The Labor Market Impact of Hurricanes: Evidence from Florida Counties

Rushaine Goulbourne

2021

Abstract

This study investigates the impact of hurricanes on wage and employment growth. I utilize a model of wind intensity to measure the hurricane impact by the presence of hurricane force winds within each Florida county. By using a measurement technique that does not restrict hurricanes to a single intensity unit, the results reveal a tempered impact of hurricanes on both wage and employment growth compared to the effects previously reported. I identify an absence of labor force spillovers due to hurricanes which speaks to labor force mobility and location choice following such disasters. Additionally, the results suggest that hurricanes depress both employment and wage growth in affected counties.

Keywords: Labor Markets, Natural Disasters, Hurricanes, Matching.

JEL Classification: J2, R0

I would like to thank the Alabama Center for Insurance Information and Research (ACIIR) for their support of this research project.

1 Introduction

The southeastern coast of the United States on a yearly basis is threatened by multiple hurricanes. More recent hurricanes such as Harvey and Irma in 2017 resulted in combined damages totalling $175 billion (Smith, 2018). Hurricane Katrina in 2005 caused damages estimated at $160 Billion, which is to date the most devastating hurricane to affect the United States, while simultaneously causing an estimated 1,833 deaths (Knabb et al., 2005). As the southernmost state, Florida is vulnerable to hurricanes traveling towards the Atlantic Ocean as well as those entering through the Gulf of Mexico. This places Florida in the path of most hurricanes that approach the southeastern coast of the United States. Though the hurricanes that affect Florida do not always make landfall in the state, the effects of these hurricanes are still experienced through wind, rain, and storm surges in areas within proximity of the reach of the hurricanes.

As capital and other economic factors are destroyed due to the effects of hurricanes (Lee, 2019; Zhang et al., 2009), the prospects for employment and by extension opportunities for earnings are significantly affected. Labor markets in affected areas are further impacted by the out-migration of labor (Strobl, 2011; Belasen and Polachek, 2009; McIntosh, 2008) or other short term population changes due to death or illness (Zhang et al., 2009). Findings presented by Emanuel (2007) suggests that tropical cyclones and therefore hurricanes, have increased in both frequency and intensity due to rising sea surface temperatures which is closely associated with global warming. In the coming years, without careful attention to climate preservation, hurricanes are poised to present significant challenges for labor markets in coastal regions of the United States. Even in the presence of actions to reverse or halt the effect of global warming, policy makers must still plan for the consequences of climate change.

I contribute to the discussion of the economic effects of natural disasters, specifically the impact of hurricanes on labor markets. I build upon the work of Belasen and Polachek (2009) by applying the wind field model developed by Boose et al. (2004) to estimate the impact of hurricanes on local labor markets in Florida counties. The wind field model is a measurement technique that estimates the wind speed of tropical cyclones. For the purposed of this study, the tropical cyclones being analyzed are those that developed into hurricanes and were formed either in the Atlantic Ocean or the Caribbean basin. This technique offers new insight in the labor market context as hurricane intensity is allowed to vary as the speed and strength of a hurricane changes over its life time.

The analysis demonstrate how landfall[1] or hurricane path as a measure of impacted areas can bias estimates of the economic impact of hurricanes. Specifically, I show that these measurement techniques fail to capture the wind speed dynamics of hurricanes as their effects are not simply confined to the geographical path of the storm's eye. The wind field model allows me to more accurately classify areas as treated and untreated units using actual wind speeds to estimate the wind intensity experienced. I also apply propensity score matching techniques to explore how hurricanes disrupt labor markets between affected and unaffected counties, matching on labor market, population trends and hurricane susceptibility.

I find that on average, hurricanes have a negative impact on employment growth in directly hit counties while having a statistically insignificant effect on earning growth. When disaggregated into different intensities, severe hurricanes cause employment growth to fall while resulting in a statistically significant increase in wage growth in affected counties. Weaker hurricane effects lead to reductions in employment growth but have no statistically significant impact on wage growth. Where statistical significance was identified, the estimates were small relative to those estimated in the previous literature using the landfall model. I do not find evidence of labor market spillovers from affected counties to geographical neighbors. Using multiple hurricanes, the propensity score matching results provided evidence that hurricanes may primarily affect labor markets through labor demand shocks rather than labor supply.

[1] Landfall as a measurement strategy uses the phenomenon of a tropical cyclone's eye crossing onto land as a means of indicating the areas that should be classified as affected by the storm.

2 Conceptual Framework for Labor Market Outcomes

The literature has shown that the impact of disasters on labor markets can take many forms. In a standard labor supply model, labor displacement due to disasters is a common result (either temporarily or permanently). Displacement will shift the labor supply curve to the left, leading to a decrease in the number of individuals employed and an increase in the wages paid to those workers who remain in the affected area (Brown, 2006; Zhang et al., 2009; Belasen and Polachek, 2009). Zhang et al. (2009) notes that affected areas face the risk of reduced labor demand as well. This outcome occurs due to a shift in consumer preferences for goods and services. Luxury goods and services and vacation services are examples of industries in which employees may be temporarily or permanently laid off conditional on the severity of the disaster. In this scenario, the labor demand curve may also shift to the left as some entities close down or require less labor due to losing a portion of their customer base.

Groen et al. (2020) highlights the fact that the effect of a hurricane, though negative in many contexts, can spur growth in certain industries such as construction, wholesale building material, and furniture providers which then causes the demand curve for labor in these industries to shift to the right. Further support for this result was presented in Zhang et al. (2009). Zhang et al. (2009) notes that an influx of construction crews from other areas into the affected locations will stimulate demand for hotels and restaurants and thereby workers in the hospitality and other related industries.

Studies such as Belasen and Polachek (2009), Strobl (2009), Brown (2006) and Groen and Polivka (2008) have noted population displacement as an avenue through which hurricanes may affect labor markets. Population displacement creates an increase in labor supply in locations outside the affected areas as labor migrates. Due to this migration, by standard economic theory, one would anticipate a reduction in the average wage in the new locations that the workers move into due to the increase in labor supply. With no real disturbance to the previous structure of the labor market in the new areas, the labor demand should remain similar to what existed prior to the influx. Therefore, we should see a shift of the labor supply curve to the right with no change in labor demand resulting in an increase in employment but a decrease in the average wage in these neighboring areas. For the directly affected areas, the labor supply curve is expected to shift to the left while labor demand as mentioned before could shift in either direction, making the overall impact uncertain.

With the evidence from the cited work above, we observe that the effect of disasters is ambiguous a priori. In some cases, the effect of a disaster can result in increased employment propelled by sectors which are needed in order to assist in recovery from damage. In other cases the outcome may be negative as businesses are destroyed, supply chains disturbed, and customer bases dissolved. Earnings are expected to fall in the affected area if the sector that labor is concentrated in is vulnerable to the effects of disasters. Where labor can migrate from place to place or sector to sector, it is expected that earnings will increase for those who remain in the affected area after the disaster due to the fall in labor supply. Overall, by standard Economics theory, both earnings and employment stand to be impacted by the demand and supply of labor in the event of a disaster. The force with the greatest impact (supply or demand) is however in question. This study offers some insight into which may be most at play in the case of hurricanes in Florida.

3 Data

The data utilized in the study is a combination of the data set compiled by Belasen and Polachek (2009) from the Quarterly Census of Employment and Wages (QCEW) and the best track HURDAT2 database provided by the National Oceanic and Atmospheric Administration (NOAA). The QCEW database provides data on monthly employment and quarterly wages of workers who are covered by State unemployment insurance (UI) and Federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program. The data is recorded at varying levels of geographical aggregations. For the present study, the aggregation used is at the county level. The period covered is quarter 1 of 1988 to quarter 4 of 2005. Since the employment data is not provided quarterly but monthly, I formulate the quarterly employment figures by taking the average of each consecutive three month employment totals for each county in each year. The selection of this period of study is primarily motivated by the desire to produce results that are comparable to the previous literature and emphasize the differences identified with the application of the measurement technique employed in this paper.

The HURDAT2 database provides spatially relevant and updated data to measure wind speeds of each storm that has maneuvered the Atlantic basin beginning in 1851. The database provides information on each tropical cyclone whether the cyclone maintained tropical storm status or transitioned into a hurricane. Each tropical cyclone is monitored in six hour intervals. As noted by Strobl (2009) tropical cyclones can move considerable distances over a short period of time. Therefore, I linearly interpolate the location and wind speeds of each hurricane from six hourly intervals to three hourly intervals. This is consistent with extant literature (Strobl, 2009; Jagger and Elsner, 2006).

Geographical data to identify county points was gathered from the United States Census Bureau county shapefile database. Recognizing that counties in some cases are considerably large, I decided against using a single centroid as the point of reference for calculating the impact of hurricanes. One hundred points were identified in each county to ensure that the boundaries of the counties were considered when a county was hit by a hurricane rather than a single point in the center of the county. This method is expected to increase the precision of hurricane estimates as a greater proportion of each county will be included in each estimation as opposed to the single centroid alternative.

4 Empirical Strategy

4.1 Wind Field Model

Unlike other studies in the literature detailing the impact of hurricanes on labor markets, Belasen and Polachek (2009) combined the effects of hurricanes over an extended time period to capture the average effect of a set of hurricanes rather than the impact of an individual hurricane. In that study, the authors utilized landfall as the measure of a hurricane's impact. Additionally, the wind intensity at landfall is used as the intensity experienced in each county affected by the hurricanes analyzed in the study. A problem that arises with this measurement strategy is that the intensity of a hurricane changes as the hurricane progresses. This is due to many factors which range from sea surface temperatures (Emanuel, 2005) to the position of the storm relative to land (Kaplan and DeMaria, 1995). Particularly, the strength of hurricanes decreases as they makes landfall.

