

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 in Florida. I utilize a model of wind intensity to measure the hurricane impact by the presence of hurricane force winds within each Florida county. By accounting for variation in hurricane intensity over the life of a hurricane, 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 indicate that when counties are matched based on similar labor market characteristics and a similar probability for hurricane exposure, hurricanes depress both employment and wage growth in affected counties.

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

JEL Classification: J0, J2, Q5, 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 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.

In this paper I contribute to this 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 a model that estimates the wind speed (known in the literature

as the wind field model) developed by Boose et al. (2004) to estimate the effect of Atlantic hurricanes on Florida's local labor markets. Additionally, I apply a Hurricane destruction proxy (Strobl, 2009) to deviate from the static classification used in the previous literature which uses a binary measure to classify whether a county was hit or not by a hurricane (known as a landfall model). This destruction proxy gives a continuous measure of hurricane impact, differing particularly in that all hurricane affected areas are not recorded as experiencing the same intensity of hurricane force winds. In addition, I include both hurricane specific as well as location specific characteristics to measure hurricane damage consistent with the literature.

The results of the analysis demonstrate how landfall¹ or hurricane path as a measure of impacted areas can bias estimates of the economic impact of hurricanes. Specifically, the results indicate that these measurements fail to capture the wind speed dynamics of hurricanes as their effects are not simply confined to geographical classifications. Failing to account for the varying intensity of hurricanes as they travel along their paths appears to paint a picture of an impact that may be more devastating than reality. Additionally, landfall models can incorrectly classify areas that experienced hurricane force winds as unaffected due to there being no formal way of estimating the extent of the hurricane's effect outside of the physical location of the hurricane.

Given that the previous literature has relied primarily on the landfall model to estimate the impact of hurricanes, I revisit the effect of hurricanes on labor markets using the wind field model. This model allows me to more accurately classify areas as treated and control units using actual wind speeds to estimate the winds actually experienced. These improved estimates can assist in the formation of policy prescriptions to properly aid labor markets that struggle after a hurricane. In addition, I apply propensity score matching techniques to explore how hurricanes disrupt labor markets between affected and unaffected counties, matching on

¹Landfall 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

labor market and population trends. With the aid of the wind field model I am able to better separate the affected and unaffected counties and in so doing identify the groups from which matches may be credibly selected.

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 dis-aggregated into different intensities, the results indicate that 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. Additionally, I do not find evidence of labor market spillovers from affected counties to geographical neighbors. The results show that the effect of hurricanes are primarily felt through employment changes with little to no impact on wages.

This paper makes two main contributions to the literature. First, within the context of the labor force effect of hurricanes, this paper is the first to address the issue using wind speed estimates at the local level to determine the units that have been treated by hurricanes. This measurement technique allows me to rely not only on the path traveled by the hurricanes but also to capture the effect of each hurricane down to the locations where the wind speed only achieves tropical storm levels. My second contribution comes by way of the application of propensity score matching, using multiple hurricanes and a specific selection method of matched groups. In applying the matching technique, I match counties affected by hurricanes in Florida to similarly hurricane prone counties across the southeastern coast of the United States, spanning six states. Other studies which have applied propensity score matching in the context of the labor market effect of hurricanes such as Groen et al. (2020), have matched only on demographic and economics factors. In this study, matches are determined by probability

of exposure to hurricanes along with economic factors. In the absence of an appreciation for hurricanes susceptibility, matches can be drawn from counties that may never stand a chance of experiencing a hurricane. Therefore, the method of match selection presented in this study, coupled with the identification of affected counties using the wind field model, ensures greater comparability between treated and matched counties.

2 Conceptual Framework for Labor Market Outcomes

In the wake of a natural disaster with significant destructive potential such as a hurricane, the literature has shown that the impact on labor markets can take many forms. In a standard labor supply model, in areas affected by disasters, the displacement of labor is a common result (either temporarily or permanently). Displacement will shift the labor supply curve to the left leading to 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) also highlight another means through which the labor market in affected areas react to the effect of hurricanes. The study notes that these affected areas face the risk of reduced labor demand as well 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 storm and its impact. In this scenario, the labor demand curve may also shift to the left as some entities may 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. Zhang et al. (2009) also notes that there may be an influx of construction crews

from other areas into the affected areas, which will stimulate demand for hotels and restaurants and thereby workers in the hospitality industry. With the urgency to meet the new wave of demand, additional positions and hours of work become available. In light of the downward pressure on labor supply coupled with the ambiguous effect on labor demand, the true effect of hurricanes on income and employment is not clear.

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 hurricanes is ambiguous a priori. In some cases, the effect of a hurricane can result in increased employment propelled by sectors which are needed in order to assist in recovery from hurricane damage. In other cases the outcome is negative on average 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 hurricanes. 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 hurricane. For the migrating population, either

due to the difficulty of assimilating or the over saturation of the new labor market, earnings tend to be lower for movers in their new location. Overall, for both earnings and employment, we see that there is room for further exploration of the effect of hurricanes on earnings and employment.

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. A problem that arises with this measurement is that the intensity of a hurricane changes as the storm progresses. This is due to many factors which range from sea surface temperatures to the position of the storm relative to land. Thus, the category of the storm may, and many times does, change as the storm makes landfall.

A prime example of such a storm is Hurricane Charley in 2004. Hurricane Charley entered Florida as a category 4 hurricane and later, before completely crossing the state, was reduced

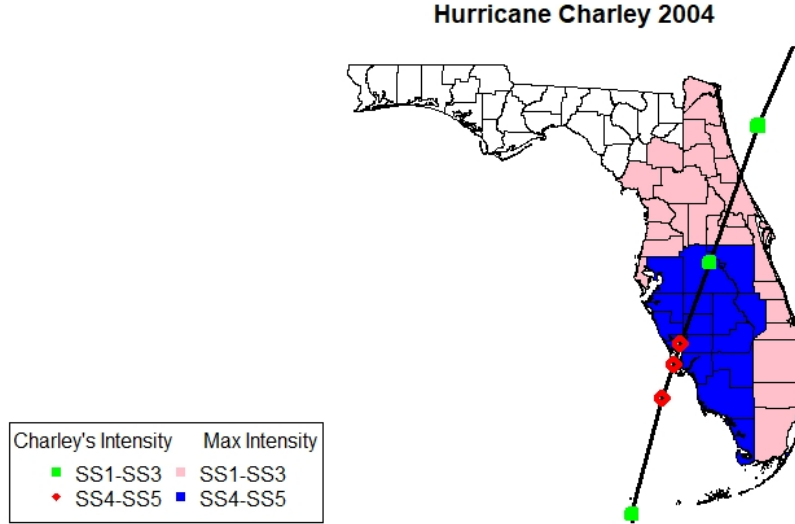


Figure 1

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. This is depicted in figure (1). The dark shaded areas 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.

To address this concern, Strobl (2009) and Strobl (2011) employed 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. This method allows the researcher to know at any given location and time interval the wind speed an area experienced. The landfall model, on the other hand, assumes all areas through

which the eye of the hurricane passes experience the same wind speeds. In my analysis I use a wind field model to 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 winds³, 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).

