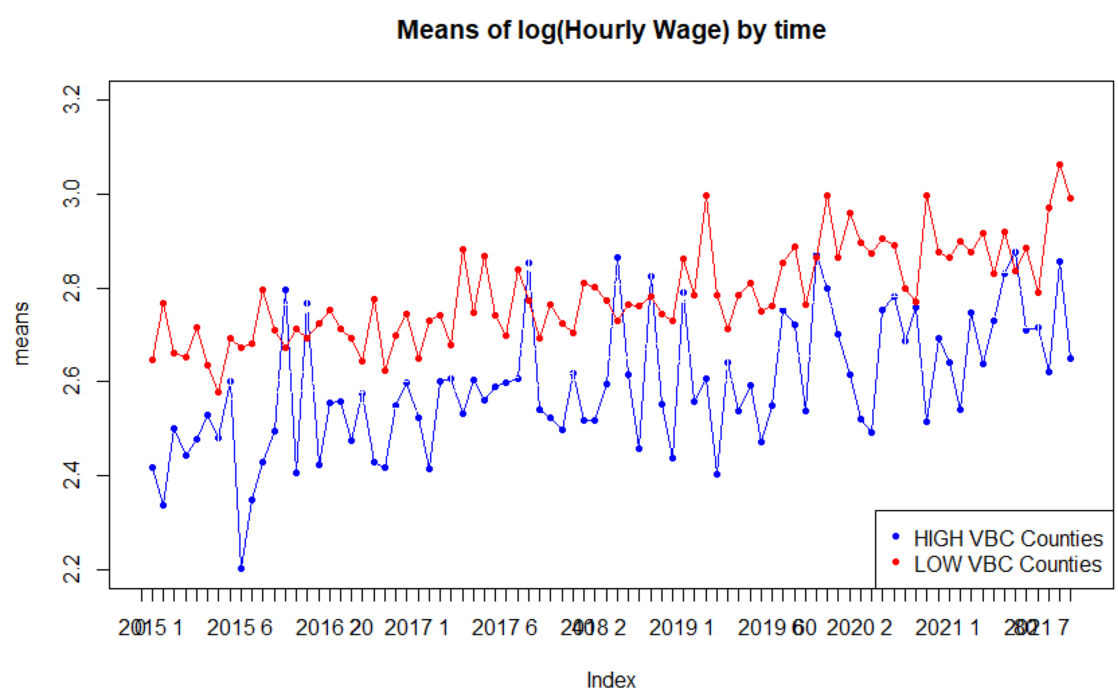


Table 2.

	Dependent variable:			
	EMPLOYED for differing levels of Vulnerability			
	(1)	(2)	(3)	(4)
VBC:MARCH2020	-0.006	-0.007*	-0.007*	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
VBC	-0.010***	-0.009***	-0.008***	
	(0.001)	(0.001)	(0.001)	
MARCH2020	0.022**	0.021**		
	(0.011)	(0.011)		
CASE	3.682e-07***	3.639e-07***	2.562e-07***	-2.762e-07 ***
	(5.274e-08)	(5.144e-08)	(6.095e-08)	(6.436e-08)
DEATH	-2.410e-05***	-2.462e-05***	-2.879e-06	3.371e-05***
	(4.452e-06)	(4.336e-06)	(6.189e-06)	(6.544e-06)
MARRIED		-0.052***	-0.052***	-0.050***
		(0.001)	(0.001)	(0.001)
DIVORCED		0.253***	0.253***	0.248***
		(0.006)	(0.006)	(0.006)
SINGLE		0.319***	0.319***	0.311***
		(0.006)	(0.006)	(0.006)
MEXICAN		-0.020***	-0.020***	0.015***
		(0.003)	(0.003)	(0.003)
NCHILD		0.077***	0.077***	0.078***
		(0.001)	(0.001)	(0.001)
MALE		0.123***	0.123***	0.122***
		(0.003)	(0.003)	(0.003)
NONCITIZEN		-0.056***	-0.056***	-0.056***
		(0.004)	(0.004)	(0.004)
Time Fixed Effects	NO	NO	YES	YES
County Fixed Effects	NO	NO	NO	YES
Constant	0.567***	0.477***	0.467***	-0.011
	(0.002)	(0.007)	(0.014)	(0.103)
Observations	143,396	143,396	143,396	143,396
R2	0.002	0.068	0.069	0.076
Adjusted R2	0.002	0.068	0.069	0.075
Residual Std. Error	0.497 (df = 143390)	0.480 (df = 143380)	0.480 (df = 143296)	0.478 (df = 143289)
F Statistic	69.148*** (df = 5; 143390)	696.243*** (df = 15; 143380)	107.889*** (df = 99; 143296)	110.571*** (df = 106; 143289)

Note: *p<0.1; **p<0.05; ***p<0.01

VBC is Vulnerability to Border Closure. CASE is total cases of COVID, and DEATH is the total deaths associated with those cases. NChild is the number of children a recipient said they have. Not included are controls for identifying as white, black, and asian, since they were not significant. Also not included are the time and county fixed effects for each term, though they are both included in the 4th column.

