The Labor Market Impact of Hurricanes: Evidence from Florida Counties

Rushaine Goulbourne

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Abstract

This study investigates the impact of hurricanes on wage and employment growth. I utilize a model of wind intensity to measure the strength of hurricanes within each Florida county. By using a measurement technique that accounts for hurricane intensity variation over time, the results provide evidence that estimates from the previous literature have overstated the true effect. In many respects, the literature supports the notion that hurricanes affect labor markets through labor supply. My results indicate that labor demand plays as much of a role in post disaster labor markets outcomes as labor supply. As a novel contribution to the literature, I test this result using propensity score matching while accounting for the probability of hurricane experience in each county. My results suggest that hurricanes depress not only employment growth but wage growth as well.

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

JEL Classification: J2, R0

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1 Introduction

The southeastern coast of the United States on a yearly basis is threatened by multiple hurricanes. More recent hurricanes such as Hurricanes 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 that enter the Gulf of Mexico. This places the state 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 the reach of the hurricanes.

As capital and other economic factors are destroyed due to 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 further suffer through 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) suggest that tropical cyclones 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 mitigate the effects of global warming, policy makers would be prudent to plan for the consequences of climate change in the form of natural disasters.

I contribute to the discussion of the economic effects of natural disasters by examining 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. In this study, the tropical cyclones analyzed are those that developed into hurricanes and formed in either the Atlantic Ocean or the Caribbean basin. This technique offers new insight into the labor market impact of hurricanes as it allows the hurricane intensity to vary as the speed and strength of a hurricane changes over its life span. This analysis demonstrates how using landfall[1] or hurricane path to identify affected 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 leading to a situation where the effect may be over-stated. The wind field model allows me to more accurately classify areas as treated and untreated using the estimated wind speeds experienced in each county.

In addition, I apply a propensity score matching technique to assess the impact of hurricanes in Florida counties relative to counties in states with similar hurricane susceptibility. I achieve this by calculating the probability of experiencing a hurricane using the wind intensity estimates for each county over seven southeastern states (Louisiana, Mississippi, Georgia, Alabama, North Carolina, South Carolina and Florida). The propensity score methodology was deemed appropriate because the effects of a single hurricane may have statewide consequences. A statewide effect could render only a small number of untreated units remaining to form comparison units for any analysis focusing only on counties in the State of Florida. For example, a severe hurricane could necessitate significant assistance from the state government, resulting in fewer funds to allocate to other areas for various programs. Additionally, the counties that are affected by a hurricane may be very different from the rest of the state, resulting in too few untreated counties. The propensity score method where Florida counties are matched to counties in other southeastern states allows for comparisons between counties that are most similar

[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.

and are unlikely to suffer from any possible statewide effects. The matching covariates used are hurricane susceptibility, labor market characteristics (average annual wage and employment), and population size.

I find that on average using counties within the state of Florida, hurricanes have a negative impact on employment growth in directly hit counties while having a statistically insignificant effect on earning growth. When dis-aggregated into different intensities, severe hurricanes cause employment growth to decrease while simultaneously increasing 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 smaller in magnitude to those reported in the previous literature using the landfall model. Assessing the concept of labor market spillovers from affected counties to neighbors revealed no evidence of labor force mobility due to hurricanes. Across multiple hurricanes, the propensity score matching results provided evidence that hurricanes may primarily affect labor markets through labor demand shocks rather than labor supply shocks.

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 (either temporary or permanent) is a common result. Displacement will shift the labor supply curve to the left in the affected area, leading to a decrease in the number of individuals employed and an increase in the wages paid to workers who remain in the affected area (Brown, 2006; Groen and Polivka, 2008; Zhang et al., 2009; Belasen and Polachek, 2009; Strobl, 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. For example, luxury goods and services and tourism are industries in which employees may be temporarily or permanently laid off depending on the severity of the disaster. In this scenario, the labor demand curve will shift to the left as businesses close or require fewer workers due to losing a portion of their customer base. On the other hand, 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. Growth in these industries would cause the labor demand curve to shift to the right. This result is supported by Zhang et al. (2009), who find that an influx of construction crews from other areas into the affected locations stimulates demand for hotels and restaurants and thereby workers in hospitality and other related industries. This influx may similarly be accompanied by a short-term increase in labor supply.

In addition to these effects on the areas directly impacted by the hurricane, population displacement may increase labor supply in locations outside the affected areas if labor migrates. By standard economic theory, one would anticipate that this migration will cause a reduction in the average wage in the new locations that the workers move into due to the increase in labor supply. Assuming there is no disturbance to the previous structure of the labor market in the new areas, labor demand should not change. Therefore, a shift of the labor supply curve to the right with no change in labor demand will result in an increase in employment but a decrease in the average wage in these neighboring areas.

Given the evidence cited above, the effect of hurricanes on wage and employment is ambiguous a priori. In some cases, the disaster may increase employment propelled by sectors which are needed in order to assist in recovery from damage. In other cases, the impact may be negative as businesses are destroyed, supply chains disturbed, and customer bases dissolved. Earnings will be negatively impacted in these cases as labor demand falls even if only in the short-run. 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. Overall, by standard economic theory, both earnings and employment will be impacted by the shift in labor demand and supply in the event of a hurricane. The force with the greatest impact, as well as the direction the curve shifts, is theoretically ambiguous as we have seen. This study offers some insight into which effect is larger in the case of hurricanes in Florida.

3 Data

The data utilized in the study is a combination of the data 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 data is analyzed at the county level. The study period spans quarter 1 of 1988 to quarter 4 of 2005. This period was chosen in order 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 QCEW provides quarterly wage data but provides employment data monthly. In light of this, I formulate the quarterly employment figures by taking the average of each consecutive three month employment total for each county in each year.

The HURDAT2 database provides updated hurricane data compared to the previously used HURRDAT database. HURRDAT2 provides various hurricane statistics which includes wind speeds and the geographical path 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 the extant literature (Strobl, 2009; Jagger and Elsner, 2006).

Geographical data used 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 a county. This method is expected to increase the precision of the hurricane impact estimates as a greater proportion of each county will be included in each estimation.

4 Empirical Strategy

4.1 Wind Field Model

Unlike other studies 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. The wind intensity at landfall was used as the intensity experienced in each county affected by the hurricanes analyzed. 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). Specifically, the strength of a hurricane decreases as it makes landfall and continues along its path.

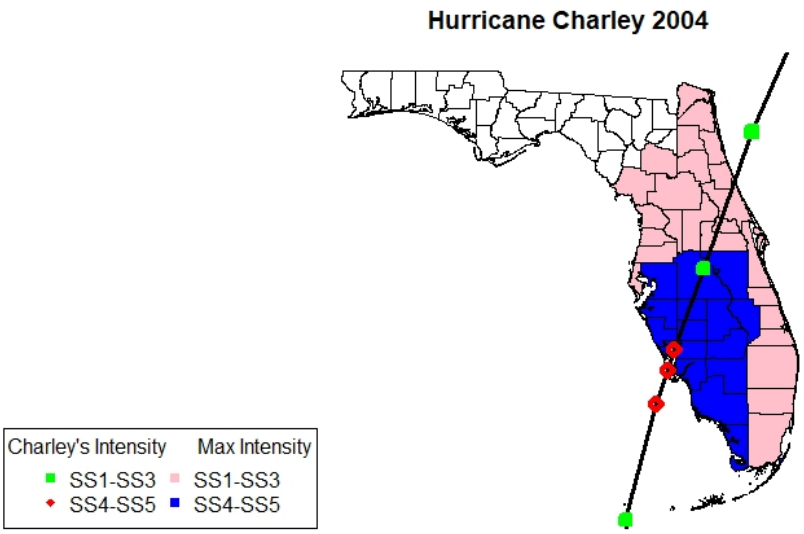

Figure 1: Declining Intensity Of Hurricane Charley

Figure (1) 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). Therefore, 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 as calculated by the wind field model. 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 square (category 1 to 3) and the diamond (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 the impact of the hurricane in some areas.