The radius of maximum wind chosen by Strobl (2011) follows the work of Hsu and Yan (1998). Hsu and Yan (1998) concluded that on average, in the 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 order to calculate an average R_m consistent with the 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 research such as this that attempt to incorporate natural sciences into economic

²Recall 100 geographical points were recorded for each county so V captures the wind speed at each

³The 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

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. This allows me to estimate the extent of hurricane exposure at varying wind speeds for each county. 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

⁴A list of all hurricanes analyzed in this study can be found in the appendix in table (6)

⁵The 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: ≥ 252 km/h

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 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) which would be classified as a group 2 hurricane, the set of counties experiencing group 2 winds will be less than that in the literature.

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 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 (2) 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.

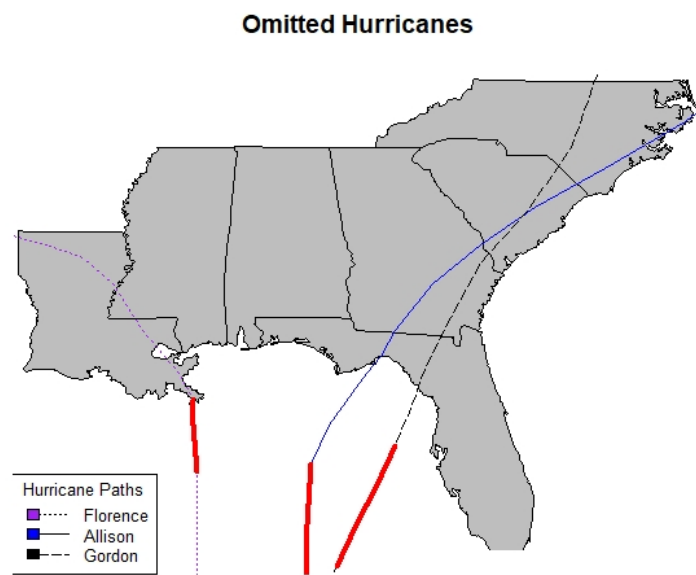


Figure 2: Hurricanes Florence, Allison, and Gordon

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 (3) (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. As such, the disaster declaration was solely caused by that hurricane that year. Panel (B) in figure (3) 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 (3), 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 this classification, 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. The choice of the neighbors in the previous literature was intended to select counties that were affected by

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

the same hurricane but to a lesser extent than the counties that were directly hit. The decision to look at the effects of hurricanes on neighboring counties in this paper is driven by the same motivation as the previous literature, taking particular note of the fact that the extent of exposure of a county to a hurricane is not confined to the physical presence of the hurricane in a county.

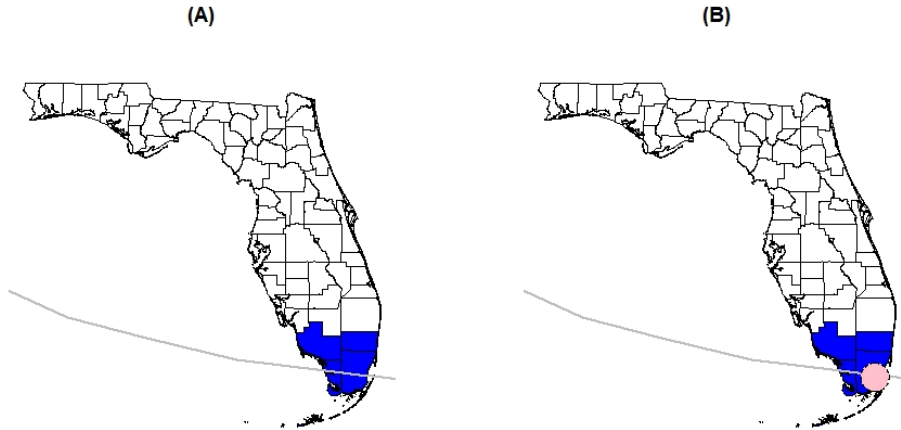


Figure 3: Hurricane Andrew 1992

4.2 Hurricane Index

Strobl (2009) and Strobl (2011) utilize the hurricane destruction index in order to capture further complexities involved in hurricane measurement. The wind index provides a proxy for hurricane damage by taking into account the wind speed experienced in each location, the length of time the hurricane impacted a location, the size of the population impacted, size of the affected area through the number of localities affected, and a parameter that relates hurricane wind speeds to the level of destruction caused by the storm. The measurement technique applied in the present study operates at the intersection of two separate views on how hurricane effects can be measured. Particularly, for the main analysis, I utilize the wind field model to estimate wind intensity in each county and apply a binary classification of affected

and unaffected counties. The use of the binary classification for hurricane affected locations in the United States was criticized by Strobl (2011) for failing to capture more of the intricacies involved in the impact of a hurricane. However, this criticism was made with particular reference to such an application when a landfall model is applied which is not the case for this study. The use of the wind field model in this study stops short of applying what Strobl (2009) refers to as a “black box” method of estimation due to the construct of the hurricane destruction index. As a robustness check to the main results and to account for another means of measuring the effects of hurricanes, I produce results from the hurricane wind index as well.

The structure of the hurricane wind index is described in equation 2 below:

$$WIND_{i,r,t} = \left(\sum_{j=1}^J \int_0^{\tau} V_{jt}^{\lambda} w_{i,j,r,t} dv \right) \text{if } V_{jt} > 119\text{km/h} (\text{SS} \geq 1) \text{ and zero otherwise} \quad (2)$$

where V is given by equation (1) and represents the estimates of local wind speed at localities j . J is the set of localities j within county i , w are weights assigned according to population size of the county to capture the economic importance of a particular county under the premise that if counties with larger populations were to be hit by hurricanes, those impacts would be of greater effect than a county with a smaller population.

Population data for each county was gathered from the Florida office of Economic and Demographic Research. Since the analysis was conducted using quarterly data and there are no official records of county population for this time horizon, I used the annual population in each county for each year. Hence, each locality in each county was weighted by the population of the county in the particular year of the hurricane. Since the focus of the paper is at the county level, the distinctions at the local level is not paramount to the outcome of the study. The premise of this design is that the damage to a county with a larger population will be of greater economic significance than one with a smaller population. The shapefile used in the calculations did not contain any locality (centroid) specific information which could be used

instead of population. Coupled with the lack of quarterly county data, the course of action taken here was the most appropriate. Strobl (2011) explored the option of both a weighted index and an unweighted. I explore both in this study. Recognizing the absence of data at the frequency of this study, I anticipate that the most appropriate means of applying the index would be the unweighted so as to not introduce any potential measurement errors into the study.

Finally, λ is a parameter that relates local wind speed to the local level of damage⁷. Table 4 below presents the wind index calculation for hurricane Andrew along with two key ingredients used in the index calculations, population and wind intensity.⁸

Table 1: Counties Most Affected By Hurricane Andrew

Counties	Broward	Collier	Miami-Dade	Hendry	Lee	Monroe	Palm Beach
Index	1499.41	152.17	893.38	51.65	345.85	143.82	984.58
Max Wind (SS)	5	5	5	4	4	5	4
Population	1,255,488	152,099	1,937,094	25,773	335,113	78,024	863,518

Hurricane index is scaled by 10,000,000,000. Max wind is stated in categories of the Saffir-Simpson hurricane intensity scale.