Table 3.

	Dependent variable:			
	LABOR FORCE PARTICIPATION			
	(1)	(2)	(3)	(4)
VBC:MARCH2020	-0.006	-0.007*	-0.007*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
VBC	-0.008***	-0.007***	-0.006***	
	(0.001)	(0.001)	(0.001)	
MARCH2020	0.018*	0.017		
	(0.011)	(0.010)		
cases	2.162e-07***	2.395e-07***	1.936e-07***	-3.266e-07***
	(5.225e-08)	(5.079e-08)	(6.020e-08)	(6.358e-08)
deaths	-9.494e-06**	-1.209e-05***	2.053e-06	3.979e-05***
	(4.411e-06)	(4.281e-06)	(6.112e-06)	(6.464e-06)
MARRIED		-0.053***	-0.053***	-0.051***
		(0.001)	(0.001)	(0.001)
DIVORCED		0.268***	0.267***	0.263***
		(0.006)	(0.006)	(0.006)
SINGLE		0.354***	0.353***	0.345***
		(0.006)	(0.006)	(0.006)
WHITEB		-0.018**	-0.016**	-0.002
		(0.007)	(0.007)	(0.007)
MEXICANB		-0.011***	-0.010***	0.025***
		(0.003)	(0.003)	(0.003)
NCHILD		0.081***	0.081***	0.081***
		(0.001)	(0.001)	(0.001)
MALE		0.130***	0.130***	0.130***
		(0.003)	(0.003)	(0.003)
NONCIT		-0.049***	-0.050***	-0.049***
		(0.004)	(0.004)	(0.004)
Constant	0.597***	0.504***	0.496***	0.979***
	(0.002)	(0.007)	(0.014)	(0.101)
Observations	143,396	143,396	143,396	143,396
R2	0.002	0.074	0.075	0.080
Adjusted R2	0.002	0.074	0.074	0.080
Residual Std. Error	0.492 (df = 143390)	0.474 (df = 143380)	0.474 (df = 143296)	0.472 (df = 143289)
F Statistic	49.512*** (df = 5; 143390)	760.261*** (df = 15; 143380)	116.662*** (df = 99; 143296)	118.139*** (df = 106; 143289)

Note: *p<0.1; **p<0.05; ***p<0.01

VBC is Vulnerability to Border Closure. CASE is total cases of COVID, and DEATH is the total deaths associated with those cases. NChild is the number of children a recipient said they have. Not included are controls for identifying as black and asian, since they were not significant. Also not included are the time and county fixed effects for each term, though they are both included in the 4th column.

Table 4.

	Dependent variable:			
	Log(Hourly Wages)			
	(1)	(2)	(3)	(4)
VBC:MARCH2020	-0.031	-0.050**	-0.047**	-0.043**
	(0.021)	(0.019)	(0.019)	(0.019)
VBC	-0.027***	-0.021***	-0.024***	
	(0.002)	(0.002)	(0.002)	
MARCH2020	0.124***	0.162***		
	(0.046)	(0.043)		
cases	7.509e-07***	2.867e-07*	8.197e-07***	-2.799e-08
	(1.836e-07)	(1.727e-07)	(2.043e-07)	(2.189e-07)
deaths	1.414e-06	3.534e-05**	-4.894e-05**	-8.530e-06
	(1.555e-05)	(1.461e-05)	(2.108e-05)	(2.255e-05)
MARRIED		-0.041***	-0.040***	-0.036***
		(0.006)	(0.006)	(0.005)
DIVORCED		0.099***	0.096***	0.084***
		(0.025)	(0.025)	(0.025)
ASIAN		0.091***	0.095***	0.071**
		(0.029)	(0.029)	(0.029)
MEXICAN		-0.192***	-0.192***	-0.129***
		(0.010)	(0.010)	(0.011)
NCHILD		0.004	0.005	0.009**
		(0.004)	(0.004)	(0.004)
MALE		0.103***	0.103***	0.104***
		(0.009)	(0.009)	(0.009)
NONCITIZEN		-0.168***	-0.165***	-0.175***
		(0.014)	(0.014)	(0.013)
Constant	2.759***	2.923***	2.822***	2.661***
	(0.007)	(0.025)	(0.047)	(0.053)
Observations	9,870	9,870	9,870	9,870
R2	0.031	0.161	0.183	0.212
Adjusted R2	0.031	0.160	0.175	0.204
Residual Std. Error	0.487 (df = 9864)	0.453 (df = 9854)	0.449 (df = 9772)	0.441 (df = 9766)
F Statistic	63.600*** (df = 5; 9864)	126.364*** (df = 15; 9854)	22.570*** (df = 97; 9772)	25.551*** (df = 103; 9766)