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, however, allows 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 at each geographical point for each county.[2]

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

V_m represents the maximum sustained wind velocity experienced anywhere along the hurricane's path. 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[3], P. V_h is the forward velocity of the hurricane, R_m is the radius of maximum winds[4], R is the radial distance from the center of the hurricane to point P, and 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 a hurricane along with the components of the wind field model.

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 a hurricane. Taking this into consideration, I use the provided R_m breakdowns as weights on the sample of hurricanes in this study 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. Note that at

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

[3] The points of interest are the centroid points in the shapefile

[4] The radius of maximum wind is sometimes referred to as the radius of destruction. This is the area bordering the eye of the hurricane at which point the strongest winds are recorded.

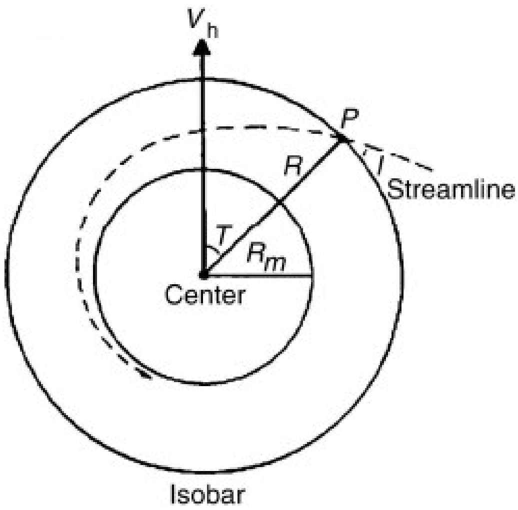

Figure 2: Source Boose et al. (2001)

the time of the writing of this paper, there was no known database of R_m for hurricanes. Such a database would assist future research that attempts to incorporate natural sciences into economic research.

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[5] that achieved wind speeds of 119 km/h or greater that affected the state of Florida between 1988 and 2005.[6] 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. Note that in

[5] A list of all hurricanes analyzed in this study can be found in the appendix in table (5).

[6] 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.

some cases, it is possible that of the 100 geographical points in a county, 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 2 intensity hurricane depending on the strength of wind estimated in the localities of the county.

In each hurricane event, the counties that were geographically neighboring a county affected by a group 1 or 2 hurricane were identified to measure the spillover impacts from a hurricane strike. Note 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. Previous studies using a landfall model would have categorized these neighbors 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 directly impacting Florida were not included in this study because 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 unlikely to 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 storms produced hurricane wind speeds within Florida.

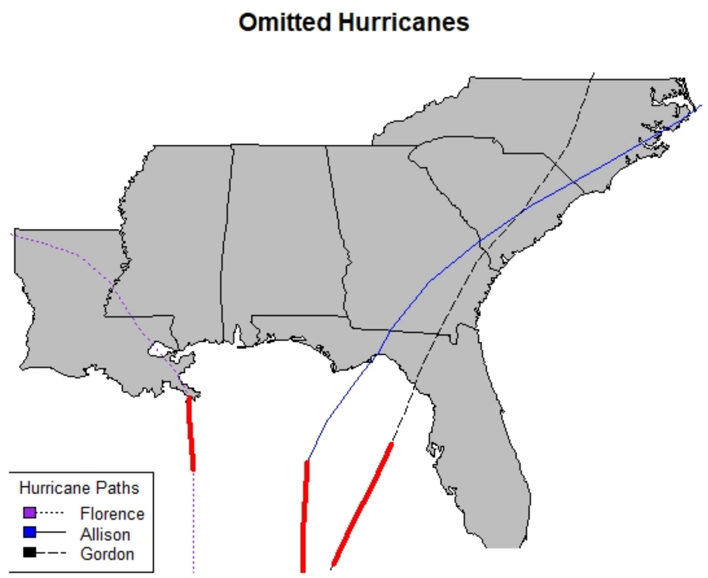

Figure 3: Hurricanes Florence, Allison, and Gordon

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 by the Federal Emergency Management Agency (FEMA) (FEMA, 2018) due to Hurricane Andrew.[7] Panel (B) plots all those counties that experienced

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

category 5 hurricane force winds 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. The light shaded circle in panel (B) has a radius of 30 km which is the maximum size of the radius of destruction used by Belasen and Polachek (2009). Using 30km as the sole means of identifying affected counties means counties that were significantly damaged by Hurricane Andrew will be classified as neighbors to directly affected counties rather than affected themselves. Due to this 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.

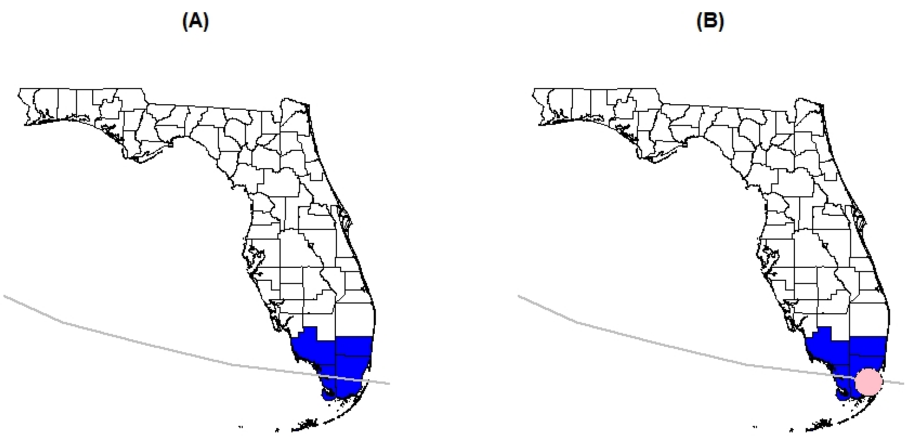

Figure 4: Hurricane Andrew 1992

4.2 Difference-in-Differences Approach

I begin my analysis by using a Difference-in-Differences estimation strategy. This methodology is used because it facilitates the comparison of treated and untreated units due to multiple

1951.

exogenous events over multiple time periods which is ideal for hurricanes. Additionally this method was used in the work of Belasen and Polachek (2009) who used the land fall measurement technique in their study. In order to assess the difference between the measurement technique specific to this study and that in the literature, it is imperative that the same estimation technique be maintained. The method compares the change in outcome before and after the hurricane for affected counties and unaffected counties. The coefficients are aggregated across counties, thus eliminating the county-specific coefficients (Belasen and Polachek, 2009).

When using this approach, I control for quarter and regional fixed effects. The regions[8] and quarters are interacted to account for region-by-quarter effects, which will absorb region-specific seasonality in employment and wage growth in the state. Some regions, such as South Florida, are heavily affected by tourism and as such may respond differently than 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 used to analyse the effect of hurricanes on employment and wage growth respectively. Equations (4) and (5) explore similar effects as equations (2) and (3), however differing in that these models account for differences in hurricane intensity.

$$(\Delta \ln Q_{i,t} - \Delta \ln Q_t) = \alpha_1 R_{i,t} + \alpha_2 \Delta H^D_{i,t} + \alpha_3 \Delta H^N_{i,t} + \epsilon_{it} \tag{2}$$

$$(\Delta \ln y_{i,t} - \Delta \ln y_t) = \gamma_1 R_{i,t} + \gamma_2 \Delta H^D_{i,t} + \gamma_3 \Delta H^N_{i,t} + \epsilon_{it} \tag{3}$$

$$(\Delta \ln Q_{i,t} - \Delta \ln Q_t) = \alpha_1 R_{i,t} + \alpha_2 \Delta H^{4-5}_{i,t} + \alpha_3 \Delta H^{1-3}_{i,t} + \epsilon_{i,t} \tag{4}$$

[8] The state was separated into four regions; North, Central, South, and Pan handle

$$(\Delta \ln y_{i,t} - \Delta \ln y_t) = \gamma_1 R_{i,t} + \gamma_2 \Delta H_{i,t}^{4-5} + \gamma_3 \Delta H_{i,t}^{1-3} + \epsilon_{i,t} \quad (5)$$