Here, I modified the index to accommodate hurricanes below category 3 unlike Strobl (2009). This was done in order to account for all hurricanes that are pertinent to this study. The wind index has a lower bound of zero and no upper limit. Higher index values indicate greater hurricane effects. Economic interpretation for the index is gathered by multiplying the coefficient on

⁷Observing the work of Strobl (2009) and taking note of the application of the model within the United States by Strobl (2011) this was chosen to be a value of 3.17

⁸The strongest winds from Atlantic hurricanes are felt on the north eastern side of the hurricanes. As such, for Hurricane Andrew, Broward county, though with a lower population size than Miami-Dade had a larger index value.

our estimated effects by the sum of the index over time for all locations. The result produced indicates the effect of an average hurricane across the data set of interest.

4.3 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 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.

There are a number of factors that affect the level of wind and rain exposure from a hurricane that an area experiences. These range from the forward speed of the storm, location relative to the area of interest, to wind gust and most of all the peak intensity in the radius of maximum wind (Boose et al., 2004). If these factors are not taken into consideration, it may lead one 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 both quarter fixed effects and a modification to the previous literature of 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 (3) and (4) present the models that are used to analyse the effect of hurricanes on Employment and wage growth respectively. Equations (5) and (6) explore similar effects as (3) and (4), however differing in that these models account for differences in hurricane intensity.

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \alpha_{1R_i} + \alpha_2 \Delta H_{it}^D + \alpha_3 \Delta H_{ijt}^N + \epsilon_{it} \quad (3)$$

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \gamma_{1R_i} + \gamma_2 \Delta H_{it}^D + \gamma_3 \Delta H_{ijt}^N + \epsilon_{it} \quad (4)$$

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

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \gamma_{1R_i} + \gamma_2 \Delta H_{it}^{4-5} + \gamma_3 \Delta H_{it}^{1-3} + \epsilon_{it} \quad (6)$$

Q_{it} represents 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 hit by hurricane force winds in time t . In equations (5) and (6), 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.

To further supplement the results from our binary estimation, I estimate equations (7) and (8) which display the models used for the estimation of the hurricane impact as measured by the hurricane wind index. The dependent variable remains as the growth rate in employment and wages while the index now captures the effect of the hurricanes.

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \gamma_1 R_i + \gamma_2 Index_{i,t} + \epsilon_{it} \quad (7)$$

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \gamma_1 R_i + \gamma_2 Index_{i,t} + \epsilon_{it} \quad (8)$$

4.4 Matching

As another novel contribution to the literature, I estimate the probability⁹ of experiencing a hurricane based on historical data and analyze the effects of individual hurricanes using nearest

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

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 the storm.

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 and average earnings per worker up to two years prior to the hurricane and total county population for each county two years prior to a hurricane. The selection of controls 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 control 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 determine the maximum wind speed experienced in each county in the state of Florida. Specifically, I was able to clearly identify those counties that experience 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 counties¹⁰. 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 (4) presents the hurricane probabilities by county.

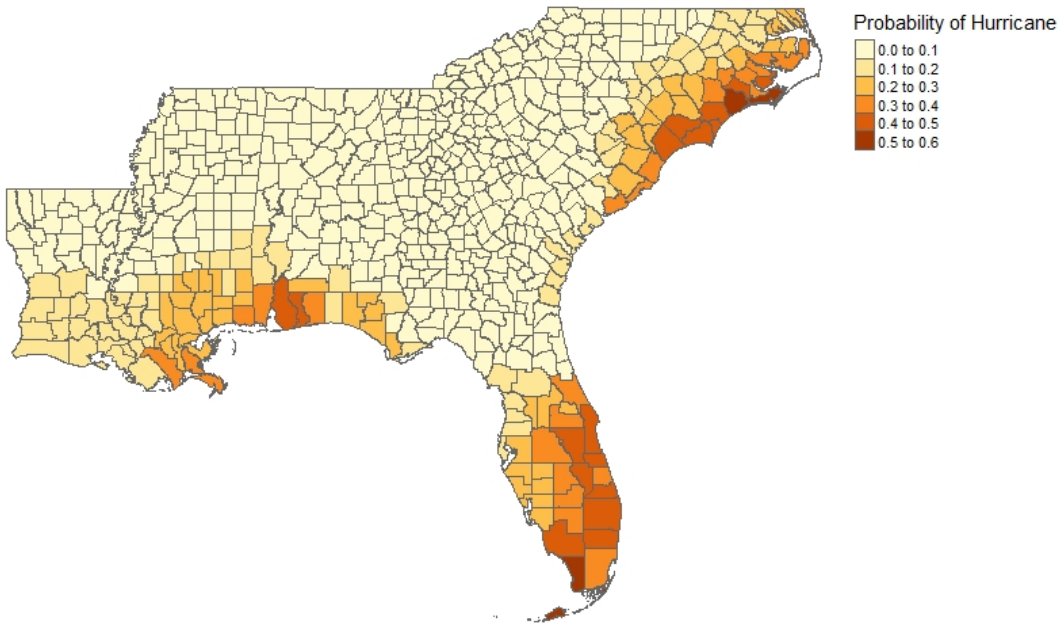


Figure 4: South East Hurricane Probability

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

¹⁰For example, imagine that Monroe county and Miami-Dade county in Florida are hit by a hurricane. If and each has calculated probability of 0.1 and 0.5 respectively, the match counties must have probabilities of hurricanes impact between 0.1 and 0.5.

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 of distributions. Coupling both means of assessing balance, strengthens the conclusion of successful balance between groups. Figure (5) below presents the absolute standardized mean differences for the pre-treatment variables while figure (6) 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.