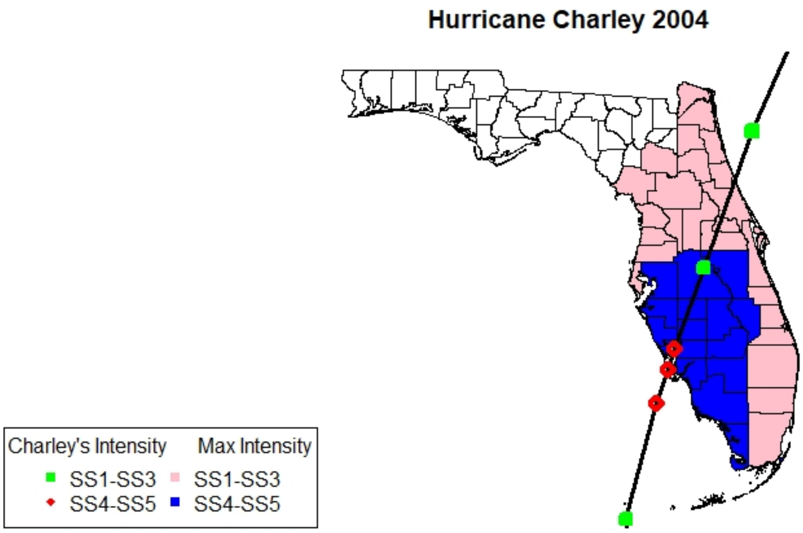

Figure 1: Declining Intensity Of Hurricane Charley

Figure (1) above depicts Hurricane Charley that made landfall in Florida in 2004. Hurricane

Charley entered Florida as a category 4 hurricane and later, before completely crossing the state, was reduced to a category 1 hurricane (Pasch et al., 2005). The counties in northeastern Florida through which Charley passed were not affected by a category 4 hurricane. The dark shaded areas in figure (1) represent those counties that experienced hurricane winds of category 4 and above. The light shaded areas represent those counties that experienced hurricane force winds between categories 1 and 3. The intensity of the storm indicated by the green (category 1 to 3) and the red (category 4 to 5) nodes along the path of the hurricane reveal the difference in the strength of the hurricane as it traversed the state. A model that does not control for this variation would incorrectly assume that all the counties through which the hurricane travelled experienced category 4 winds and over report damage.

To address this concern, I use the wind field model developed by Boose et al. (2004). The wind field model estimates the wind intensity of hurricanes at any geographical point in relation to the radius of maximum wind in a hurricane. The landfall model on the other hand, assumes all counties through which the eye of the hurricane passes experience the same wind speeds. The wind field model allow for variation in the wind speeds experienced by different counties along the path of each hurricane analyzed. Equation (1) below illustrates the structure of the wind field model as presented by Boose et al. (2004) where V represents the estimate of wind intensity in each geographical point for each county.[2]

$$V = GF\left[V_m - S(1-\sin(T))\frac{V_h}{2}\right]\left[\left(\frac{R_m}{R}\right)^B exp\left(1-\left[\frac{R_m}{R}\right]^B\right)\right]^{\frac{1}{2}} \quad (1)$$

V_m represents the maximum sustained wind velocity anywhere in the hurricane. T is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the point of interest, P. V_h is the forward velocity of the hurricane, R_m is the radius of maximum winds[3], R is the radial distance from the center of the hurricane to point P, and

[2] Recall 100 geographical points were used for each county so V captures the wind speed at each.

[3] The radius of maximum wind is sometimes referred to as the radius of destruction. This is the area bordering

G is the gust wind factor. The remaining variables, F, S, and B, are scaling parameters for surface friction, asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively (Strobl, 2011). Figure (2) below provides a visual representation of the a hurricane along with components of the wind field model.

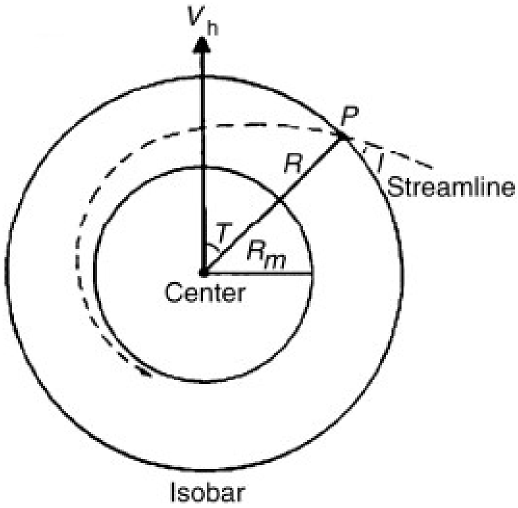

Figure 2: Source Boose et al. (2001)

Hsu and Yan (1998) concluded that on average, in their sample of hurricanes analyzed between 1893 and 1979, the R_m was 50 km. In addition, the authors provided a breakdown of the average R_m based on the intensity of the hurricanes. Taking this into consideration, I use the R_m breakdowns as weights on the sample of hurricanes in this study in order to calculate an average R_m consistent with my sample. The resultant R_m was 40 km. This R_m was used in all calculations of the impact of each hurricane on each county in Florida. It is worth noting that at the time of the writing of this paper, there is no known database of R_m for hurricanes. Such a database would assist studies such as this that attempt to incorporate natural sciences into economic research.

the eye of the hurricane at which point the strongest winds are recorded.

4.1.1 Application of Wind Field Model

Using the wind field model, I identify affected counties by the maximum wind speed experienced within counties across the state of Florida over the life of a hurricane. The wind field model identified a total of 17 tropical cyclones that achieved wind speeds of 119 km/h or greater that affected the state of Florida between 1988 and 2005.[4] A county is classified as affected by a hurricane if geographical localities within the county experienced wind speeds greater than or equal to 119 km/h. Due to the construction of the wind field model, some of the hurricanes that were identified as affecting the state of Florida did not make landfall. However, they passed within reasonable distance to produce wind speeds greater than or equal to that produced by a category 1 storm according to the Saffir-Simpson (SS) scale.[5] At this point it is worth acknowledging the possibility that of the 100 geographical points in a county, in some cases, a majority may not have experienced hurricane force winds. To address this potential shortfall, each hurricane's estimates were plotted against the state map of Florida to verify credibility of the locations selected as impacted.

Keeping in line with the work of Belasen and Polachek (2009), I separate hurricanes into two groups; category 1-3 in group 1 and category 4-5 in group 2. However, I deviate from the literature in that I do not classify a hurricane into a specific category based solely on the wind speed that was recorded when the hurricane made landfall and maintain this classification over the life of the hurricane. Instead, I look at the maximum estimated wind speed experienced within each county. In so doing, a county is classified as experiencing a group 1 or group 2 intensity hurricane depending on the strength of wind estimated in the localities of the county. Localities were determined by the geographical points provided in the state shapefile sourced

[4] A list of all hurricanes analyzed in this study can be found in the appendix in table (4).

[5] The Saffir-Simpson scale categorizes wind speeds from hurricanes into 5 separate categories. Category 1:119–153 km/h, Category 2: 154–177 km/h, Category 3: 178–208 km/h, Category 4: 209–251 km/h, Category 5: $\geq$ 252 km/h.

from the United States Census Bureau. Designating a hurricane's impact based on the wind speed a county experienced results in counties being classified differently than landfall models. Therefore, for the case where a hurricane such as Charley shown in figure (1) would be classified as a group 2 hurricane, the set of counties experiencing group 2 winds will be less than that in the literature due to decreasing wind speeds.

In each hurricane event, the counties that were geographically neighboring a county that was affected by a hurricane of either the groupings described above were identified such that the spillover impact of employment and wage growth could be assessed. At this point, it should be apparent that in the event of a group 2 hurricane (category 4-5) classification, there are nearby counties that experience hurricane winds of category 1-3. This study accounts for those additional group 1 hurricane effects that previous studies using a landfall model would have categorized as either group 2 if the hurricane traveled through the county or treated as unaffected neighbors if not on the direct hurricane path.

Three of the hurricanes (Florence, 1988; Allison, 1995; and Gordon, 2000) identified by Belasen and Polachek (2009) as having directly hit Florida were eliminated from the set of hurricanes employed in this study due to the fact that the best track data provided by the National Oceanic and Atmospheric Administration (NOAA) did not indicate that they produced hurricane strength winds upon arriving in the vicinity of Florida. Implementing the wind field model for these hurricanes support this finding. The wind field model accounts for the effect of hurricanes within 500km of the hurricanes' eye and gave no indication of hurricane force winds in any Florida county from these hurricanes. Hurricane Florence in particular, did not make landfall in Florida, but in Louisiana. Figure (3) illustrates the path of all three hurricanes. The thick section of the track for each storm represents the points where the hurricane was greater than or equal to a category 1 hurricane. The slim sections represent the points where the tropical cyclones maintained tropical storm strength winds. This figure makes it clear that even for the two storms that made landfall in Florida, they were not hurricanes at the time they made landfall and thus would not cause the level of damage that would be associated with a hurricane. Two hurricanes were added to the list previously compiled by Belasen and Polachek (2009), Hurricane Hugo, 1989 and Hurricane Floyd, 1999. Both storm produced hurricane wind speeds within Florida.