$Q_{i,t}$ represents average employment in county i in quarter t while $y_{i,t}$ represents average wage per worker in county i in quarter t. Q_t and y_t represent the state average employment and state average wage per worker in quarter t. The dependent variables can then be interpreted as the deviation in county average employment growth $(\Delta \ln Q_{i,t} - \Delta \ln Q_t)$ and wage growth $(\Delta \ln y_{i,t} - \Delta \ln y_t)$ from the average Florida county. $R_{i,t}$ represent the region-by-quarter effects where R_i indexes the region of county i. $H_{i,t}^D$ represents the dummy variable which takes a value of 1 for county i that was hit by hurricane force winds from a hurricane in quarter t. $H_{i,t}^N$ is a dummy variable which takes a value of 1 for a county that was neighbor to a county that was hit by hurricane force winds in quarter t. In equations (4) and (5), $H_{i,t}^{4-5}$ and $H_{i,t}^{1-3}$ 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 superscripts. 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 Propensity Score Matching

I use propensity score matching in an effort to obtain more precise estimates of the effect of a hurricane in Florida. Prior to the initiation of the matching process, I calculated an estimate of the probability of hurricane exposure for each county which helped to guide the selection of the counties to which the treated counties were matched [9]. Groen et al. (2020) utilized propensity score matching in a similar study of the effects of Hurricanes Katrina and Rita on income in a longitudinal study. However, Groen et al. (2020) did not factor in the probability

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

of hurricane exposure in the set of untreated counties. As a result of this omission, counties that face effectively no chance of experiencing hurricanes could be used as matched untreated counties. I believe it is important to incorporate the likelihood of experiencing a hurricane into this matching process because counties that experience hurricanes should have systems in place that are designed for the effects of hurricanes. These systems may include building codes and/or local hurricane protocols for disaster mitigation.

There are a few reasons why the use of a propensity score method was deemed appropriate, chief of which is the possible violation of the Stable Unit Treatment Value Assumption (SUTVA) condition in equations (2) and (3). The SUTVA conditions states that the outcome in one unit in a study should not be influenced by the treatment status of another unit. According to (Rubin, 1986), violation of the SUTVA condition prevents us from achieving unit specific inference that are reliably causal. Given that in the application of the Difference-in-Differences model we acknowledge that there is potential for spillover from the directly impacted counties to those that are near by, we are led to conclude that neighboring impact is influenced by the impact on the directly affected counties. Belasen and Polachek (2009) highlight that the spillover effect can be identified in counties that are up to two counties away from the directly hit counties. This finding in particular suggests that for counties that would credibly form a part of the untreated group in the models of equations (2) and (3), they could be impacted by the treatment status of the directly affected counties.

Other reasons for the implementation of propensity score matching include the geographical proximity of the counties in Florida to each other. When a hurricane affects the state it is plausible that there will not be many unaffected counties from which comparison counties can be drawn. There is also the possibility that the counties that are the most similar (i.e. counties in South Florida) are the only ones impacted by a particular hurricane. Therefore, the unaffected counties to which the affected counties are being compared may have different economic structures. Using only Florida counties in this situation would render the set of appropriate matches extremely small. Another concern is that when there is a major hurricane, the effect may have statewide repercussions, especially if there are expenditures incurred by the state government.

Due to these concerns, I use counties outside of the state of Florida as untreated units for matching. Matches are selected from six southeastern states (Louisiana, Mississippi, Alabama, Georgia, South Carolina, and North Carolina) that were not impacted when a hurricane affected the Southeast United States. In order to ensure that the counties used as matches are as similar as possible to the treated counties, the 518 counties across the six states was reduced to 220 as only those 220 counties had calculated probabilities of hurricane exposure greater than zero. In each matching case, based on the counties affected by a particular hurricane, the set of possible matches was reduced to only counties that had a probability of exposure that fell within the probability range of the hurricane exposed counties. For example, suppose Monroe county and Miami-Dade county are the only counties hit by a hurricane. If the two counties have calculated hurricane impact probabilities of 0.1 and 0.5 respectively, the match counties must have probabilities of hurricanes impact between 0.1 and 0.5, inclusive. Additionally, recognizing that the counties selected as matches could experience hurricanes in the same year, all possible control counties that experienced a hurricane in the year of interest were removed from the set of possible matches. Figure (5) presents a graphical representation of the calculated hurricane probabilities by county.

According to Rosenbaum and Rubin (1983), propensity score matching allows a researcher 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 for each county up to two years prior to each hurricane. The selection of untreated counties is conducted with replacement which helps to maintain the quality of matches. A com-

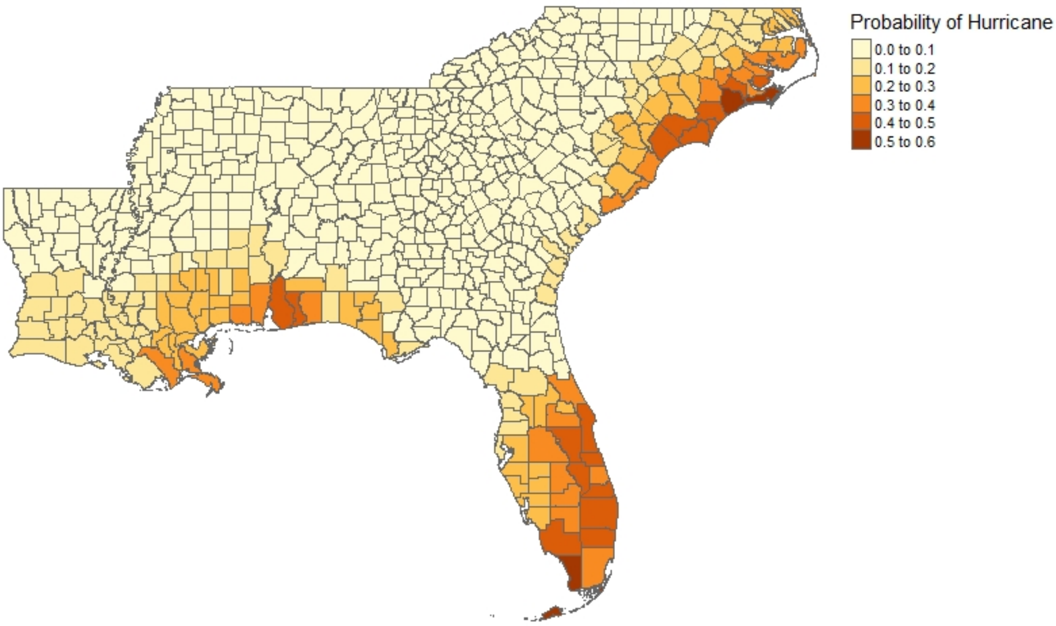

Figure 5: South East Hurricane Probability

bination of both nearest-neighbor matching and a caliper[10] provides better matching outcomes in terms of standardized mean differences between treated and untreated units when compared to matching on either by themselves (ibid). In this regard, a caliper of 0.25 standard deviations was used. 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.

The two identifying assumptions for propensity score matching are unconfoundedness and common support in the covariates between the treated and control groups (Imbens and Rubin, 2015). The unconfoundedness assumption requires that the assignment of the treatment (in our case, hurricanes) is independent of the potential outcome in the treated units. While this assumption is not testable, given the nature of hurricanes, there is no way to "assign" a hurricane conditional on any anticipated outcome in the treated units. In this regard, I believe that the unconfoundedness condition is satisfied.

[10] A caliper is buffer limit on the acceptable propensity score for matches

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 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 and result in a mean difference of zero. Thus, along with mean differences, common support is assessed by 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) 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.