Note: *p<0.1; **p<0.05; ***p<0.01

VBC is Vulnerability to Border Closure. CASE is total cases of COVID, and DEATH is the total deaths associated with those cases. NChild is the number of children a recipient said they have. Not included are controls for identifying as black and white, since they were not significant. Also not included are the time and county fixed effects for each term, though they are both included in the 4th column.

Table 5

	Dependent variable:			
	EMPLOYED for differing levels of Vulnerability (Among counties with 0<VBC<2)			
	(1)	(2)	(3)	(4)
VBC:MARCH2020	-0.039	-0.048	-0.050*	-0.052*
	(0.031)	(0.030)	(0.030)	(0.030)
VBC	-0.122***	-0.132***	-0.132***	
	(0.005)	(0.006)	(0.006)	
MARCH2020	-0.020	-0.030		
	(0.027)	(0.026)		
CASE	9.976e-08*	1.501e-07***	4.630e-09	-2.758e-07***
	(5.535e-08)	(5.353e-08)	(6.592e-08)	(6.928e-08)
DEATH	-6.527e-06	-1.167e-05**	9.303e-06	3.446e-05***
	(4.690e-06)	(4.537e-06)	(6.937e-06)	(7.431e-06)
MARRIED		-0.053***	-0.053***	-0.052***
		(0.001)	(0.001)	(0.001)
DIVORCED		0.256***	0.256***	0.254***
		(0.006)	(0.006)	(0.006)
SINGLE		0.325***	0.325***	0.321***
		(0.007)	(0.007)	(0.007)
MEXICAN		-0.0003	-0.001	0.009***
		(0.003)	(0.003)	(0.004)
NCHILD		0.075***	0.075***	0.074***
		(0.001)	(0.001)	(0.001)
MALE		0.127***	0.127***	0.126***
		(0.003)	(0.003)	(0.003)
NONCITIZEN		-0.039***	-0.040***	-0.040***
		(0.004)	(0.004)	(0.004)
Time Fixed Effects	NO	NO	YES	YES
County Fixed Effects	NO	NO	NO	YES
Constant	0.660***	0.562***	0.565***	0.001
	(0.004)	(0.009)	(0.016)	(0.103)
Observations	118,576	118,576	118,576	118,576
R2	0.005	0.071	0.073	0.076
Adjusted R2	0.005	0.071	0.072	0.075
Residual Std. Error	0.495 (df = 118570)	0.478 (df = 118560)	0.478 (df = 118476)	0.477 (df = 118471)
F Statistic	131.019*** (df = 5; 118570)	607.287*** (df = 15; 118560)	94.312*** (df = 99; 118476)	93.437*** (df = 104; 118471)

Note: *p<0.1; **p<0.05; ***p<0.01

VBC is Vulnerability to Border Closure. CASE is total cases of COVID, and DEATH is the total deaths associated with those cases. NChild is the number of children a recipient said they have. Not included are controls for identifying as white, black, and asian, since they were not significant. Also not included are the time and county fixed effects for each term, though they are both included in the 4th column. This table does not include observations from either of the two outlier counties.

Table 6.