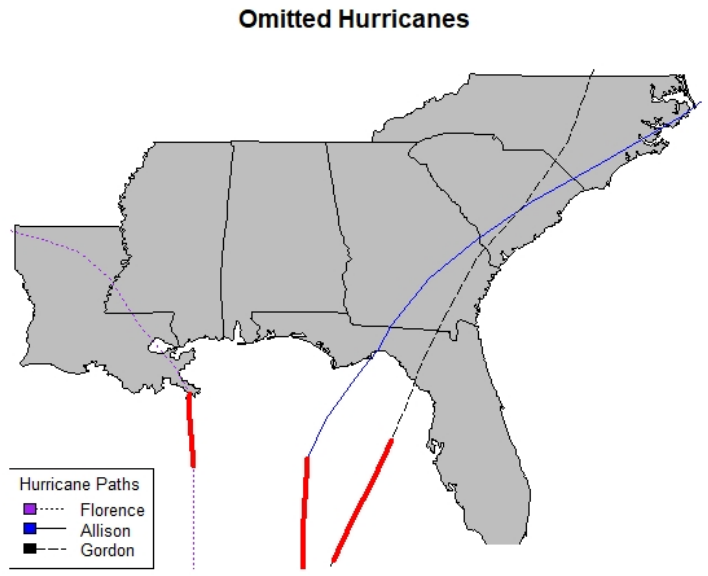

Figure 3: Hurricanes Florence, Allison, and Gordon

4.1.2 Robustness Check of Wind Field Model

I discussed earlier the extent to which landfall models are not sufficient to fully capture the exposure of an area to the impact of a hurricane. Taking note of Hurricane Andrew in 1992, we see that the hurricane directly crossed two counties in Florida; Miami-Dade and Monroe. Figure (4) panel (A) depicts those counties that were designated as disaster areas (dark shaded) by the Federal Emergency Management Agency (FEMA) (FEMA, 2018) due to Hurricane Andrew.[6] Andrew was the only tropical cyclone in 1992 that affected Florida with hurricane force winds.

[6] FEMA provides a platform which allows the viewing of areas affected by disasters in each state beginning in 1951.

As such, the disaster declaration was solely caused by hurricane Andrew that year. Panel (B) in figure (4) plots all those counties that experienced hurricane force winds of category 5 based on the calculations from the wind field model. From both plots, it is evident that the same counties that were classified as disaster areas, are the same counties that, according to the wind field model, experienced the strongest winds from the hurricane. This gives credence to the use of the wind field model in determining the affected counties.

In panel (B) of figure (4), we see the light shaded circle which is plotted along the path of hurricane Andrew as it entered the state of Florida. This circle has a radius of 30 km which is the maximum size of the radius of destruction used by Belasen and Polachek (2009). The authors used this distance off the path of the hurricane as the determinant of those counties that were hit by the hurricane directly. A neighbor was classified as a county that was geographically next to a county that was hit by a hurricane (ibid). Note from both panels (A) and (B) that using this method, counties that were significantly damaged by hurricane Andrew would be classified as neighbors to directly affected counties rather than affected themselves. This situation highlights one of the main criticisms of landfall models as areas that experienced category 4-5 winds are classified as unaffected neighboring counties. It is therefore evident that there needs to be a more precise measure for identifying where the directly affected counties were and the impact on their respective neighbors. Due to the apparent measurement challenge, I anticipate that the geographical neighbors utilized in the literature, when assessed with the measurement methods in this study, will experience effects similar in sign but lower in magnitude to the impact on the directly affected counties.

4.2 Generalized Difference-in-Differences Approach

The primary estimation technique utilized in this paper is the Generalized Difference-in-Difference (GDD) estimation strategy, commonly known as the Two-Way Fixed effects model. This

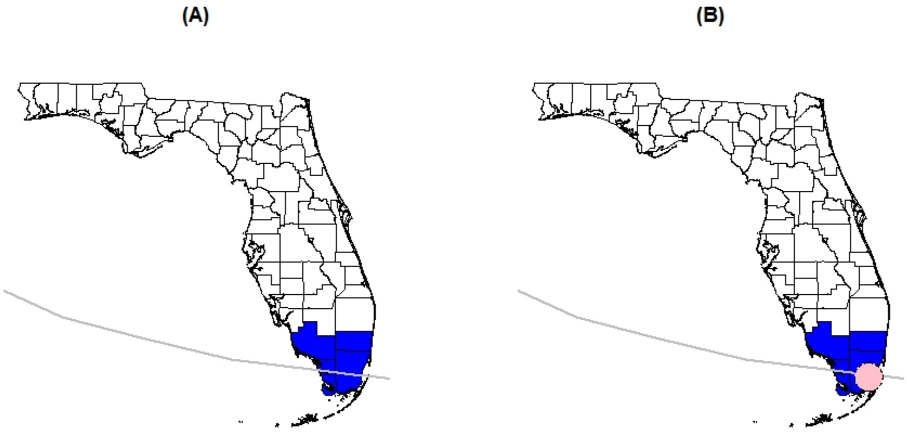

Figure 4: Hurricane Andrew 1992

methodology is used due to the fact that the method uses multiple random control and treatment groups. Additionally, the GDD allows for comparisons to be made across multiple exogenous events and time periods (Belasen and Polachek, 2009).

There are two main reasons why previous estimates of the effect of hurricanes on local labor markets using the GDD may be biased. First, since the method proposed to identify counties affected by storms is narrow, it is likely that some of the counties that were selected as comparison units experienced hurricane force winds that would render them to be better classified as treated counties. Without addressing this issue, Belasen and Polachek (2009) potentially fell prey to one of the main problems that they set out to solve, the selection of appropriate comparison units. Second, it is unlikely that the effect of a hurricane on a county that is a neighbor to one directly hit by a category 4 or 5 hurricane is vastly different from the county that was hit directly. Based on the size of the average hurricane, which is approximately 500 km, and the position to the neighboring county, there is a great chance that the neighbor experiences similar wind speeds and levels of damage.

If the various factors contributing to a hurricanes strength and impact (Boose et al., 2004) are not taken into consideration, the omission may lead to incorrect conclusions. Hence, if neighboring counties are experiencing hurricane force winds similar to the "directly" affected group of counties, this limits the extent to which spillovers could be identified, especially to the extent that the impact on the neighboring county is strictly opposite to the directly hit county. With the inability of landfall models or models which only look at small areas such as the area in the vicinity of the eye of the hurricane, to capture these additional impacts, those results are potentially biased and the comparisons made between counties may thus not be accurate.

In the application of the model, I control for quarter fixed effects and a modification to the previous literature of regional fixed effects which is interacted with the quarter dummy variable. The interaction between the regional dummy variable and the quarter dummy variable is included to account for the seasonality in the labor markets in the state. Some regions, such as South Florida, are heavily affected by tourism and as such will respond different from regions such as Central and North Florida that may not see as much fluctuation in labor demand and supply throughout the year. Equations (2) and (3) present the models that are used to analyse the effect of hurricanes on Employment and wage growth respectively. Equations (4) and (5) explore similar effects as (2) and (3), however differing in that these models account for differences in hurricane intensity.

$$(\Delta lnQ_{it} - \Delta lnQ_t) = \alpha_{1R_i} + \alpha_2 \Delta H^D_{it} + \alpha_3 \Delta H^N_{ijt} + \epsilon_{it} \tag{2}$$

$$(\Delta lny_{it} - \Delta lny_t) = \gamma_{1R_i} + \gamma_2 \Delta H^D_{it} + \gamma_3 \Delta H^N_{ijt} + \epsilon_{it} \tag{3}$$

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \alpha_{1R_i} + \alpha_2 \Delta H^{4-5}_{it} + \alpha_3 \Delta H^{1-3}_{it} + \epsilon_{it} \tag{4}$$

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \gamma_{1R_i} + \gamma_2 \Delta H^{4-5}_{it} + \gamma_3 \Delta H^{1-3}_{it} + \epsilon_{it} \tag{5}$$

Q_{it} represents average employment in county i at time t while y_{it} represents average wage per worker in county i at time t. Q_t and y_t represent the state average employment and state average wage per worker at time t. The subscript i indicates an affected county while j indicates a county that was a neighbor to the directly affected county, i. R_i are the regional fixed effects. H_{it}^{D} represents the dummy variable which takes a value of 1 for county i that was hit by hurricane force winds from a hurricane in time t. H_{ijt}^{N} is a dummy variable which takes a value of 1 for a county j that was neighboring to a county i that was hit by hurricane force winds in time t . In equations (4) and (5), H_{it}^{4-5} and H_{it}^{1-3} represent the dummy variables which take a value of 1 for a county that experienced hurricane force winds commensurate with the category of the hurricane as given by the superscript. Thus, in this manner I account for the full extent of the impact from each hurricane. This includes those counties that experienced categories 1-3 winds speeds from hurricanes that were between categories 4 and 5.

4.3 Matching

As another novel contribution to the literature, I estimate the probability[7] of experiencing a hurricane based on historical data and analyze the effects of individual hurricanes using nearest neighbor one-to-one matching, accounting for pre-hurricane labor market trends in matched groups. The essence of this exercise was not so much to see the effects of individual storms as it was to see the differences in outcomes or the lack thereof when the impact of the hurricanes are contextualized with similar counties. Thus, I compare the effects of hurricanes across counties that have similar labor market trends prior to each hurricane.

According to Rosenbaum and Rubin (1983), the propensity score allows one to assess the probability of a treatment based on observable covariates. For this study, the observable covariates are the average employment, average earnings per worker and total county population

[7] The probability of experiencing a hurricane was calculated as $\frac{\#hurricanes}{\text{18 year period of the study}}$.

for each county up to two years prior to each hurricane. The selection of untreated counties is conducted with replacement which allows for units to be matched more than once. Matching with replacement helps to maintain the quality of matches. Some untreated counties may be good matches for multiple treated counties so this method allows such counties to be matched to more than one treated counties. Observing the work of Rosenbaum and Rubin (1985), a caliper of 0.25 standard deviations is used as a measure of appropriate matching. A combination of both nearest-neighbor matching and caliper designation provides better matching outcomes in terms of standardized differences between treated and untreated units when compared to matching on either by themselves (ibid). Additionally, I utilize the bias corrected estimator proposed by Abadie and Imbens (2006) which corrects for the bias generated when greater than one continuous variable is used in a matching process.

Exploiting the spatial properties of the wind field model, I was able to clearly identify those counties that experienced hurricane force wind speeds. Once identified, the affected counties were matched with counties that had similar labor market trends prior to the specific hurricane being analysed. This method of matching was chosen in order to explore deviations in the growth rate in employment and wages due to a major economic shock which for Florida, tends to occur most frequently due to hurricanes in the height of the hurricane season.