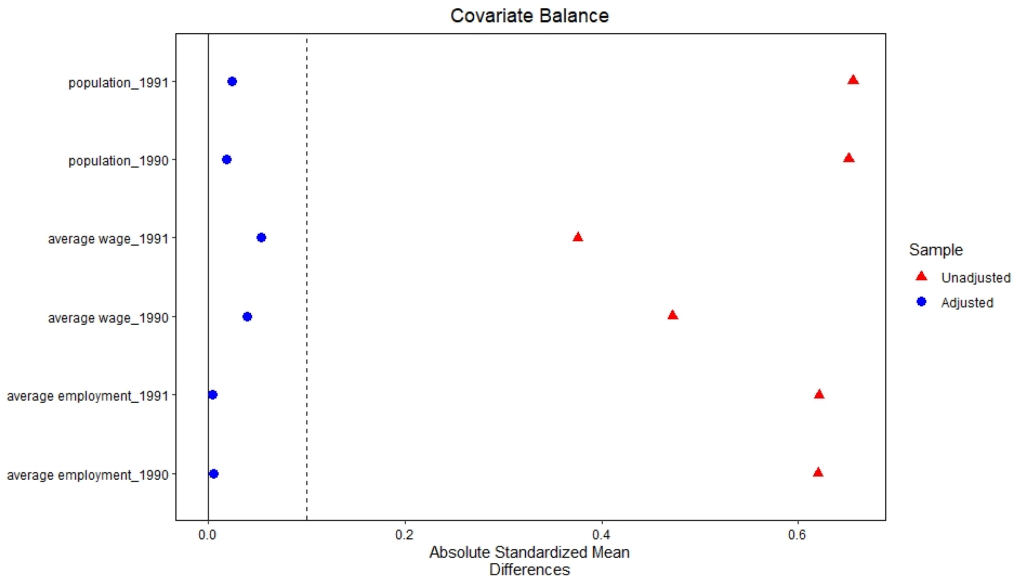

Figure 6: Mean Difference Hurricane Andrew 1992

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

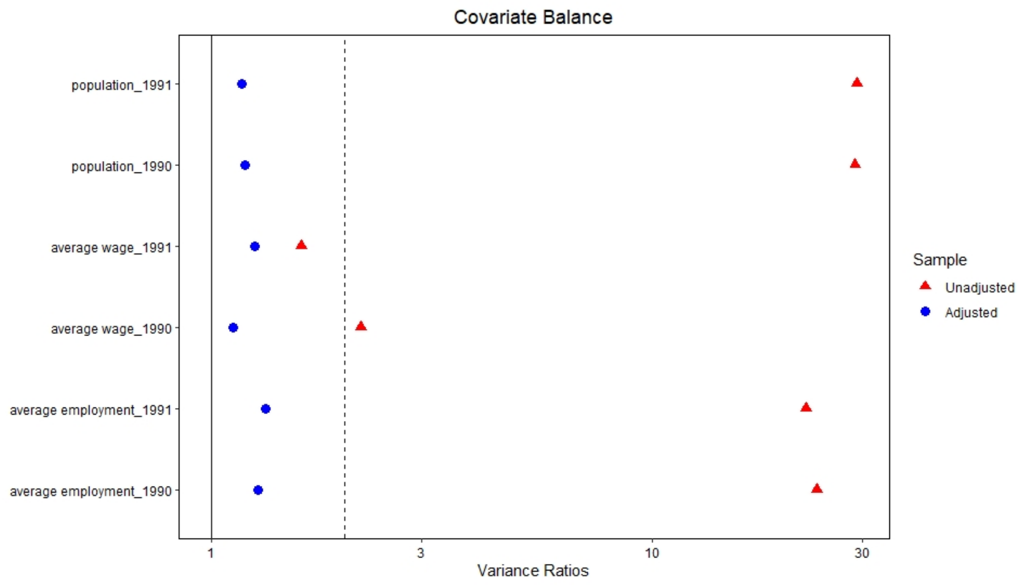

Figure 7: Variance ratio Hurricane Andrew 1992

matched groups.

5 Results

5.1 Aggregate Results

I begin my analysis by reproducing the models from Belasen and Polachek (2009) using the wind field model to identify the affected counties. The results are presented in table (1). Similar to the previous 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 (at the 10% level) on employment growth in neighboring counties which is 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 to a lesser extent. My estimates support this hypothesis and 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 estimated effect of a hurricane is smaller after accounting for the variation in hurricane wind speeds afforded by the wind field model compared to the effect estimated using landfall measurement. In particular, the estimate of the direct effect is 1.12 percentage points lower for employment growth relative to the findings of Belasen and Polachek (2009). This result was not surprising due to the fact that the landfall model does not account for the change in the hurricane intensity as the hurricane travels along its path and gets weaker over time as shown earlier in figure (1).

Contrary to the previous literature, the results in table (1) 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 should increase earning growth in the directly affected counties. By the same logic, in the neighboring counties, the 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.

If there is a decrease in both labor supply and labor demand, then theory predicts a clear reduction in employment growth but an uncertain impact on wage growth. For neighboring counties, if the hurricane damage sustained is similar to the directly affected county, then labor is not expected to relocate into those counties and thus labor supply will not increase in those areas. 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

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. Specifically, 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. Table 2 shows a 4.36% decline in employment growth due to strong hurricanes while recording a 2.29% increase in wage growth in affected counties in the quarter when a strong hurricane struck. These results support 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. Note that this does not mean there could not be a decrease in labor demand as well. What we can gather from the result is that the reduction in labor supply due to the strong hurricane is significantly larger than any decline in labor demand a county may simultaneously experience.

Each hurricane that causes category 4-5 winds in a county likely will cause some adjacent counties to experience category 1-3 winds. Since only those counties hit by category 4-5 wind are classified as affected when such a hurricane occurs with the landfall measurement technique, the analysis of the hurricane effect is not complete. To be thorough, the nearby counties which experienced hurricane winds must be accounted for as well. As such, for this section of the analysis I grouped these neighboring counties that would be neglected with counties that were affected by weaker hurricanes (category 1-3). This innovation is necessary since many locations experienced hurricane force winds which would not be classified as category 4 or 5 but satisfied the condition for a 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 reduce employment growth by 0.85% relative to the average Florida county not affected by a hurricane. 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 category 1-3 hurricane wind speeds lead to a reduction in both labor demand and labor supply that offset one another. The overall outcome is thus a statistically significant decline in employment growth with a statistically insignificant impact on wage growth.[11]

5.3 Matching Results

Finally, I present the result from the application of the propensity score matching technique. Table (3) presents the average treatment effect on the treated (ATT) counties for employment

[11] Due to the overlap between neighbors of counties that experienced strong hurricanes and counties hit by weak hurricanes, I was unable to explore the impact of strong hurricanes on neighboring counties. 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. These results are not presented in the interest of space but are available upon request.

Table 2: Hurricane Intensity Results

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.

growth and wage growth. Of the 17 hurricanes recorded during the sample period, table (3) presents the results from the eight hurricanes for which balance was achieved in the covariates utilized in the matching procedure. Columns 4 to 7 detail the number of treated[12] 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, respectively[13].

Overall, the results from the matching strategy confirm the earlier finding that the effect of hurricanes on employment growth is negative. The treatment effect of hurricanes on wage growth is less clear. In all cases where statistical significance was identified for the effect of hurricanes on wages however, barring Hurricane Opal, the effect was negative. This result speaks to the fact that hurricanes have the potential to cause labor markets to shrink. So, there are fewer jobs and for the jobs that do remain, relative to similar counties outside the state of Florida, wage growth is smaller. This result highlights the fact that the impact of

[12] Treated is defined as counties that experienced hurricane force winds from each hurricane.

[13] Matching with replacement allowed for each untreated county to be matched with more than one treated county.