	Dependent variable:			
	LABOR FORCE PARTICIPATION (Among counties with 0<VBC<2)			
	(1)	(2)	(3)	(4)
VBC:MARCH2020	-0.052*	-0.061**	-0.062**	-0.066**
	(0.031)	(0.030)	(0.030)	(0.030)
VBC	-0.116***	-0.134***	-0.134***	
	(0.005)	(0.005)	(0.006)	
MARCH2020	-0.034	-0.043*		
	(0.027)	(0.026)		
CASE	-4.604e-08	9.694e-09	-5.329e-08	-3.191e-07***
	(5.480e-08)	(5.282e-08)	(6.507e-08)	(6.841e-08)
DEATH	8.062e-06*	2.352e-06	1.066e-05	3.740e-05***
	(4.643e-06)	(4.477e-06)	(6.848e-06)	(7.339e-06)
MARRIED		-0.053***	-0.053***	-0.053***
		(0.001)	(0.001)	(0.001)
DIVORCED		0.270***	0.270***	0.268***
		(0.006)	(0.006)	(0.006)
SINGLE		0.358***	0.358***	0.354***
		(0.007)	(0.007)	(0.007)
ASIAN		-0.024***	-0.023**	-0.019**
		(0.009)	(0.009)	(0.009)
MEXICAN		0.008**	0.008**	0.017***
		(0.003)	(0.003)	(0.004)
NCHILD		0.077***	0.077***	0.078***
		(0.001)	(0.001)	(0.001)
MALE		0.134***	0.134***	0.134***
		(0.003)	(0.003)	(0.003)
NONCITIZEN		-0.040***	-0.040***	-0.040***
		(0.004)	(0.004)	(0.004)
Time Fixed Effects	NO	NO	YES	YES
County Fixed Effects	NO	NO	NO	YES
Constant	0.686***	0.595***	0.597***	0.988***
	(0.004)	(0.009)	(0.015)	(0.101)
Observations	118,576	118,576	118,576	118,576
R2	0.005	0.077	0.078	0.080
Adjusted R2	0.005	0.077	0.077	0.079
Residual Std. Error	0.490 (df = 118570)	0.472 (df = 118560)	0.472 (df = 118476)	0.471 (df = 118471)
F Statistic	118.463*** (df = 5; 118570)	661.745*** (df = 15; 118560)	101.475*** (df = 99; 118476)	99.294*** (df = 104; 118471)

Note: *p<0.1; **p<0.05; ***p<0.01

VBC is Vulnerability to Border Closure. CASE is total cases of COVID, and DEATH is the total deaths associated with those cases. NChild is the number of children a recipient said they have. Not included are controls for identifying as black and asian, since they were not significant. Also not included are the time and county fixed effects for each term, though they are both included in the 4th column.

Table 7.

	Dependent variable: Log(Hourly Wages) (Among counties with 0<VBC<2)			
	(1)	(2)	(3)	(4)
VBC:MARCH2020	-0.296**	-0.294**	-0.274**	-0.242**
	(0.129)	(0.121)	(0.120)	(0.120)
VBC	-0.420***	-0.320***	-0.342***	
	(0.019)	(0.020)	(0.020)	
MARCH2020	0.372***	0.380***		
	(0.117)	(0.110)		
CASE	-0.00000	-0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
DEATH	0.0001***	0.0001***	-0.00002	-0.00003
	(0.00002)	(0.00002)	(0.00002)	(0.00003)
MARRIED		-0.037***	-0.036***	-0.035***
		(0.006)	(0.006)	(0.006)
DIVORCED		0.100***	0.096***	0.094***
		(0.028)	(0.028)	(0.028)
BLACK		-0.064*	-0.065*	-0.065*
		(0.036)	(0.036)	(0.036)
ASIAN		0.073**	0.076**	0.074**
		(0.031)	(0.031)	(0.031)
MEXICAN		-0.144***	-0.138***	-0.125***
		(0.012)	(0.012)	(0.012)
NCHILD		0.015***	0.014***	0.014***
		(0.005)	(0.005)	(0.005)
MALE		0.103***	0.105***	0.105***
		(0.010)	(0.010)	(0.010)
NONCITIZEN		-0.181***	-0.180***	-0.181***
		(0.015)	(0.015)	(0.015)
Time Fixed Effects	NO	NO	YES	YES
County Fixed Effects	NO	NO	NO	YES
Constant	3.076***	3.116***	3.062***	2.645***
	(0.016)	(0.030)	(0.053)	(0.057)
Observations	8,058	8,058	8,058	8,058
R2	0.076	0.177	0.201	0.208
Adjusted R2	0.076	0.176	0.191	0.197
Residual Std. Error	0.479 (df = 8052)	0.452 (df = 8042)	0.448 (df = 7960)	0.446 (df = 7956)
F Statistic	133.252*** (df = 5; 8052)	115.629*** (df = 15; 8042)	20.581*** (df = 97; 7960)	20.626*** (df = 101; 7956)

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 4.