Seeing that the locations that hurricanes affect are not truly random (southeastern states are more prone to hurricanes than other regions of the country), I estimated the probability of experiencing a hurricane based on historical data for all counties in six other southeastern states (Louisiana, Mississippi, Alabama, Georgia, South Carolina, and North Carolina) and Florida, which is the state of focus. Each of these states have similar hurricane vulnerability. The 518 counties from these 6 states formed the set of counties from which untreated matches could be drawn.

Due to the geographical proximity of the counties in Florida, when a hurricane affects the state it is possible that there will not be many counties that did not experience an effect from a hurricane such that appropriate matches can be selected. Additionally, there is also the possibility that the counties that are the most similar (counties in a region such as South Florida), are the only ones impacted by a particular hurricane. In this case, the set of appropriate matches will be reasonably small and thus, limits the estimates that could be derived from the matching procedure. Another concern is that when there is a major hurricane, the effect on a number of counties in Florida may have statewide repercussions. This was particularly concerning since spillovers in the treatment would violate the Stable Unit Treatment Value Assumption (SUTVA) (Rubin, 1986).

On account of these concerns, I use only counties outside of the state of Florida as untreated units for matching. Matches are therefore selected from the set of counties outside of Florida in the six states mentioned previously that were not treated by the hurricane in question. In order to ensure that the counties used as matches are as similar as possible to the treated counties, the set of 585 counties across the seven states was further reduced to 220 as there were only 220 counties that had calculated probabilities of hurricane exposure greater than zero over the period of study. In each matching case, based on the counties affected by a particular hurricane, the set of counties from which matches was drawn was reduced to only counties that had probabilities of exposure that fell within the probability range of the hurricane exposed counties[8]. Additionally, recognizing the that the counties being selected as matches could possibly experience hurricanes in the same year, all possible control counties experiencing a hurricane in the year of interest were removed from the set of possible matches. Figure (5) presents the hurricane probabilities by county.

According to Imbens and Rubin (2015), the two identifying assumptions for propensity score

[8] For example, imagine that Monroe county and Miami-Dade county in Florida are the only counties hit by a hurricane. If each has calculated hurricane impact probability of 0.1 and 0.5 respectively, the match counties must have probabilities of hurricanes impact between 0.1 and 0.5.

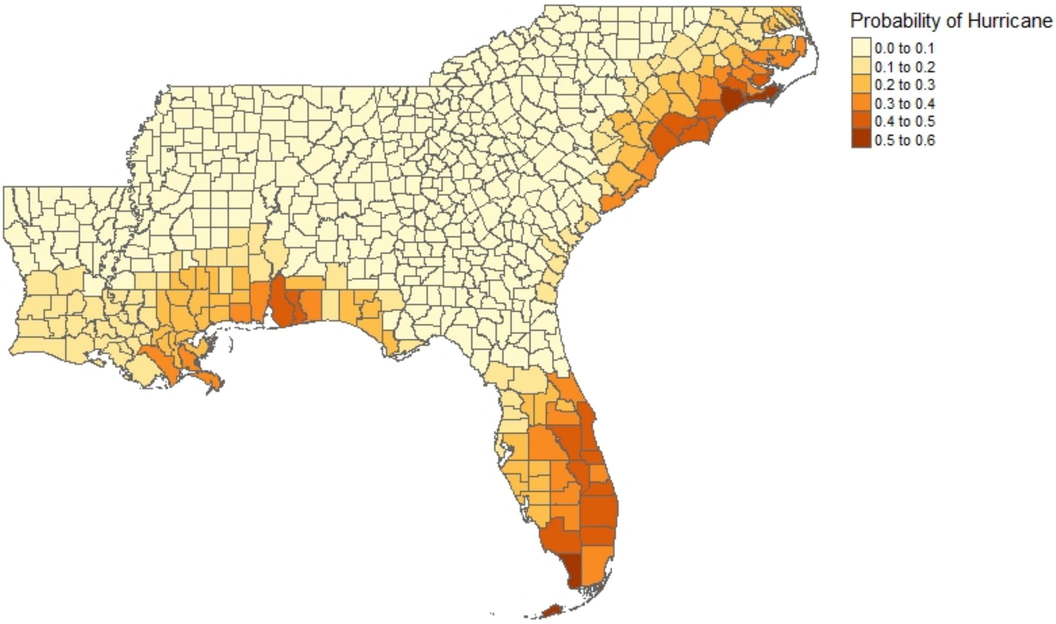

Figure 5: South East Hurricane Probability

matching are unconfoundedness and common support in the covariates between the treated and control groups. The unconfoundedness assumption is not testable but by the nature of the treatment, we can confirm that the propensity score method is appropriate in the context of hurricanes. The assumption requires that the assignment of the treatment (in our case, hurricanes) is independent of the potential outcome in the treated units. Considering the nature of hurricanes, there is no way to "assign" a treatment in this context conditional on any anticipated outcome in the treated units. In this regard, I proceed with confidence that the unconfoundedness condition is satisfied.

The second condition of common support in the covariates is testable. This condition ensures that there is overlap in the distribution of the characteristics of the treated and untreated units. In order to see if this condition is met, I assess the balance in the covariates. This can be achieved via statistical tests for the absolute standardized differences in the mean for the distribution of covariates between the two groups. As noted by Lunt (2014), a large difference in means in opposite directions could cancel to give a mean difference of zero. Thus, along with mean differences, common support is assessed by way of the variance ratio test which tests for the overlap in the variance of distributions of treated and untreated counties. Coupling both means of assessing balance, strengthens the conclusion of successful balance between groups. Figure (6) below presents the absolute standardized mean differences for the pre-treatment variables while figure (7) presents the variance ratio test for overlap used for matching with hurricane Andrew. Both figures indicate an improvement in balance due to the matching procedure.

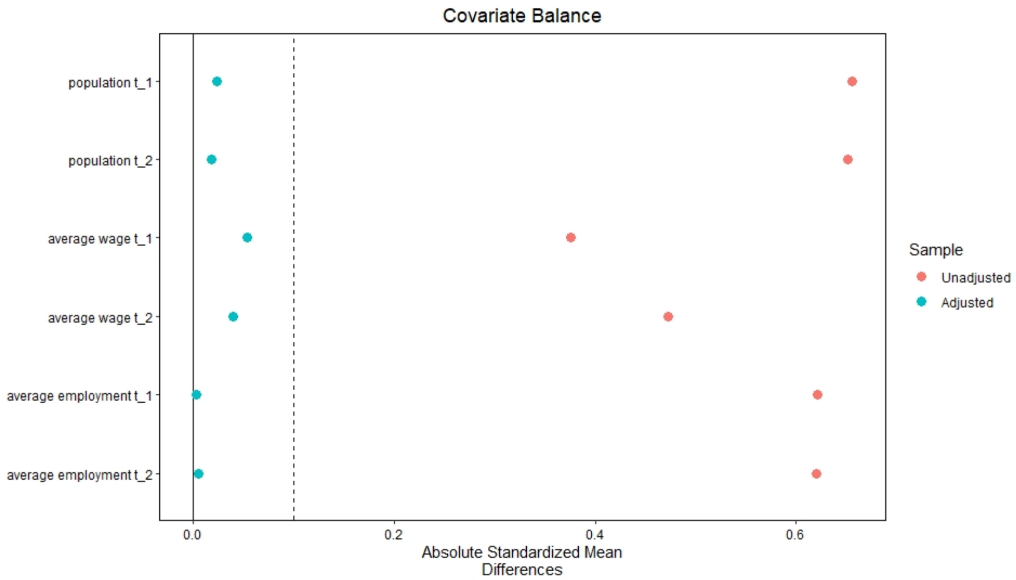

Figure 6: Mean Difference Andrew 1992

For each hurricane analyzed, I use a standardized mean difference threshold of 0.1 (Stuart et al., 2013) and a variance ratio threshold of 2 (Zhang et al., 2019) for balance. The resulting estimates from the matching procedures are presented once matching is concluded and both unconfoundedness and covariate balance is achieved for all pre-treatment covariates across the matched groups.

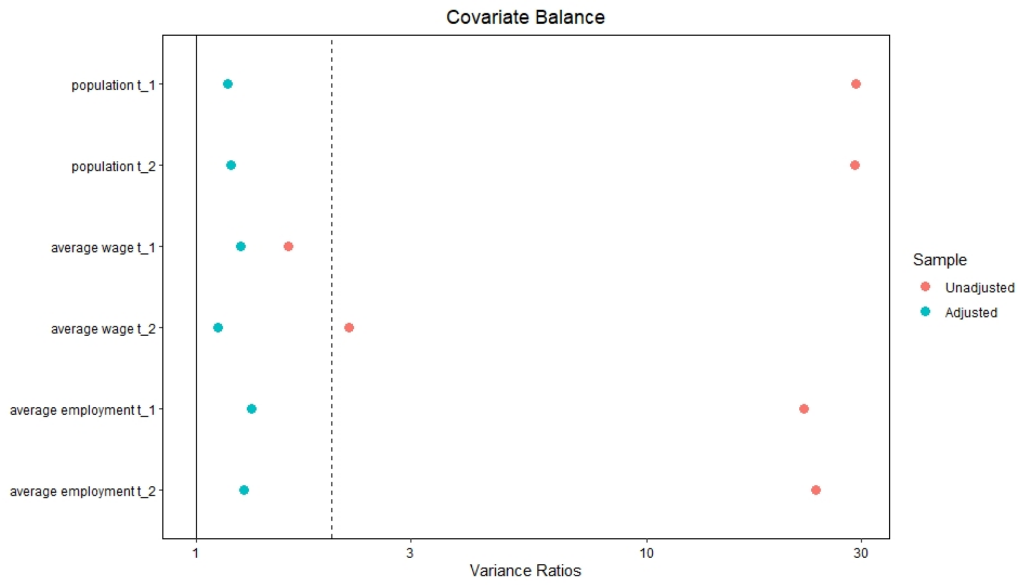

Figure 7: Variance ratio Hurricane Andrew 1992

5 Results

5.1 Aggregate Results

Reproducing the models from Belasen and Polachek (2009) using the wind field model to identify the affected counties, I obtain the results presented in table (1). Similar to the findings in the literature, my results indicate that hurricanes have a statistically significant and negative impact on employment growth in the counties where hurricane force winds were recorded. However, I find a negative and statistically significant effect on employment growth in neighboring counties, contrary to the previous literature. This negative but smaller effect is the anticipated result for neighboring counties. A county that neighbors one that experienced hurricane force winds, especially of strong intensity, is expected to still be negatively affected by the hurricane but not to the same extent. Thus, these estimates indicate that a directly affected county will experience a 1.25% decrease in employment growth relative to the average Florida county in the quarter that a hurricane occurs while in the neighboring counties employment growth is reduced by 0.71%.