Table 3: Match Results: Probabilities

Hurricane	ln(Employment)	ln(Earnings)	Treated	Control	Matched Treated	Matched Control
Andrew 1992	-0.1025***	0.0445	25	78	13	11
	(0.0187)	(0.0292)				
Erin 1995	-0.0720***	-0.0169*	37	147	23	19
	(0.0153)	(0.0098)				
Opal 1995	-0.2963*	0.5240*	8	117	6	6
	(0.1536)	(0.2971)				
Charley 2004	-0.0801***	-0.0136***	40	119	19	17
	(0.0133)	(0.0047)				
Frances 2004	-0.2543***	-0.0923***	20	29	9	8
	(0.0433)	(0.0355)				
Jeanne 2004	-0.3178***	-0.0778***	27	34	11	9
	(0.0519)	(0.0162)				
Wilma 2005	0.1065***	-0.0720***	24	24	12	12
	(0.0177)	(0.0148)				
Dennis 2005	0.0089	-0.0155	17	79	12	10
	(0.0121)	(0.0222)				

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

hurricanes is not solely experienced through labor supply but also through labor demand. The shock to the labor market results in the labor demand curve shifting to the left. The result of this shift is that the equilibrium level of employment and wages will fall. This also occurs if, for a negative supply shock, the demand shock has a greater impact.

Only Hurricane Wilma had a positive effect on employment growth. Given the clear divergence from the remainder of the hurricanes, I proceeded to look further into the possible reason for this result. Figure (8) presents the counties that were matched for Hurricane Wilma to produce the estimates observed in table (3). Six counties[14] (Monroe, Miami-Dade, Collier,

[14] Counties numbered respectively on figure

Broward, Hendry, Palm Beach) experienced major damage from the hurricane. However, only one (Hendry) of the six was matched. The remaining treated counties that were matched, experienced decreased wind speeds from the hurricane. Therefore, the estimates observed do not account for the more severely damaged counties for Wilma, which included Miami-Dade County. Lunt (2014) highlighted this possibility as a shortfall of propensity score matching. Matches may not always be found for some treated counties and as such, the results we observes are no longer the treatment effect on the treated but the treatment effect on the treated for which matches could be found.

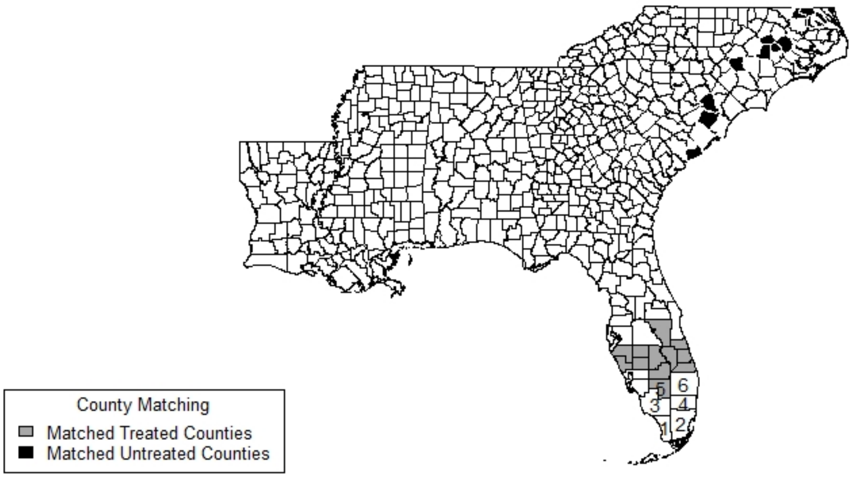

Figure 8: Hurricane Wilma Match Counties

Similar to Hurricane Wilma, the counties affected by Hurricane Andrew were not all matched. There were four counties (Monroe, Broward, Miami-Dade, Collier) that experienced significant damage from the Hurricane Andrew. Only two were matched (Collier and Monroe). However, given the ratio of matched severely affected treated counties in Andrew ($\frac{2}{4}$) to that in Wilma ($\frac{1}{6}$), Hurricane Andrew is more likely to give accurate result and as such does not raise as much concern.

For Hurricane Dennis, no statistically significant effect was found. Hurricane Dennis, similar to Hurricane Opal, caused primarily category 1 wind speeds in the state of Florida. In addition, most of the impact from both of these hurricanes was felt in the Panhandle region of Florida. Though we could attempt to explain the difference in the outcomes between these two storms through the difference in the number of counties affected, the result for Hurricane Opal presents a positive earning growth impact that is unique to that storm in the study. Similar to the results for Hurricane Wilma, the estimates for these two hurricanes may be influenced by the matches that were formed. Given the evidence that the results obtained are potentially due to the treatment effect on the treated counties for which matches could be found, I estimated the effects presented in table (3) without limiting the matching set to counties that had similar probabilities for hurricane exposure. Table (4) presents these results.

The number of control counties in table (4) is much larger than that in table (3). Apart from the differences that can be seen in the coefficients, the conclusion derived from expanding the control set is the same. Hurricane impact results in employment and wage growth declining in Florida counties. Hurricane Wilma again revealed a positive impact on employment growth. The reason for this outcome is the same as described previously. Note that the matched controls in table (4) increased for all hurricanes except Andrew and Wilma. For these two hurricanes, the matches that satisfied the condition of the caliper distance of 0.25 standard deviations rendered the sets smaller.

6 Conclusion

As anticipated, the use of the wind field model in this analysis produced differing results from the previous literature which relied primarily on the landfall model. When pooled together, hurricane effects were less severe on average using the measurement strategy proposed in this study. This result is attributed to the ability of the wind field model to capture both the

Table 4: Match Results: No Probabilities

Hurricane	ln(Employment)	ln(Wage)	Treated	Control	Matched Treated	Matched Control
Andrew 1992	-0.0933***	0.0445	25	464	11	11
	(0.0165)	(0.0292)				
Erin 1995	-0.0805***	-0.0552***	37	504	23	22
	(0.0147)	(0.0134)				
Opal 1995	-0.0668	-0.3133**	8	504	6	6
	(0.0467)	(0.1453)				
Charley 2004	-0.0865***	-0.0175***	40	473	21	21
	(0.0132)	(0.0061)				
Frances 2004	-0.1269***	-0.0272**	20	473	12	12
	(0.0233)	(0.0125)				
Jeanne 2004	-0.1023***	-0.0280***	27	473	14	14
	(0.0189)	(0.0088)				
Wilma 2005	0.0706***	0.0103	24	433	11	11
	(0.0143)	(0.0066)				
Dennis 2005	-0.0048	-0.0292*	17	433	16	16
	(0.0060)	(0.0176)				

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

decline in hurricane intensity over the life of a hurricane as well as impacts that are spread over a wider area. The severity of a hurricane also plays an important part in the determination of the impact hurricanes have on local labor markets. Results for stronger hurricanes adhere to the literature, supporting the findings of Belasen and Polachek (2009) who along with Strobl (2011) and Brown (2006) suggest that labor supply is the primary source of the labor market disruptions.

With regards to the spillover effects of hurricanes, no evidence was found to support such labor mobility. This result does not discredit the possibility that migration does indeed occur subsequent to a hurricane as this is 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 significantly impacts labor markets in counties that are geographically next to counties that experience hurricane force winds. This finding is a notable deviation from the literature as Belasen and Polachek (2009) identified a decrease in earnings in neighboring counties up to 4.51% due to the effects of migrating labor in response to hurricanes. Confirming my hypothesis, neighboring counties had similar impacts as the directly affected counties but the magnitude of the effect was smaller. 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.

Finally, the results using propensity score matching strengthened the conclusion that hurricanes have a negative impact on employment growth. Wage growth, similar to employment growth, decreased due to hurricanes when matched with similar counties outside of the state of Florida. While a labor supply shock is still possible, the matching strategy suggests that the impact on labor demand is greater on average than the labor supply impact. This was made evident from the decline in both employment and wage growth, an outcome which by standard economic theory can only occur with a leftward shift of the labor demand curve.

The key contribution of 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). Using an improved measure, 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 primarily through a shift in labor supply. What is still unclear is the degree to which either labor demand or labor supply can be credited for the outcomes observed and in what circumstances either is more dominant. Future research exploring the effects of hurricanes can assist in elucidating this issue. Additionally, future research can address the direction aid programs should take following a hurricane. Particularly, it will be beneficial to know whether aid programs should be directed to commercial or residential entities. If there are circumstances that cause the impact of hurricanes to be felt more through labor demand, then assistance will be best directed towards commercial aid. Alternatively, if labor supply is more affected by hurricanes then assistance will be best directed to residential aid. This study presents an interesting dynamic and impetus for future exploration of the effects of hurricanes which can be extended to other coastal states and countries.