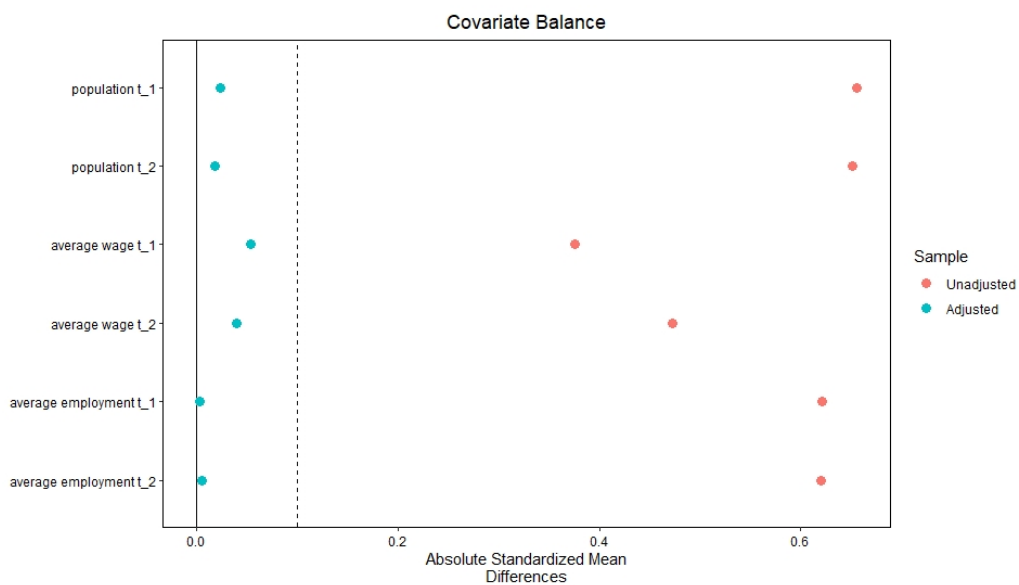


Figure 5: Mean Difference Andrew 1992

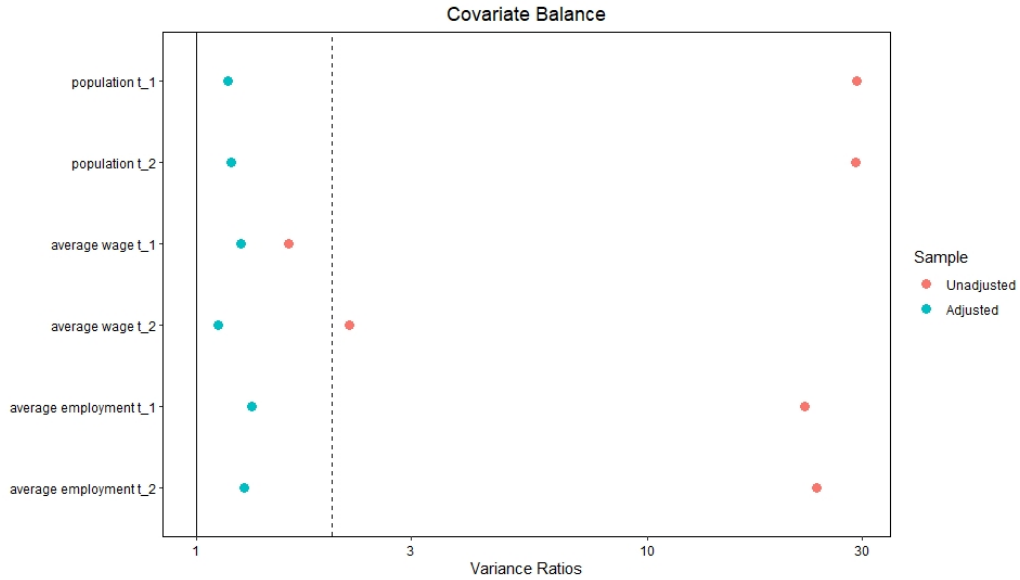


Figure 6: Variance ratio Hurricane Andrew 1992

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 matched groups.

5 Results

5.1 Aggregate Results

Reproducing the models from Belasen and Polachek (2009) using the wind field model, I obtain the results presented in table (2). 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 degree. 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's effect is lessened when accounting for the variation in hurricane wind speeds than the effect estimated from the landfall model. In particular, the results differ by 112 percentage points for the directly affected county's employment effect relative to the findings of Belasen and Polachek (2009). Such an effect is 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. Accounting for the variation in the hurricane intensity using the measurement techniques described in this study reveals a major shortfall in previous estimations.

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. For the neighboring counties, the literature suggests that the labor force will rise due to migration and result in a fall in earning growth. As was revealed in table (2), my results do not support for 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 similar declines in 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. Note that the employment growth impact for the directly affected counties was mirrored in the neighboring counties. Additionally, the insignificant result presented for wage growth in the neighboring counties is consistent with the directly affected counties.

Table 2: Aggregate Results (GDD)

Coefficients	ln(Employment)	ln(Earnings)
Direct	-0.0125*** (0.0035)	0.0033 (0.0033)
Neighbor	-0.0071* (0.0043)	-0.0034 (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 3 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 2. Table 3 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 followed by an increase in wage growth. Due to possible infrastructural damage and the impact on the customer base labor demand may also play a role in the outcome identified (Zhang et al., 2009).

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. Other forms of measurement such as the landfall model would ignore this dynamic. 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 2, the insignificant result for wage growth speaks to the fact that the hurricane leads to a reduction in both labor demand and labor supply, resulting in a statistically significant decline in employment with an insignificant impact on wage growth.

Due to the fact that there is overlap between the counties that would be classified as geographical neighbors to counties 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 3: Hurricane Intensity Results (GDD)

Coefficients	ln(Employment)	ln(Earnings)
Category 4-5 Hurricanes	-0.0436*** (0.0072)	0.0229*** (0.0068)
Category 1-3 Hurricanes	-0.0085** (0.0036)	-0.0004 (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 Wind Index Results

The results using the wind index are reported in table (4). Looking at the table, one can see that the results are similar to those presented for the more severe hurricanes as shown in table 3, suggesting that the average hurricane in Florida will lead to a reduction in employment growth and an increase in wage growth. Particularly, the wind index results suggest that an average hurricane in the state of Florida will cause employment growth in the affected counties to fall by 0.612 percentage points and cause average wage growth to rise by 0.614 percentage points. As mentioned in section 4.2 in the description of the components of the hurricane wind index, the index is usually weighted by population characteristics in order to indicate economic relevance of a location when a hurricane strikes. The premise of this inclusion is the assumption that more populated locations will be of greater economic importance and as such, the effect of a hurricane would be greater in these locations. Though an important part of the index calculation, Strobl (2011) showed that index results without population weights are still valid. Since population

data for the frequency of this study was not available at the time of the development of this discourse, the index was estimated without population weights. The results of the index clearly mirror that of the strong hurricanes. This result is not surprising since stronger hurricanes would produce both stronger winds and affect more locations significantly. These are factors that play a major role in the composition of the index.

Table 4: Wind Index (LSDV)

Coefficients	ln(Employment)	ln(Earnings)
Direct	-1.762e-07*** (7.462e-08)	1.767e-07** (6.985e-08)
Effect	-0.612	0.614
n,group	4757,67	4746,67

Note: ***,**,* denotes significance at the 1%, 5%, and 10% level, respectively. Standard errors reported in parentheses. Quarter and region fixed effects (not shown) are included in each model. Index not weighted.

5.4 Matching Results

In this study, I hypothesize that the various counties in the state of Florida have different labor market trends. However, some counties that have similar economic structures may follow similar trends. Additionally, there are counties that are outside the borders of the state that may facilitate valid comparison due to similarities not only in labor market trends but also vulnerability to hurricanes. If we are able to compare the effect of hurricanes across counties based on their labor market similarities, we can develop an understanding of the labor market disruption, or lack thereof, attributable to hurricanes. Thus, I next explore the labor market

effect of individual hurricanes to determine if there is a significant difference in the outcomes between affected and unaffected counties when we account for their labor market trends. In this section, I utilize a matching technique to aid in elucidating this effect.