The extent of the hurricane effect is less when accounting for the variation in hurricane wind speeds compared to the effect estimated from the landfall measurement strategy. In particular, the results of this study proved to be 1.12 percentage points lower for the directly affected county's employment effect and though not statistically significant, 1.59 percentage points lower for earning growth relative to the findings of Belasen and Polachek (2009). This results was not surprising due to the fact that the landfall model fails to account for the change in the hurricane intensity as the hurricane travels along its path as shown in figure (1).

Based on standard economic theory, one would anticipate a negative relationship between employment and wages. The results here do not indicate a statistically significant impact on wage growth for neither the directly affected counties nor the neighboring ones. The prevailing argument in the literature suggests that the labor supply in the directly hit counties should fall as labor migrates to neighboring counties and thus result in an increase in earning growth for the directly affected counties. By the same logic, in the neighboring counties, labor force will rise due to migration and result in a fall in earning growth. As shown in table (1), my results do not support this conclusion. The lack of growth in wages is potentially due to the fact that the reduction in the labor supply is accompanied by a reduction in labor demand. Zhang et al. (2009) suggested a number of ways labor demand may be impacted by hurricanes; infrastructural damage, establishments shutting down or downsizing, and the loss of ones customer base, either temporarily or permanently due to displacement.

The resultant outcome of falling labor supply and labor demand is a clearly defined reduction in employment growth but a statistically insignificant impact on wage growth. For neighboring counties, if hurricane damage sustained is similar to the directly affected county, then those counties would not be appropriate locations to relocate to. Note that both the employment and wage growth impact for the directly affected counties was mirrored in the neighboring counties. This suggests that the effect on neighboring counties was similar but less severe.

Table 1: Aggregate Results (GDD)

Coefficients	ln(Employment)	ln(Earnings)
Direct	-0.0125***	0.0033
	(0.0035)	(0.0033)
Neighbor	-0.0071*	-0.0034
	(0.0043)	(0.0040)
n,group	4757,67	4746,67

Note: ***,**,* denotes significance at the 1%, 5%, and 10% level, respectively. Standard errors reported in parenthesis. Region fixed effects and region quarter interaction (not shown) are included in each model along with quarter-year effects.

5.2 Hurricane Intensity Results

When broken down into the two groups based on hurricane intensity, the results in table 2 echo those in the literature for the most severe hurricanes. We see that the results observed in the aggregate model were primarily driven by strong hurricanes (Categories 4-5). Strong hurricanes reduce employment while positively impacting earnings. Additionally, the results indicted that weaker hurricanes did indeed assuage the estimates obtained for hurricanes overall as presented in table 1. Table 2 shows a 4.36% decline in employment growth due to strong hurricanes while recording a 2.29% increase in wage growth for affected counties in the quarter when a strong hurricane struck. These results support to some degree the argument that major hurricanes have a significant impact on labor supply (Brown, 2006; Zhang et al., 2009; Belasen and Polachek, 2009; Abadie and Imbens, 2006). The effect on labor supply results in a significant reduction in employment growth which by standard economic theory is accompanied by an increase in wage growth.

The group of counties that were impacted by hurricane winds between categories 1 and 3 include those that experienced wind speeds from strong hurricanes that fell within this range. This innovation was deemed necessary since many locations experienced hurricane force winds which would not be classified as category 4 or 5 but satisfied the condition for category 1 to 3 classification as the strong hurricane traveled along its path. The results indicate that experiencing hurricane force winds of categories 1-3 will cause employment growth to fall by 0.85% relative to the average Florida county. The effect on wages was statistically insignificant. Similar to the results presented in table 1, the insignificant result for wage growth speaks to the fact that the hurricanes being considered lead to a reduction in both labor demand and labor supply relative to the average unaffected county. The outcome is then a statistically significant decline in employment growth with an insignificant impact on wage growth.

Due to the overlap between the counties that would be classified as geographical neighbors to those experiencing category 4 to 5 wind intensity and those counties that experienced hurricane force wind between category 1 and 3 from the same storms, I was unable to explore the difference in neighboring effects by hurricane group for strong hurricanes. However, I produced results for neighbors of those counties that experienced category 1 to 3 winds but the effects were insignificant across both employment and wages.

Table 2: Hurricane Intensity Results (GDD)

Coefficients	ln(Employment)	ln(Earnings)
Category 4-5 Hurricanes	-0.0436***	0.0229***
	(0.0072)	(0.0068)
Category 1-3 Hurricanes	-0.0085**	-0.0004
	(0.0036)	(0.0034)
n,group	4757,67	4746,67

Note: ***,**,* denotes significance at the 1%, 5%, and 10% level, respectively. Standard errors reported in parenthesis. Region fixed effects and region year-quarter interaction (not shown) are included in each model.

5.3 Matching Results

Table (3) presents the average treatment effect on the treated (ATT) counties for employment growth and wage growth. Of the 17 hurricanes recorded during the sample period, table (3) present the results from the seven for which balance was achieved in the covariates utilized in the matching procedure. Columns 4 to 7 detail the number of treated[9] counties, total potential untreated counties based on the criteria laid out in section 4.3, the number of treated counties for which successful matches were identified and the number of matched untreated counties[10] respectively.

The results solidify the previous finding that the effect of hurricanes on employment growth is negative. This was consistent for six of the seven hurricanes that had statistically significant results. A particularly interesting result identified here is the fact that along with employment growth, wage growth falls for all hurricanes for which statistically significant results were obtained. This result speaks to the fact that hurricanes cause the entire labor market to shrink. So, there are less jobs and for the jobs that remain, relative to similar counties outside the state of Florida, wage growth is lower. This result highlights the fact that the impact of hurricanes is not solely experienced through labor supply and may in fact be experienced more through labor demand. A shift of the labor demand curve to the left results in both wage and employment falling which would explain the sign similarity in the impact on both employment and wages shown in table (3).

Only Hurricane Wilma had a positive effect on employment growth along with a negative and statistically significant impact on wage growth. Hurricane Wilma took place in the fourth quarter of 2005. This result is not particularly surprising since employers will desire to get their businesses back to normal operations as soon as possible to meet the holiday rush at the

[9] counties that experienced hurricane force winds from each hurricane

[10] matching with replacement allowed for each untreated county to be matched with more than one treated county

end of the fourth quarter at which point labor market data for the quarter would have become available. The outcome observed here could be driven by an increase in the demand for labor (Groen et al., 2020; Zhang et al., 2009) along with a similar increase in the supply of labor. Seeing that the fourth quarter would constitute a period when there will be an increase in job seekers, particularly those who are temporary, labor supply should increase. As identified by Belasen and Polachek (2009), the increase in labor supply should result in an increase in employment as well as a fall in earnings. The particular period within which Belasen and Polachek (2009) recorded this phenomenon was the summer but given that the winter holidays are present in the fourth quarter, similar to the summer, there will be an increase in job seekers which could produce a similar result.

The result for Hurricane Dennis indicated that the hurricane did not have a statistically significant impact on neither employment nor wage growth. Hurricane Dennis, similar to Hurricane Erin, caused primarily category 1 wind speeds in the state of Florida. However, Hurricane Erin affected a larger number of counties than Dennis which included South Florida and the Florida Panhandle. The insignificant impact both in terms of employment and wage is possibly due to less severe and wide-spread impact from hurricane Dennis.

6 Conclusion

As was anticipated, the use of the wind field model produced results that differed from the literature. First, this study found no evidence of spillovers of labor from affected counties to neighboring counties by way of standard labor market theory. This result does not discredit the possibility that migration does indeed occur subsequent to a hurricane. This is in fact documented in the literature (Strobl, 2011; Brown, 2006; Zhang et al., 2009). However, what we observed here indicates that over the time horizon of this study, there is no movement of labor that impacts labor markets in counties that are geographically next to counties that

Table 3: Match Results

Hurricane	ln(Employment)	ln(Earnings)	Treated	Control	Matched Treated	Matched Control
Andrew 1992	-0.0886***	0.01887	25	115	13	13
	(0.0174)	(0.0275)				
Erin 1995	-0.0720***	-0.0169*	37	147	23	19
	(0.0153)	(0.0098)				
Charley 2004	-0.0746***	-0.0088*	40	129	22	20
	(0.0131)	(0.0052)				
Frances 2004	-0.1159***	-0.0210***	20	36	12	11
	(0.0258)	(0.0095)				
Jeanne 2004	-0.0889***	-0.0353***	27	44	13	16
	(0.0195)	(0.0117)				
Wilma 2005	0.0726***	-0.0538***	24	37	14	14
	(0.0130)	(0.0113)				
Dennis 2005	0.0222	0.0147	17	109	13	12
	(0.0181)	0.0294)				

Note: ***,**,* denotes significance at the 1%, 5%, and 10% level, respectively. Abadie and Imbens (2006) Standard errors reported in parenthesis.

experience hurricane force winds. This finding is a significant deviation from the literature as Belasen and Polachek (2009) identified a decrease in earnings in neighboring counties up to 4.51 percent due to the effects of migrating labor in response to hurricanes.