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7 Appendix

Table 5: 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

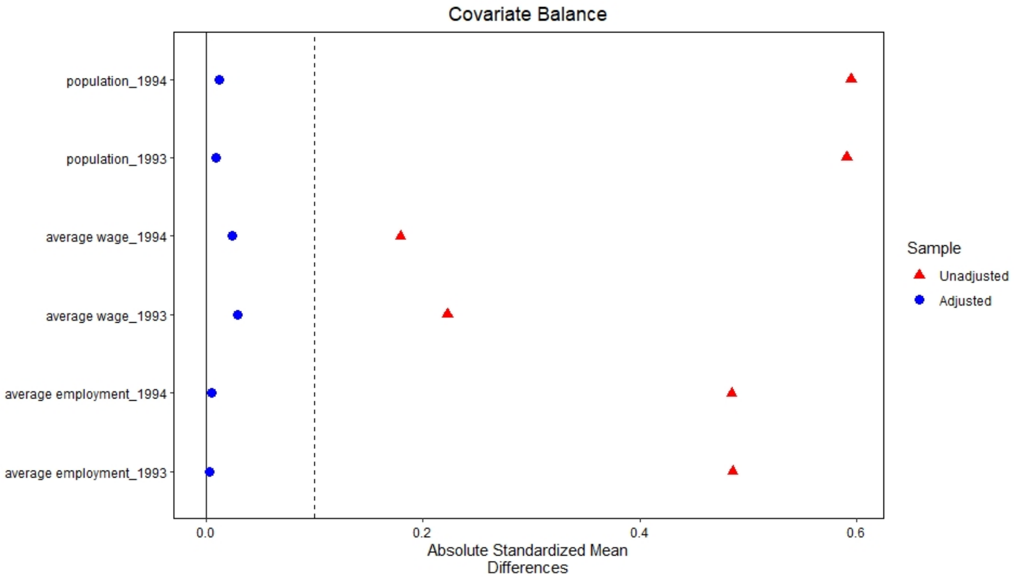

Figure 9: Erin 1995

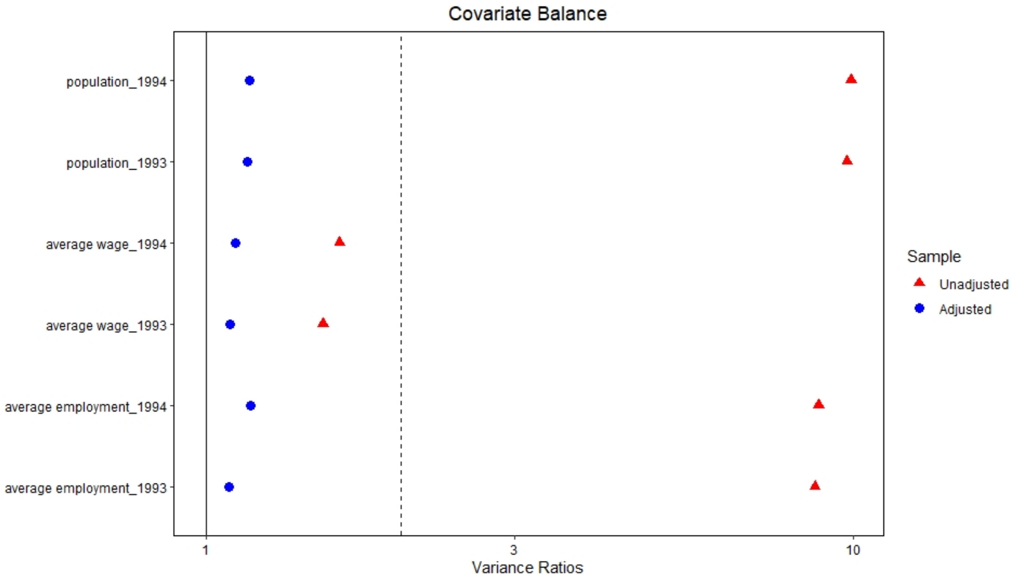

Figure 10: Erin 1995

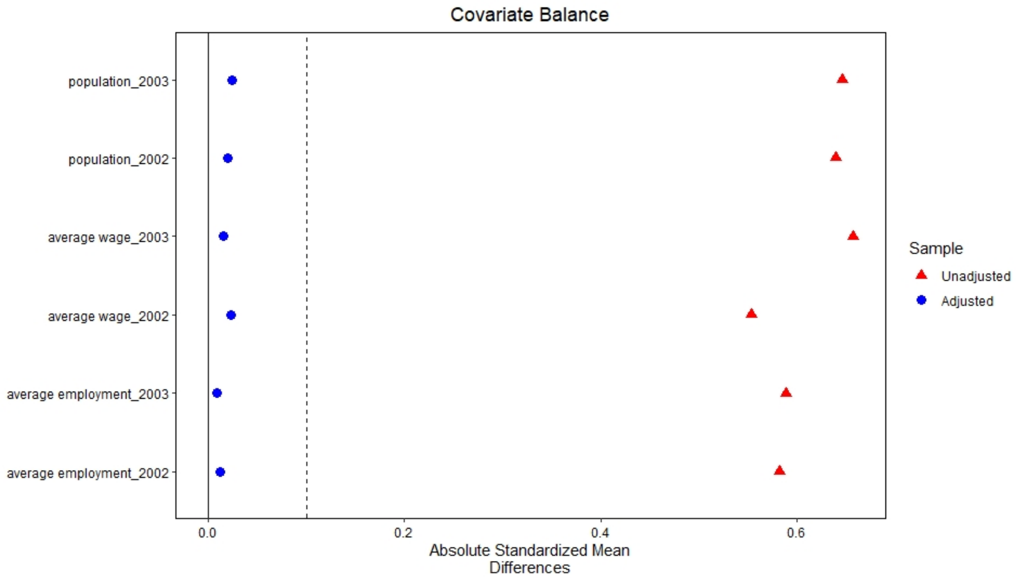