Table (5) 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 (5) present the results from the seven hurricanes for which balance was achieved in the covariates utilized in the matching procedure. Columns 4 to 7 detail the number of treated¹¹ counties, total potential control counties based on the criteria laid out in section 4.4, the number of treated counties for which successful matched were identified and the number of matched control counties¹² respectively.

The results solidify the previous findings 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 relative to counties with similar pre-hurricanes labor market characteristics for all but two 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.

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 end of the fourth quarter at which point labor market data for the quarter would have become

¹¹counties that experienced hurricane force winds from each hurricane

¹²matching with replacement allowed for each control county to be matched with more than one treated county

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 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 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

Applying a novel measurement strategy to the same data as has been used in previous literature, I observe clear differences in the effect of hurricanes than has been previously documented. Particularly, the results indicated no evidence of spillovers of labor from affected counties to neighboring counties. The result obtained in this study 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 bear the brunt of

Table 5: Match Results

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

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

hurricanes. 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.

Considering that the spatial effects of hurricanes are not known to be confined to the geographical space within 30 km of the eye of the hurricane only, I hypothesized that carefully accounting for the hurricane intensity over the life of the hurricane would produce results that showed similar effects in neighboring counties as the directly affected counties. This hypothesis was confirmed as the neighboring employment growth decreased similar to the directly affected county, only differing in the magnitude of the effect as one would expect. Wage growth in neighboring counties also reflected the directly affected counties similar to employment. If the locations are close enough to be neighbors, then the effects will not deviate significantly between them. The differences in the findings between this study and the previous literature was anticipated based on the findings 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 insignificant effect on wage growth is a particularly interesting result. The result indicates that the effect of hurricanes cannot be classified solely as a matter of labor supply but must also be viewed through the lens of a shift in labor demand as well. The results suggest similar to the findings of Zhang et al. (2009) that establishments face destruction from hurricanes and the effects are manifested in the labor market. The damage sustained in some cases takes time to repair and in others, establishments may shut down. This causes the labor demand curve to shift to the left along with the labor supply curve. The inward shift of both curves results in a reduction in the level of employment in the affected locations while wage growth is unaffected.

The severity of the hurricane seems to play an important part in the determination of the

impact hurricanes have on labor markets. Stronger hurricanes adhere to the literature and support the findings of Belasen and Polachek (2009) who along with Strobl (2011) and Brown (2006) who suggest that labor supply is the primary source of the labor market disruptions.

Recognizing that the impact of a hurricane can possibly have a state-wide effect as well as the fact that I could improve the counterfactuals utilized in the models of section 4.3, I proceeded to implement the nearest-neighbor matching technique to further the analysis of the impact of hurricanes on employment and wage growth in Florida. The analysis focused on all the counties that experienced hurricane force winds from each of the hurricanes analyzed. Thus, the results did not reflect the models which presented results that were dependent on the intensity of the hurricanes such as those shown in equations 5 to 8. Barring Hurricane Wilma which was a fourth quarter hurricane and produced opposing results, the hurricanes which produced statistically significant results strengthened the conclusion that hurricanes will have a negative impact on employment growth. The results revealed a statistically significant impact on wage growth. Wage growth similarly to employment growth fell due to hurricanes when matched with similar counties outside of the state. This result indicated a negative shock to the labor market on a whole, not just employment growth.

We have seen in this study that when compared to other counties in Florida, hurricanes affected counties will generally see employment growth fall while wage growth increases primarily in the case of major hurricanes. When the impact on labor markets are viewed relative to counties with similar labor market characteristics and probability of hurricanes impact outside of the state of Florida, the results present a picture of an overall decline in the labor market as both employment and wage growth fall for most hurricanes. This overall decline is interesting particularly in the context of wage growth. Though in comparison to the unaffected Florida county, wage growth may be positive, it may be best to look at the impact of hurricanes relative to similarly positioned out-of-state counties rather than internal counties which may be

on different labor market trajectories.

As hurricanes remain a constant threat to the state of Florida and other coastal states, the result that labor from the affected counties does not spillover to other counties in a manner which impacts the neighboring labor market is a cause for concern. If the affected population does not move and secure jobs after the hurricane, then at least in the short run, there is a portion of the affected population that will remain unemployed. This challenge calls for policy makers, especially in the event of major hurricanes, to consider programs to assist displaced workers and affected establishments to maintain employment flows after hurricanes. Of particular interest for future work is the source of the labor market effects that we observe. From this study and the previous literature, both labor demand and labor supply have been put forward as reasons but to what extent can one credit either and in what circumstances would either be more dominant? This finding will assist in understanding whether aid programs after hurricanes should be directed to commercial or residential entities. This study presents 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.