Confirming my hypothesis, neighboring counties had results that reflected that of the directly affected counties. The outcome differences in the findings between this study and the previous literature was anticipated based on the work of Strobl (2011) who highlighted that landfall models would be insufficient to develop conclusions regarding the impact of hurricanes on directly hit counties and neighboring counties.

The results of the matching mechanism in this study strengthened the conclusion that hurricanes have a negative impact on employment growth. Wage growth similar to employment growth fell due to hurricanes when matched with similar counties outside of the state as well. This result indicated a negative shock to the labor market on a whole. Due to the fall in labor demand, at all wage levels, both equilibrium employment and wage will be at a lower.

Of particular interest in this paper is the importance of using physical measures of disasters to identify more precisely, the impact of natural disasters on economic variables (Noy, 2009; Cavallo et al., 2013). By way of the measurement improvement, this study has shown that labor demand is a viable avenue through which employment and wage growth are impacted in hurricane hit counties. This is against the prevailing literature that posits that the labor market shock of hurricanes is felt through labor supply. What is still unclear is the degree to which either can be credited for the outcomes observed and in what circumstances would either be more dominant. Future research exploring this issue will assist in understanding whether aid programs after hurricanes should be directed to commercial or residential entities. If there are circumstances that render the impact of hurricanes to occur more through labor demand then assistance will be best directed towards commercial aid. If on the other hand, supply is the most impacted then assistance will be best directed to residential aid. This study present an interesting dynamic and impetus for future exploration of the effects of hurricanes and the measurement of the same which can be extended to other coastal states and other studies.

References

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *econometrica*, 74(1):235–267.

Belasen, A. R. and Polachek, S. W. (2009). How disasters affect local labor markets the effects of hurricanes in florida. *Journal of Human Resources*, 44(1):251–276.

Boose, E. R., Chamberlin, K. E., and Foster, D. R. (2001). Landscape and regional impacts of hurricanes in new england. *Ecological Monographs*, 71(1):27–48.

Boose, E. R., Serrano, M. I., and Foster, D. R. (2004). Landscape and regional impacts of hurricanes in puerto rico. *Ecological Monographs*, 74(2):335–352.

Brown, S. P. (2006). The effect of hurricane katrina on employment and unemployment. *Monthly Lab. Rev.*, 129:52.

Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5):1549–1561.

Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature*, 436(7051):686.

Emanuel, K. (2007). Environmental factors affecting tropical cyclone power dissipation. *Journal of Climate*, 20(22):5497–5509.

FEMA (2018). Summary of disaster declarations and grants. Available at https://www.fema.gov/data-visualization-summary-disaster-declarations-and-grants.

Groen, J. A., Kutzbach, M. J., and Polivka, A. E. (2020). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, 38(3):653–685.

Groen, J. A. and Polivka, A. E. (2008). The effect of hurricane katrina on the labor market outcomes of evacuees. *American Economic Review*, 98(2):43–48.

Hsu, S. and Yan, Z. (1998). A note on the radius of maximum wind for hurricanes. *Journal of coastal research*, 14(2).

Imbens, G. W. and Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Jagger, T. H. and Elsner, J. B. (2006). Climatology models for extreme hurricane winds near the united states. *Journal of Climate*, 19(13):3220–3236.

Kaplan, J. and DeMaria, M. (1995). A simple empirical model for predicting the decay of tropical cyclone winds after landfall. *Journal of Applied Meteorology and Climatology*, 34(11):2499–2512.

Knabb, R. D., Rhome, J. R., and Brown, D. P. (2005). Tropical cyclone report hurricane katrina. Available at https://www.nhc.noaa.gov/data/tcr/AL122005_Katrina.pdf. [Online; posted 20-December-2005].

Lee, J. (2019). Business recovery from hurricane harvey. *International journal of disaster risk reduction*, 34:305–315.

Lunt, M. (2014). Selecting an appropriate caliper can be essential for achieving good balance with propensity score matching. *American journal of epidemiology*, 179(2):226–235.

McIntosh, M. F. (2008). Measuring the labor market impacts of hurricane katrina migration: Evidence from houston, texas. *American Economic Review*, 98(2):54–57.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development economics*, 88(2):221–231.

Pasch, R. J., Brown, D. P., and Blake, E. S. (2005). Tropical cyclone report: Hurricane charley. Available at http://www. nhc. noaa. gov/2004charley. shtml.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–38.

Rubin, D. B. (1986). Statistics and causal inference: Comment: Which ifs have causal answers. *Journal of the American Statistical Association*, 81(396):961–962.

Smith, A. B. (2018). 2017 U.S. billion-dollar weather and climate disasters: a historic year in context. Available at https://www.climate.gov/news-features/blogs/beyond-data/2017-us-billion-dollar-weather-and-climate-disasters-historic-year.

Strobl, E. (2009). The macroeconomic impact of natural disasters in developing countries: evidence from hurricane strikes in the central american and caribbean region. *Journal Development Economics*.

Strobl, E. (2011). The economic growth impact of hurricanes: evidence from us coastal counties. *Review of Economics and Statistics*, 93(2):575–589.

Stuart, E. A., Lee, B. K., and Leacy, F. P. (2013). Prognostic score–based balance measures can be a useful diagnostic for propensity score methods in comparative effectiveness research. *Journal of clinical epidemiology*, 66(8):S84–S90.

Zhang, Y., Lindell, M. K., and Prater, C. S. (2009). Vulnerability of community businesses to environmental disasters. *Disasters*, 33(1):38–57.

Zhang, Z., Kim, H. J., Lonjon, G., Zhu, Y., et al. (2019). Balance diagnostics after propensity score matching. *Annals of translational medicine*, 7(1).

7 Appendix

Table 4: Hurricanes

Hurricane	Year	Intensity (SS)	No. Counties
Hugo	1989	1-3	3
Andrew	**1992**	**4-5**	**7**
Erin	1995	1-3	37
Opal	1995	1-3	8
Danny	1997	1-3	2
Earl	1998	1-3	5
Georges	1998	1-3	4
Irene	1999	1-3	11
Floyd	1999	1-3	11
Charley	**2004**	**4-5**	**15**
Frances	2004	1-3	20
Ivan	2004	1-3	5
Jeanne	**2004**	**4-5**	**5**
Wilma	**2005**	**4-5**	**9**
Katrina	2005	1-3	7
Rita	2005	1-3	1
Dennis	2005	1-3	17

Hurricanes organized in chronological order.