Figure 11: Charley 2004

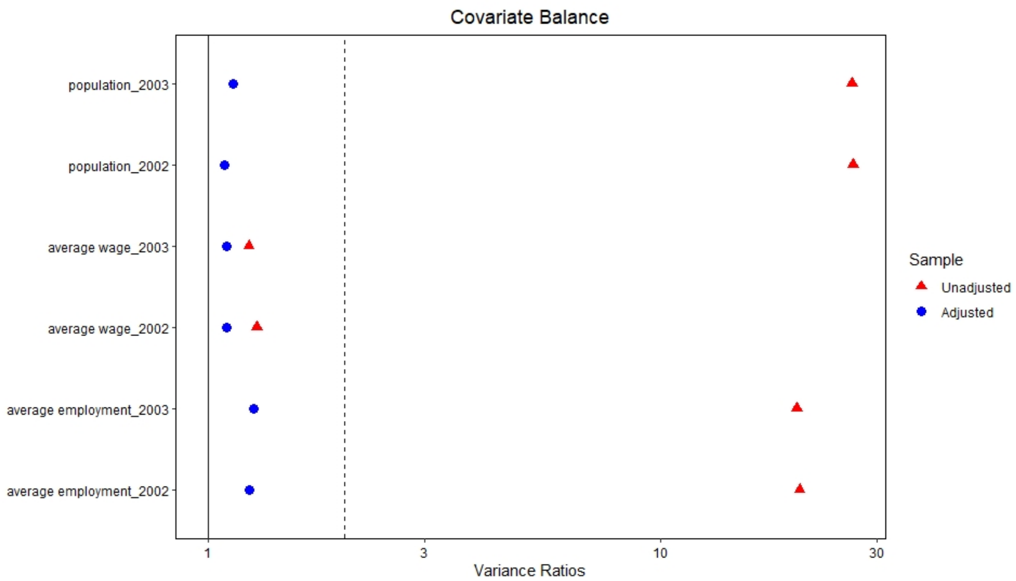

Figure 12: Charley 2004

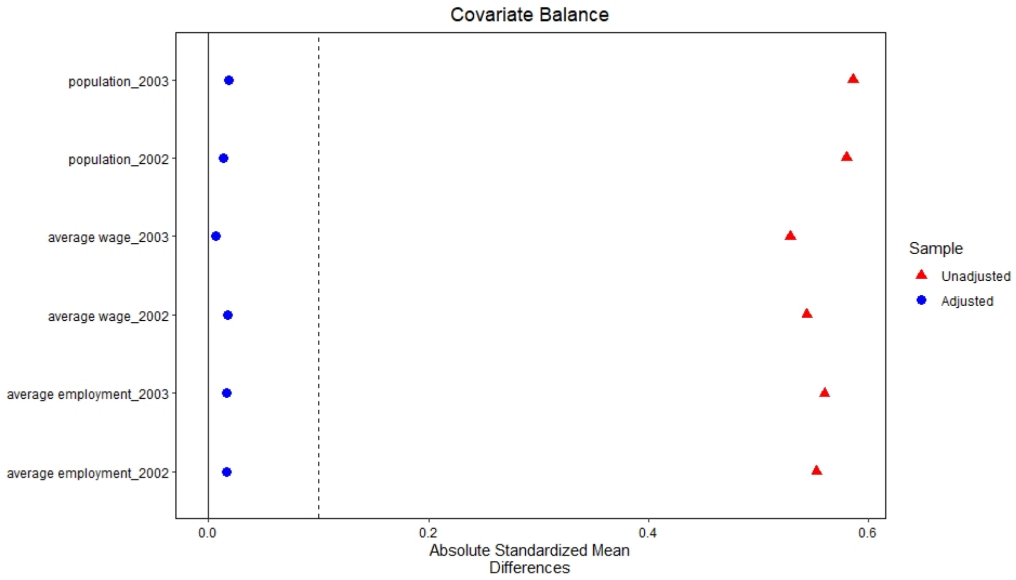

Figure 13: Frances 2004

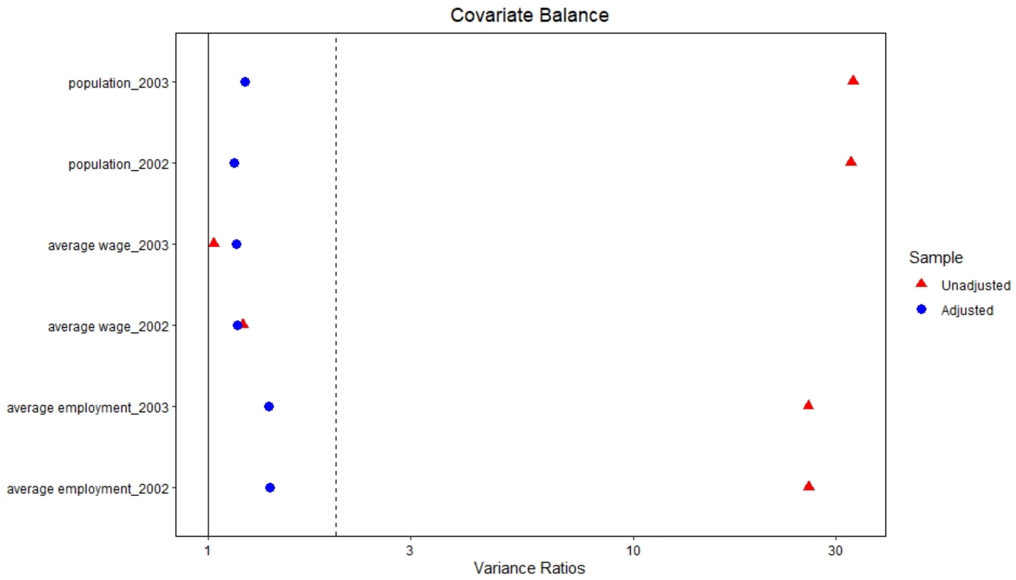

Figure 14: Frances 2004

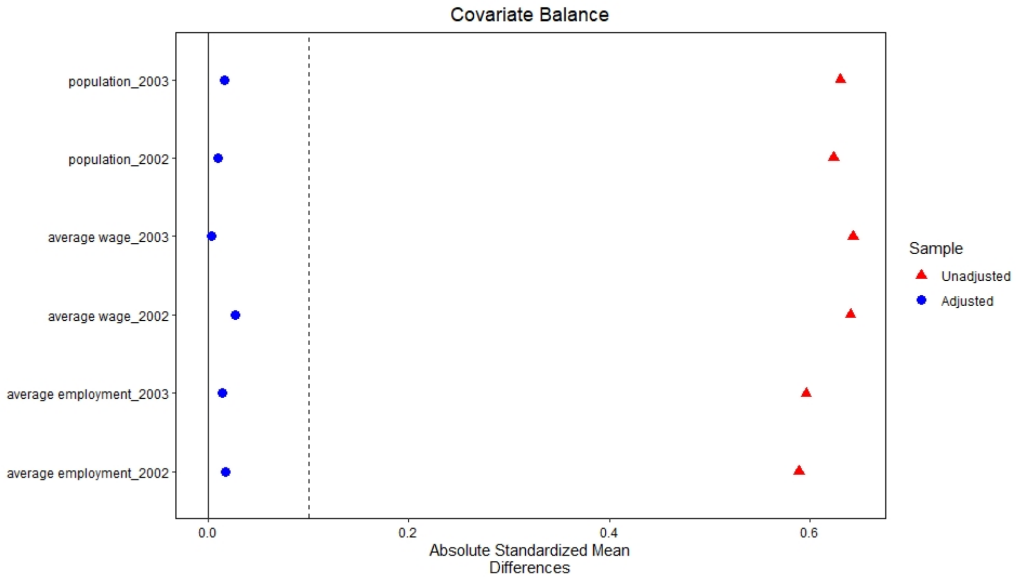

Figure 15: Jeanne 2004