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7 Appendix

Table 6: 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

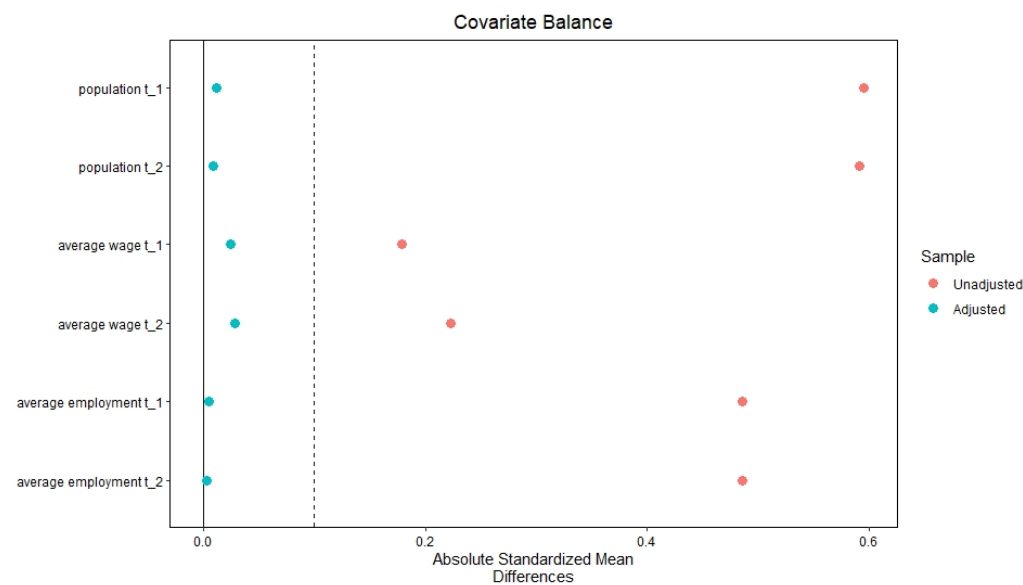


Figure 7: Erin 1995

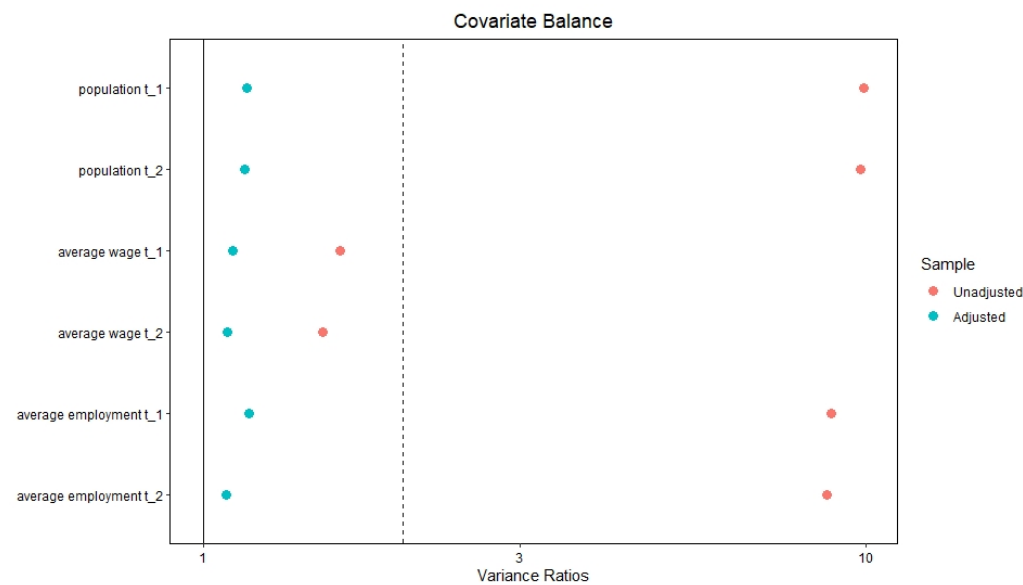


Figure 8: Erin 1995

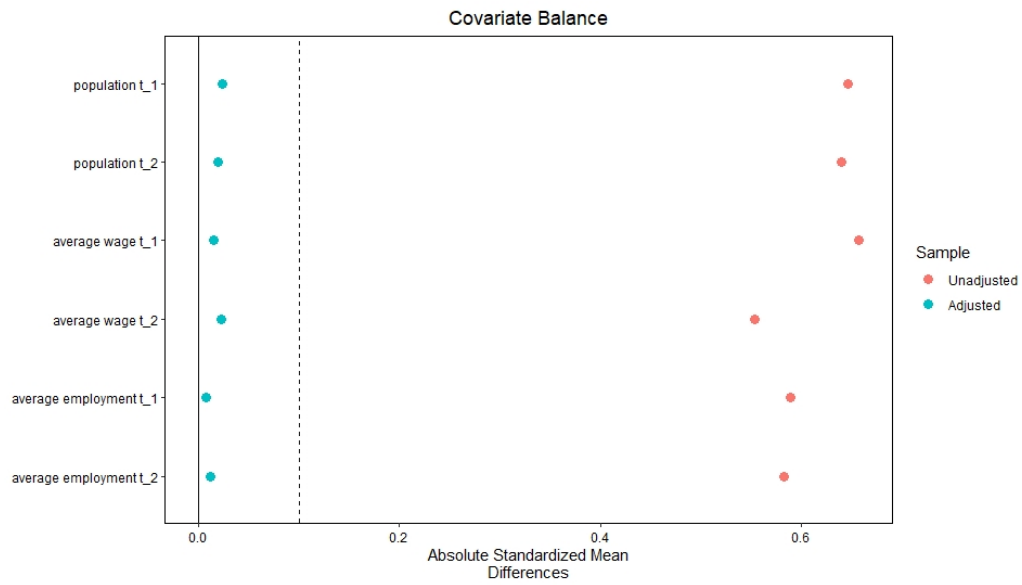