7.1 Balance Statistics

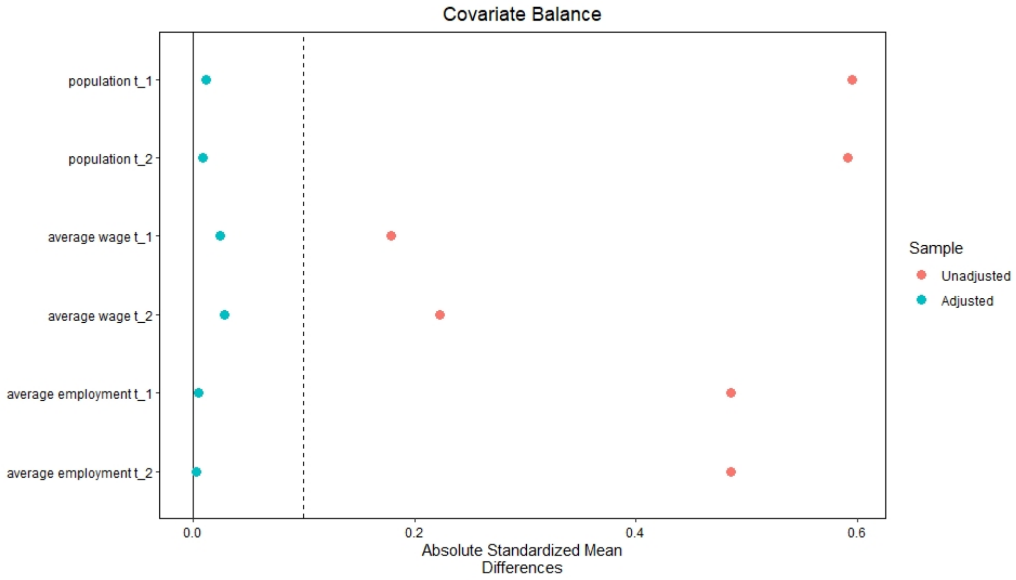

Figure 8: Erin 1995

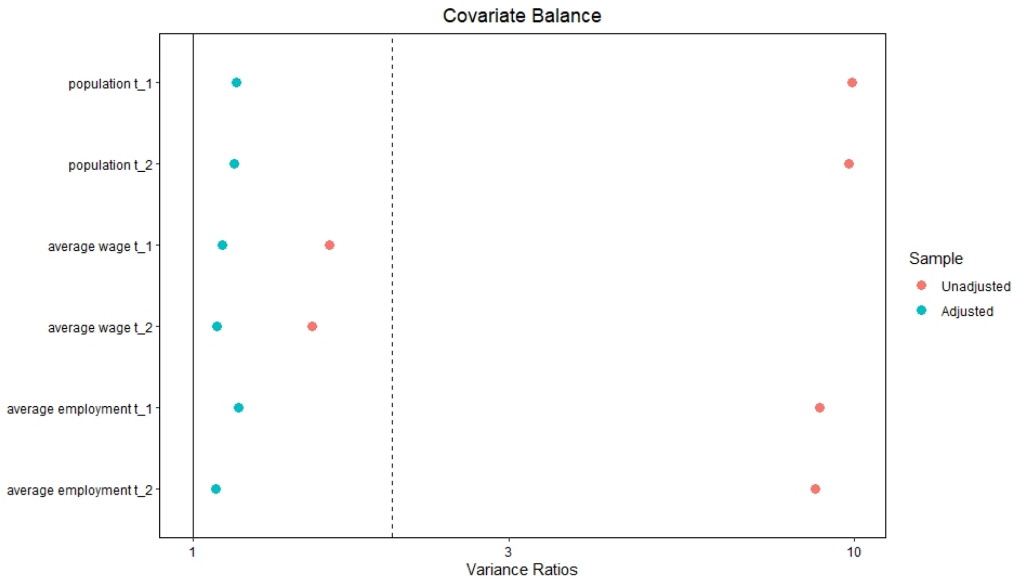

Figure 9: Erin 1995

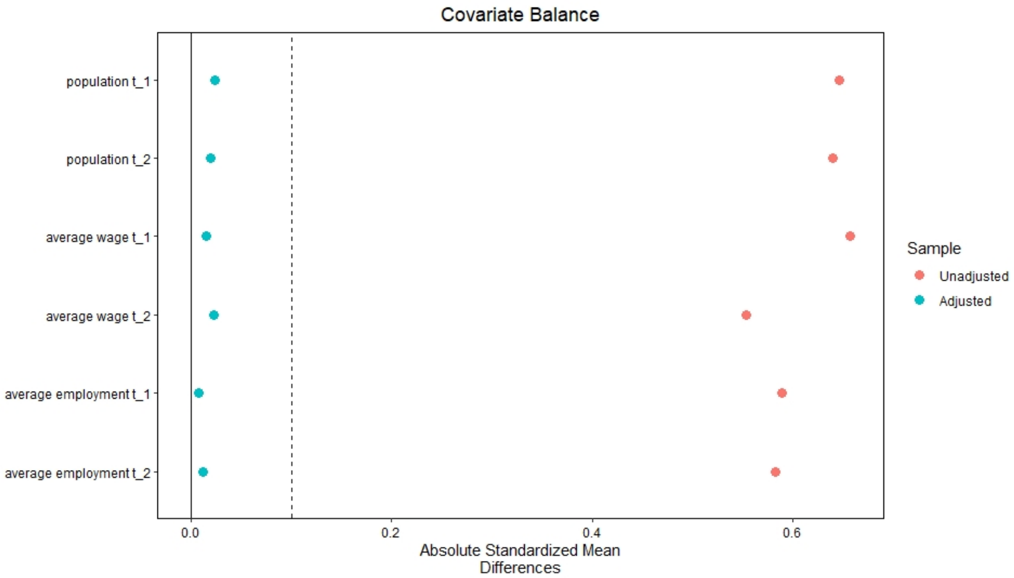

Figure 10: Charley 2004

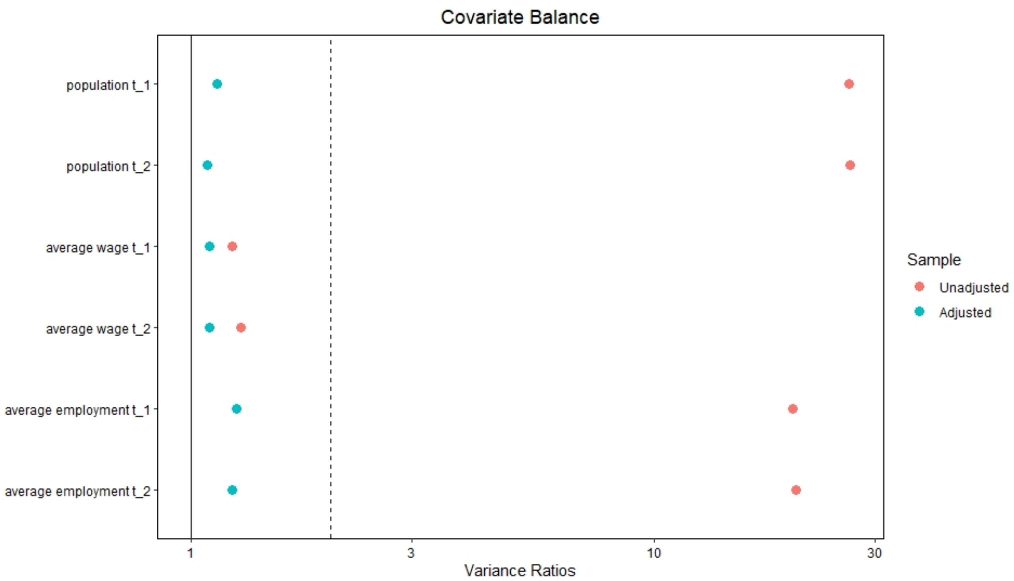

Figure 11: Charley 2004

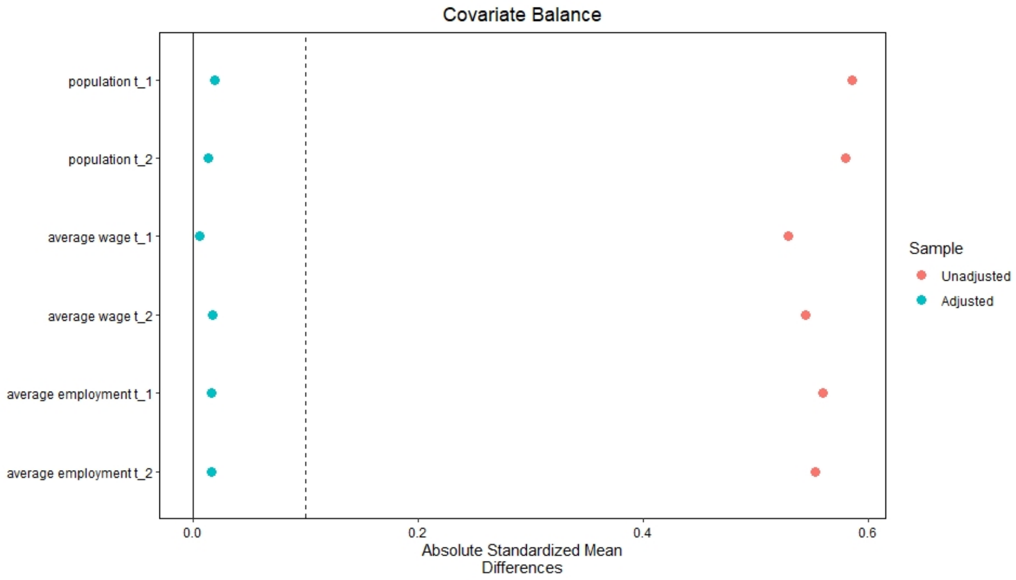

Figure 12: Frances 2004

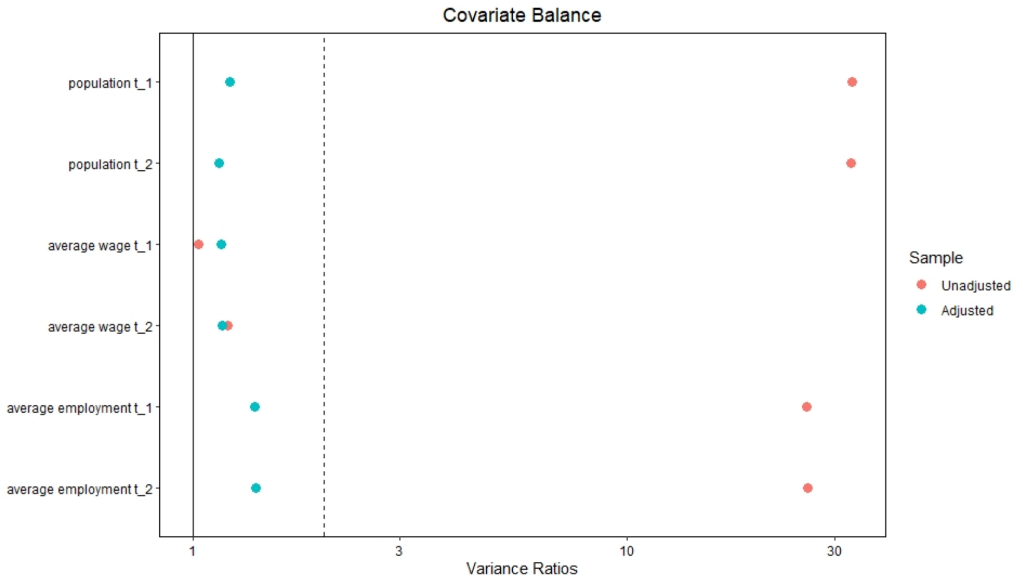