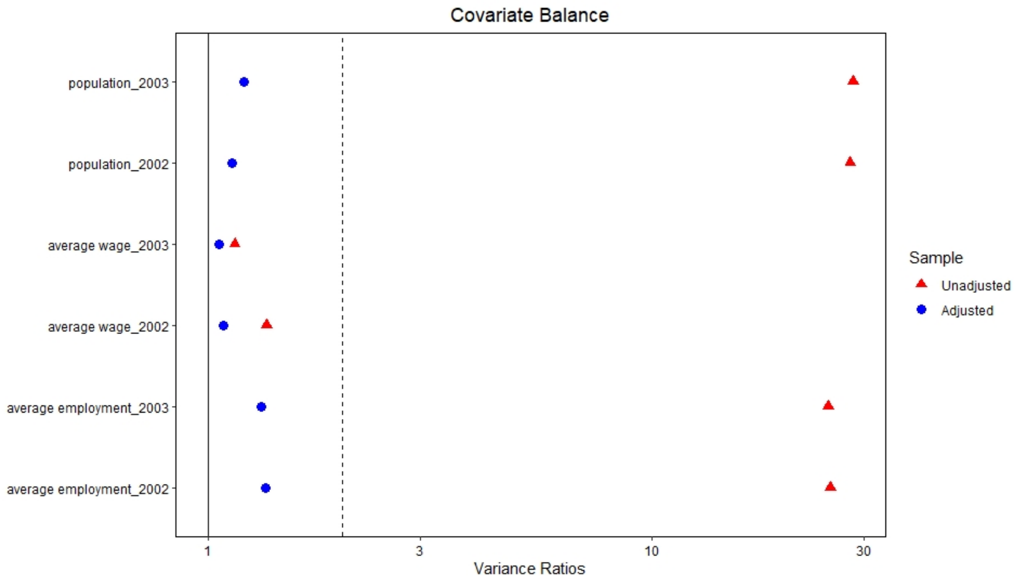

Figure 16: Jeanne 2004

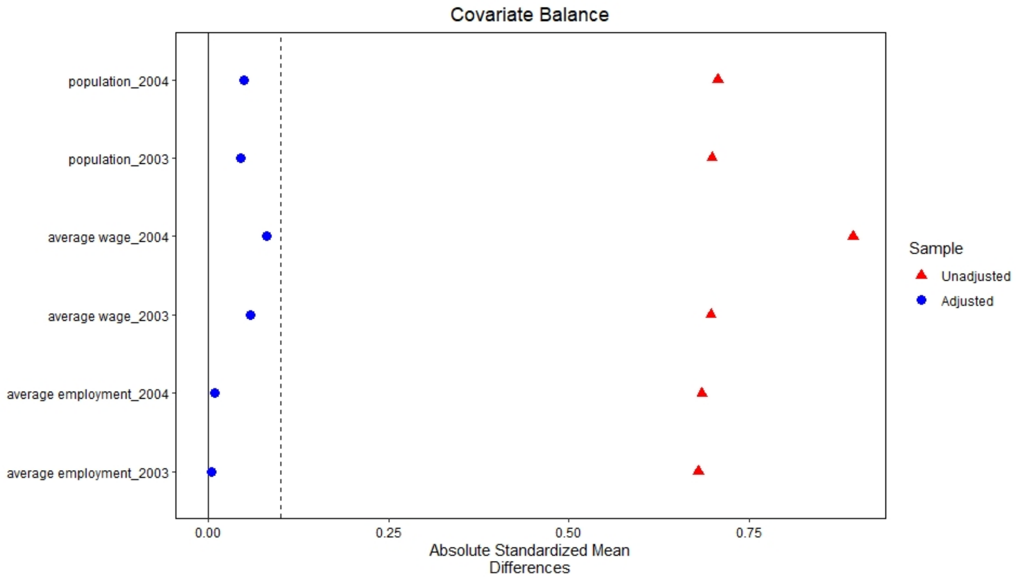

Figure 17: Wilma 2005

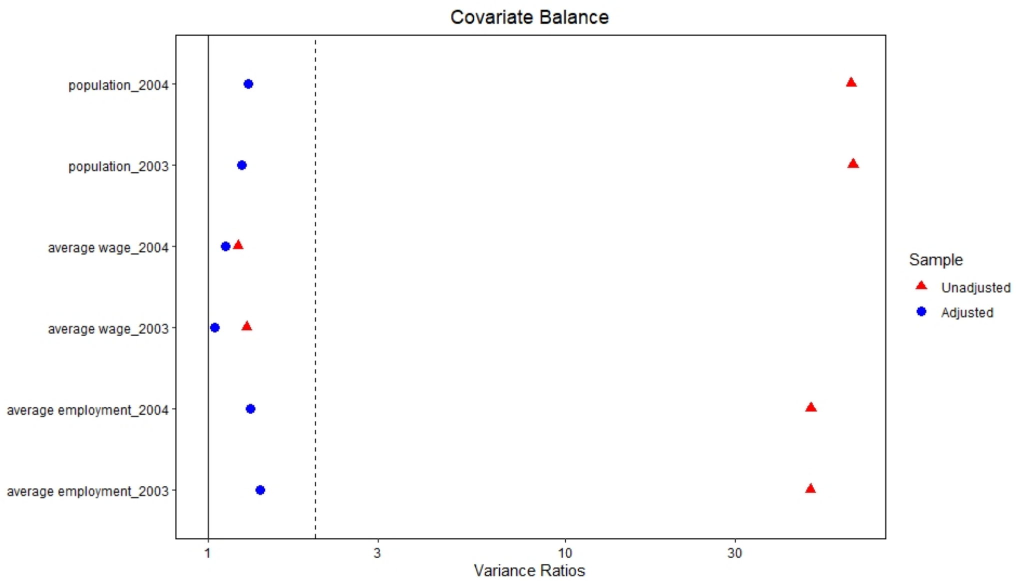

Figure 18: Wilma 2005

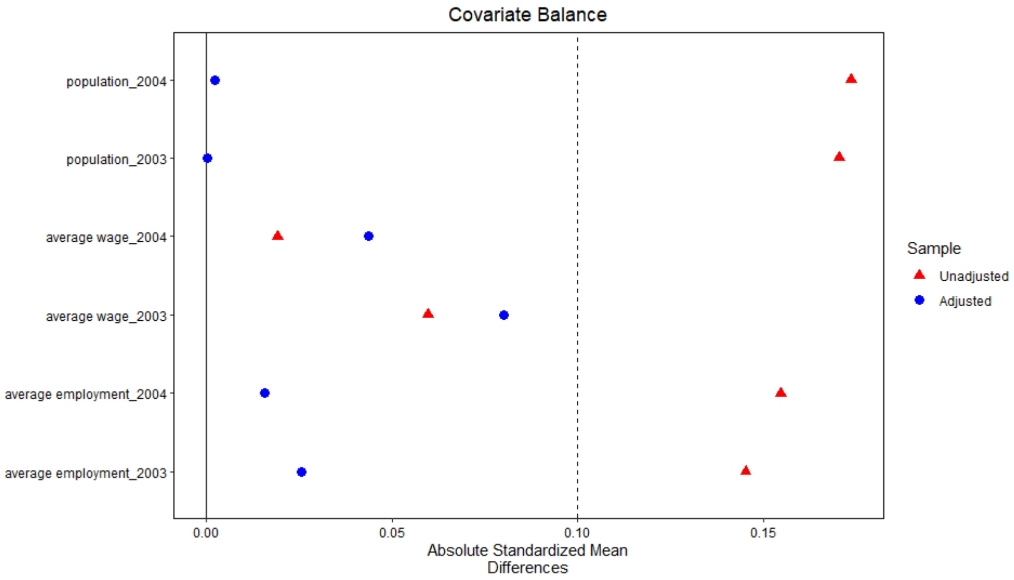

Figure 19: Dennis 2005

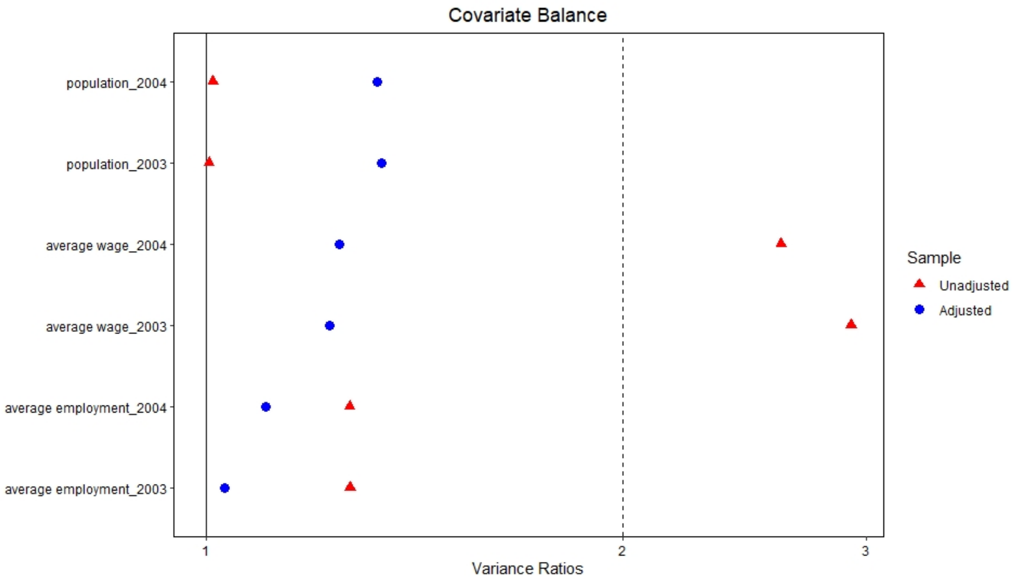

Figure 20: Dennis 2005