Figure 9: Charley 2004

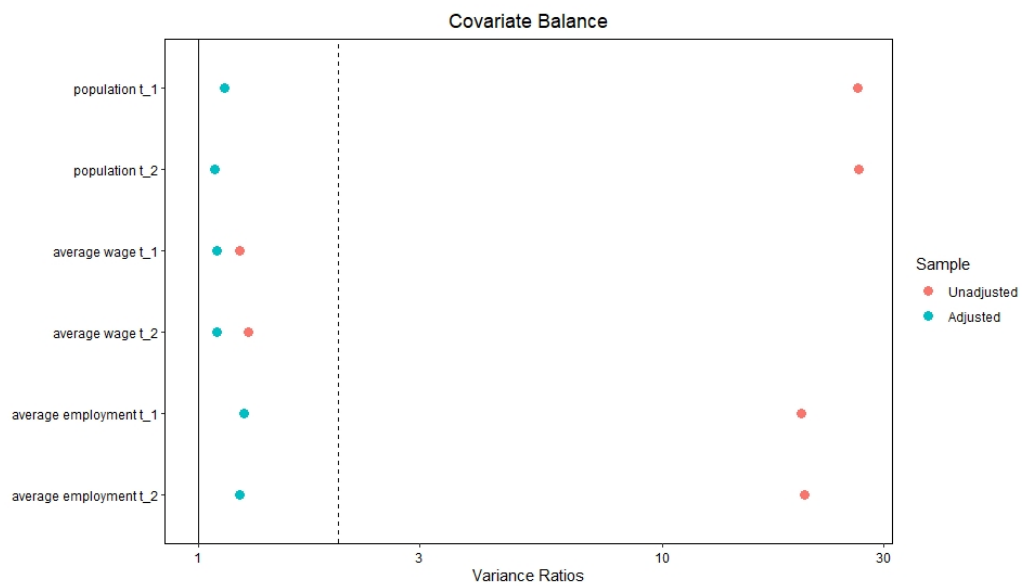


Figure 10: Charley 2004

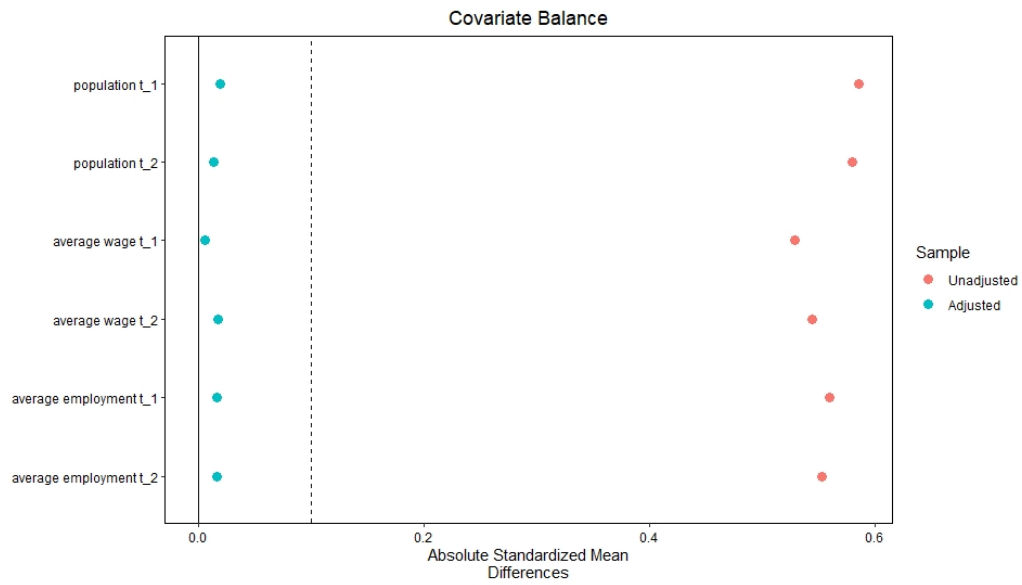


Figure 11: Frances 2004

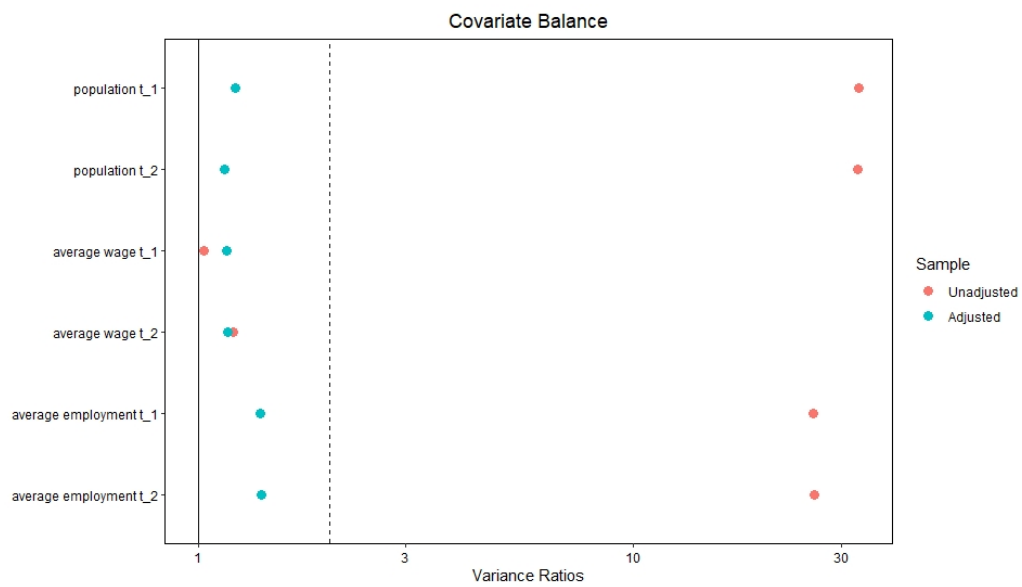


Figure 12: Frances 2004

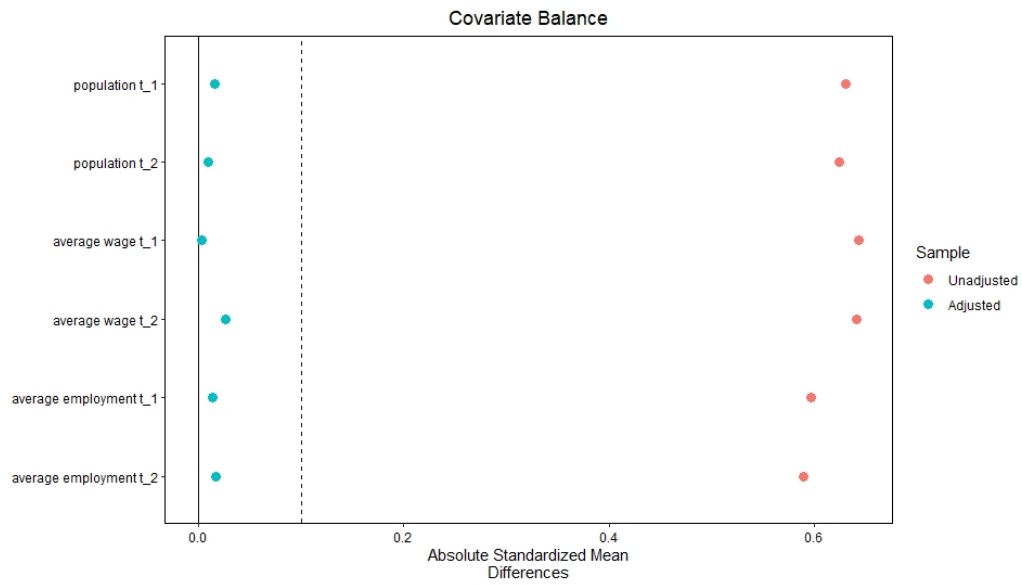


Figure 13: Jeanne 2004

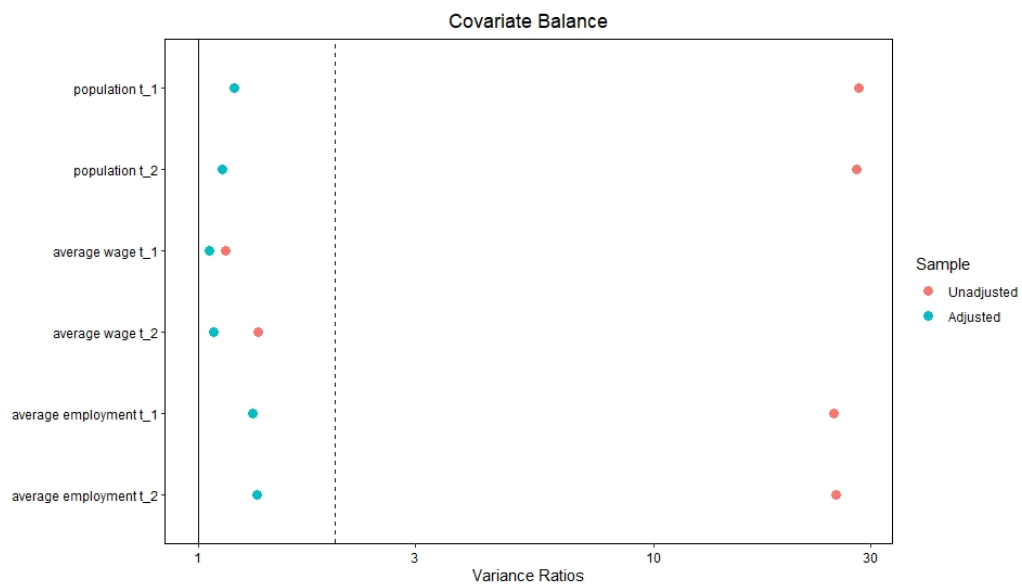