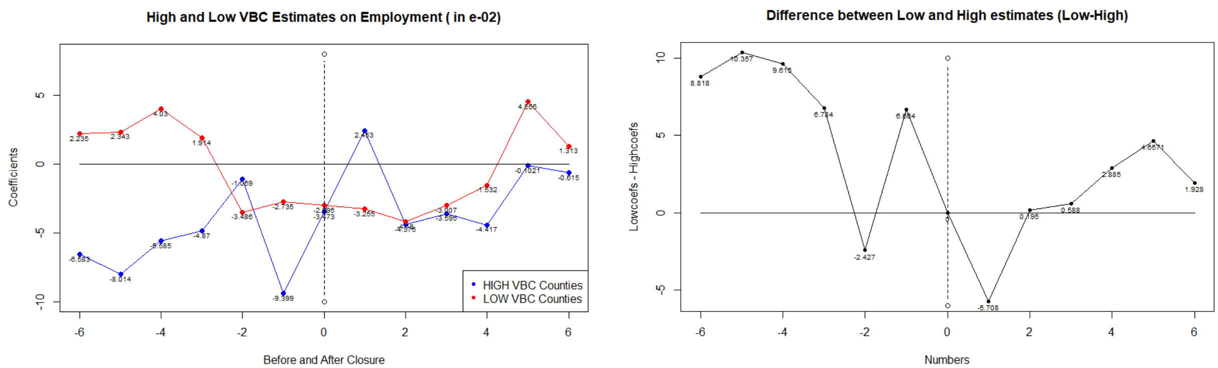


Figure 5.

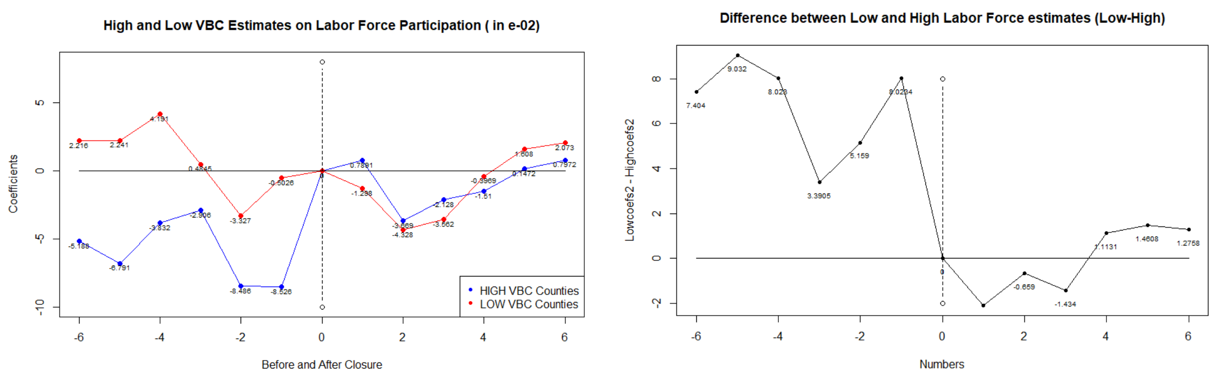
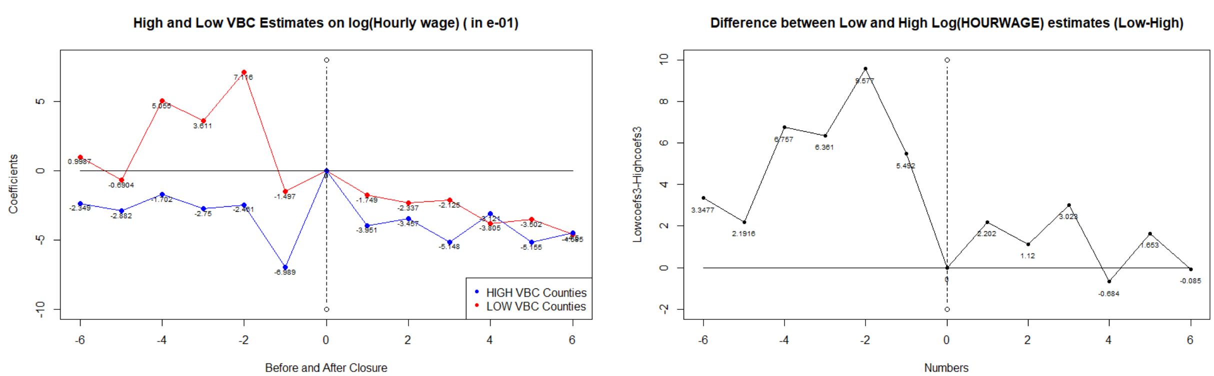


Figure 6.



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