Figure 13: Frances 2004

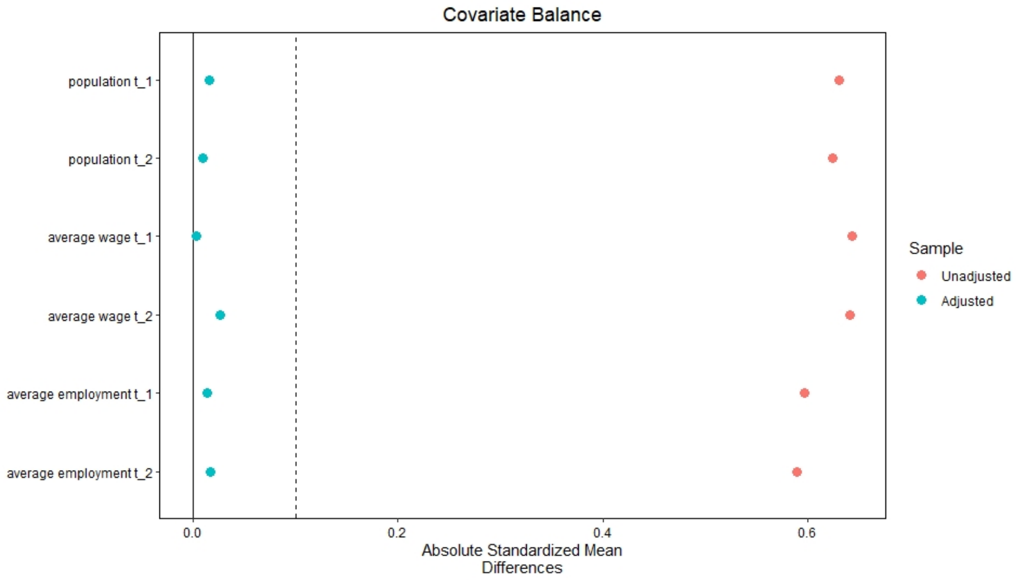

Figure 14: Jeanne 2004

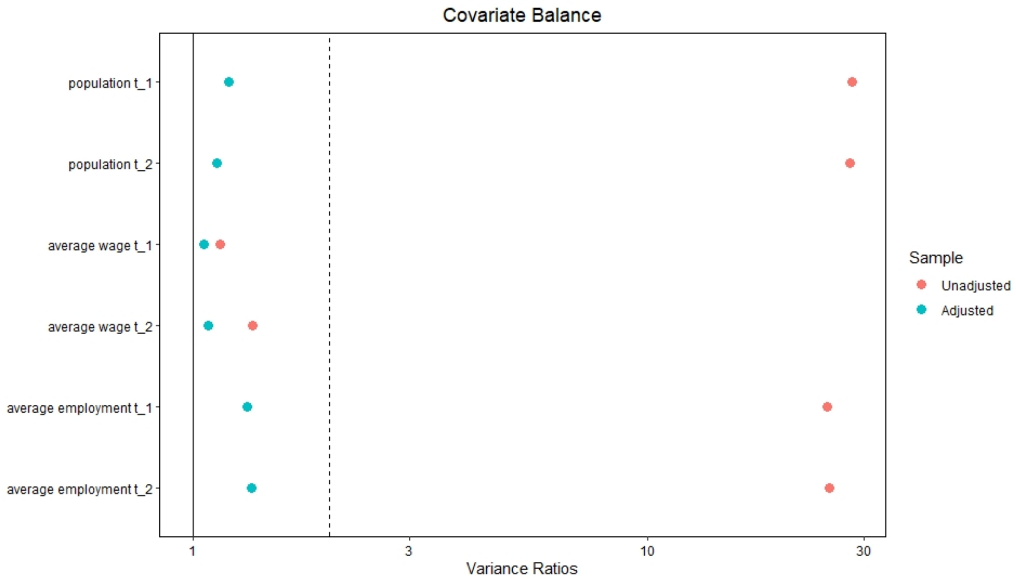

Figure 15: Jeanne 2004

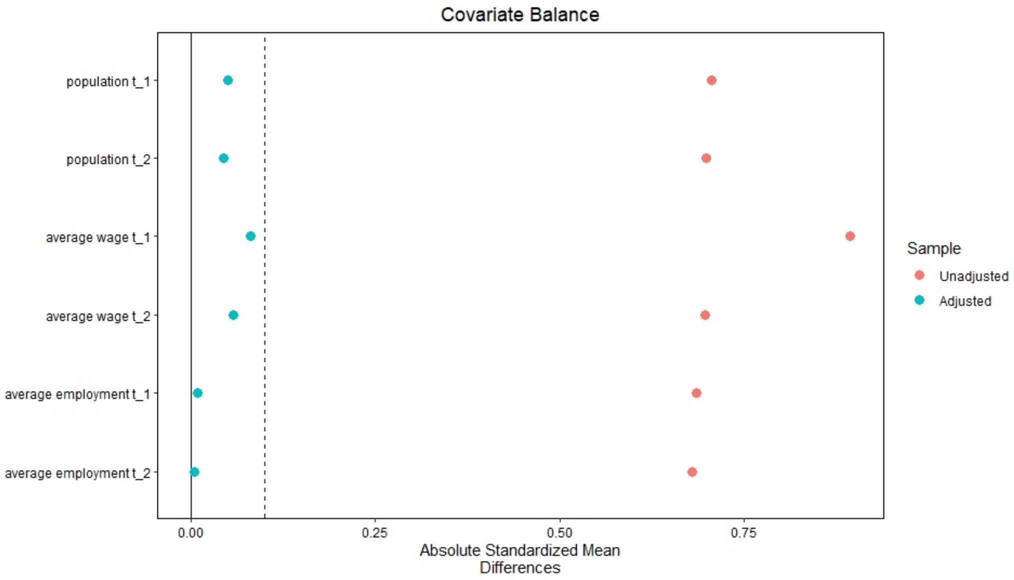

Figure 16: Wilma 2005

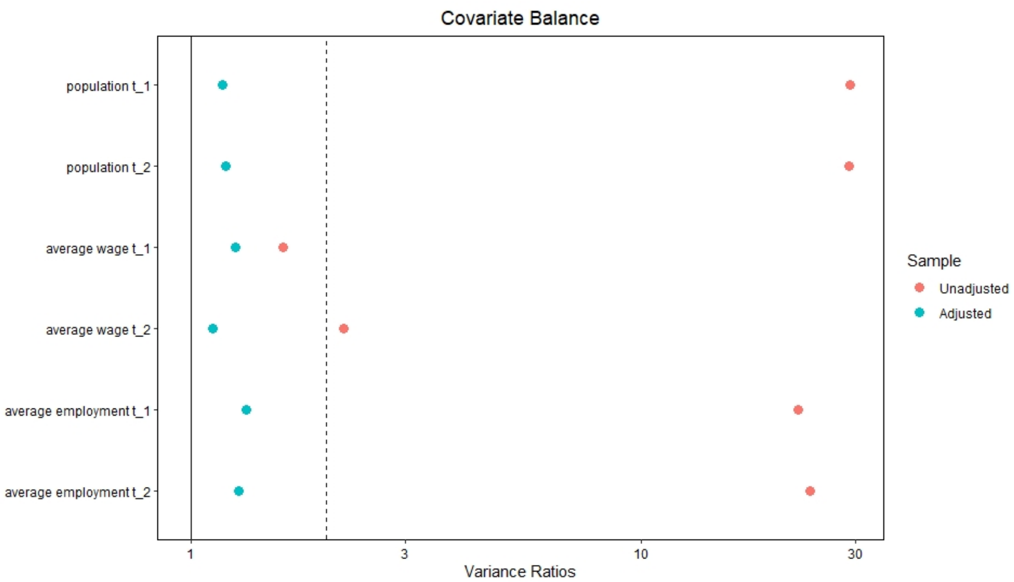

Figure 17: Wilma 2005

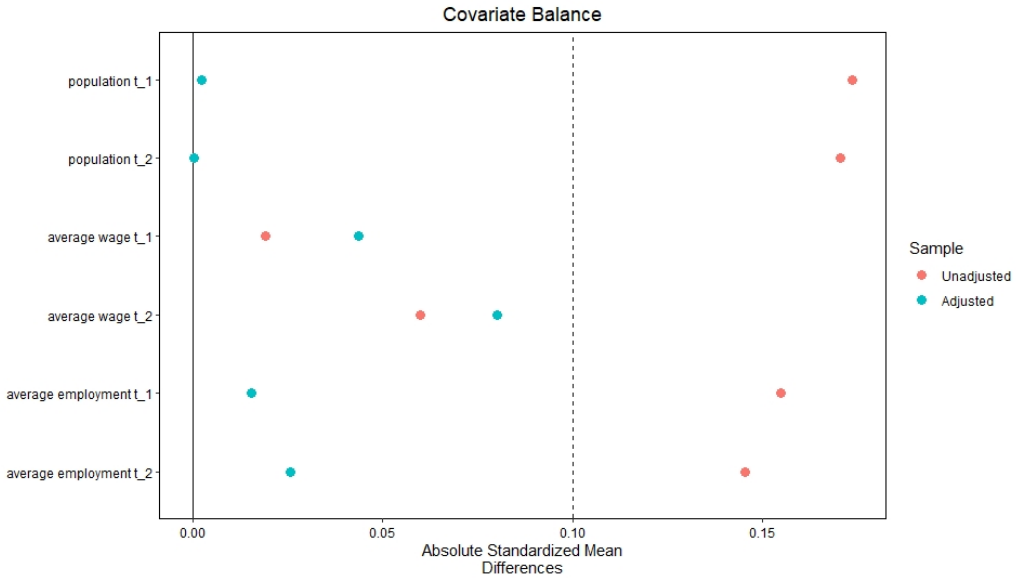

Figure 18: Dennis 2005

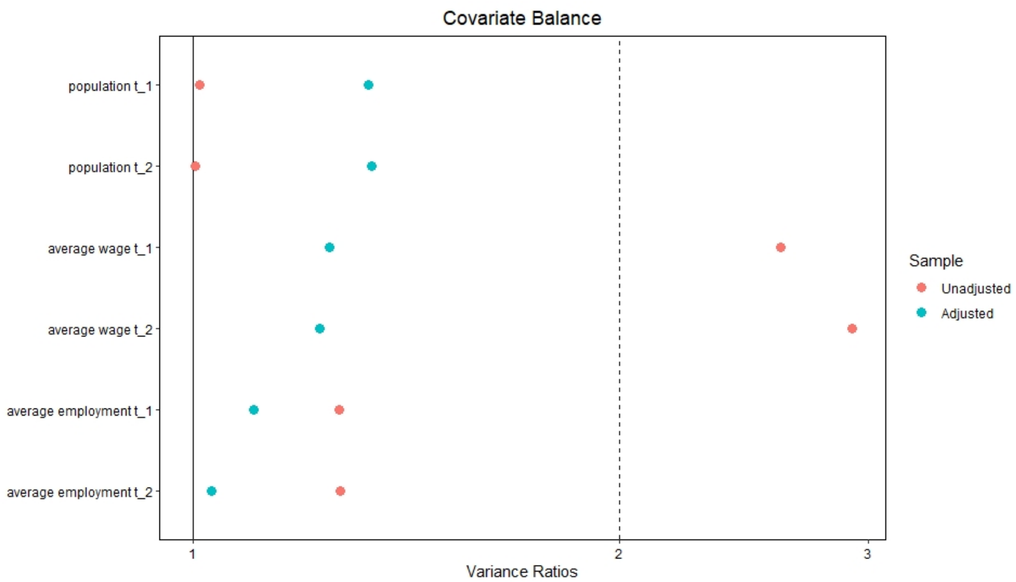

Figure 19: Dennis 2005