Figure 14: Jeanne 2004

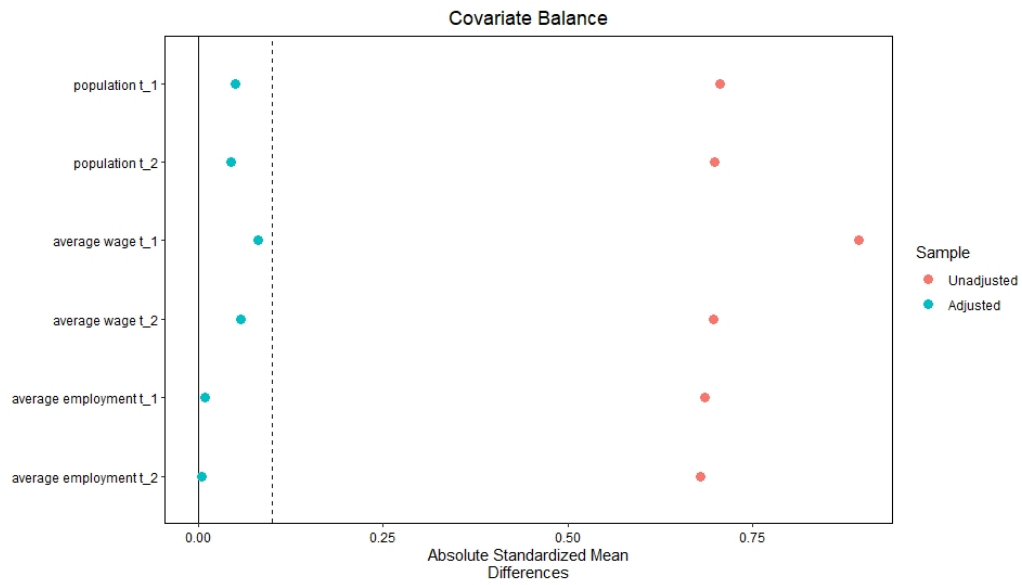


Figure 15: Wilma 2005

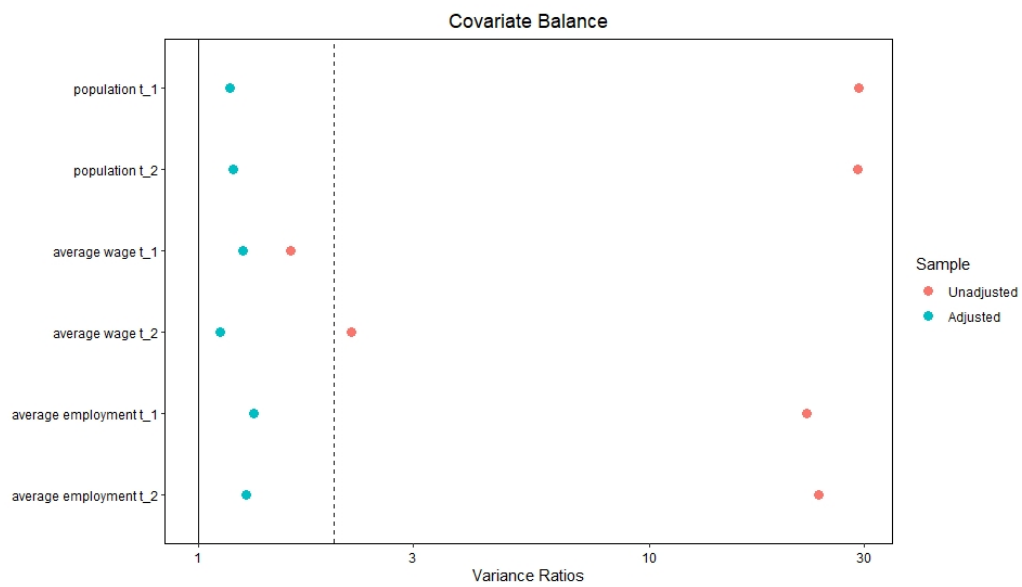


Figure 16: Wilma 2005

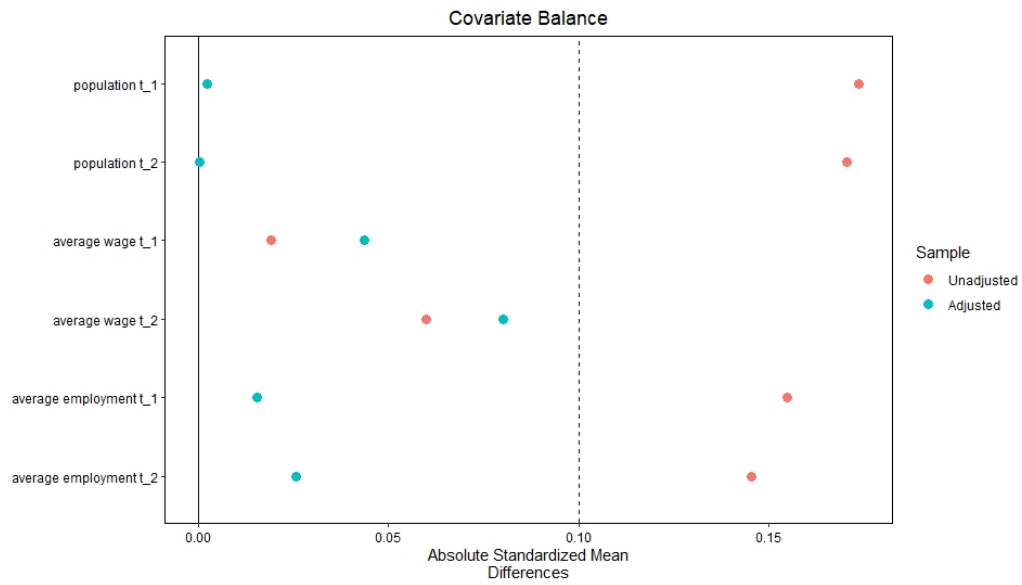


Figure 17: Dennis 2005

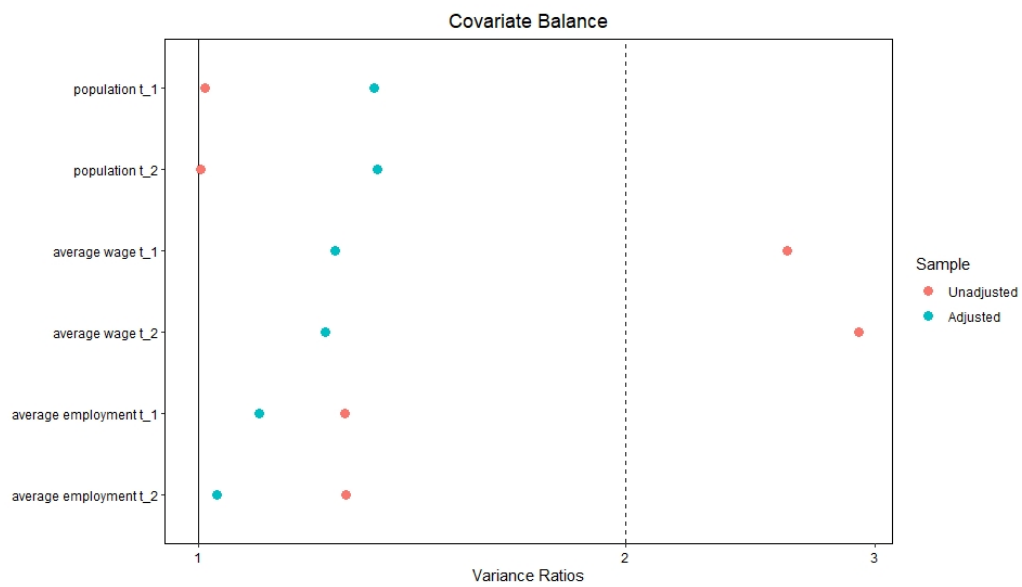


Figure 18: Dennis 2005