Florida's Rising Tide: Income Inequality Effects by County

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FLORIDA'S RISING TIDE: INCOME INEQUALITY BY COUNTY

by

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ABSTRACT

Income inequality in Florida is higher than in many states and has been getting worse over time. Inequality has been argued as responsible for a wide-ranging array of economic and social problems, including suppression of lower- and middle-income growth, social fragmentation and separatism, urban sprawl, poor health and mental illnesses, violence, and shortened life expectancy. What explains variance in Florida county income inequality as measured by the GINI coefficient? Bivariate and multivariate weighted least square regressions are conducted for the years 2000 and 2016, and for the change between 2000 and 2016. Three variables achieve statistical significance in all three multivariate models: poverty rate and population density have a positive effect as does educational attainment (although that variable is negative in the 2000 model). Income per capita has a statistically significant positive relationship with inequality in the 2000 model and in the change model. Unemployment rate is statistically significant in the 2016 model and in the change model but has a positive association with the GINI index in the former and a negative association in the latter. Several variables were statistically significant in just one model: cost-burdened housing with a positive relationship to inequality and percentage of minorities with a negative relationship in 2016; and county tax rate with a positive association with inequality in the change model. Conclusions are drawn regarding policy that might be implemented to mitigate worsening inequality in the Sunshine State.

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INTRODUCTION

In the United States, income inequality has risen and fallen in waves, peaking in 1928, declining rapidly through the 1930s and 1940s, and continuing a gradual decline in which all wage earners experienced similar income growth until 1979, a year generally noted as the beginning of the rapid expansion of rising inequality. Current levels of inequality are now near the peak seen in 1928 (Piketty and Saez 2003). At its most basic, income inequality is simply the extent of of the gap between rich and poor; in the United States broadly and Florida specifically, this gap has been widening for decades, and it has been a lopsided widening that has largely benefited the upper income shares and left lower income ranges stagnant or declining slightly. If subscribing to fundamental values like fairness, equality, and an American dream by which hard work leads to beneficial rewards, we like to think of a rising tide lifting all boats, economically speaking. However, an expansion of income inequality and relative decline in wages and incomes has been the reality for many Americans and most Floridians (Sommeiler, Price, and Wazeter 2016), seeming to signal that in the Sunshine State, the rising tide is only lifting a few boats.

Factors that develop or are exacerbated as a result of income inequality can be societally problematic, including poverty, crime, health concerns and mortality, education levels, employment levels, and even happiness (Glaeser, Resseger, and Tobio 2009, 642). These inequalities do not just affect the upper and lower tiers of income earners. For the middle incomes, inequality can hinder an improvement in standard of living; if the growth of middle incomes had maintained the same rate as overall growth from 1979 to 2007, the middle class would have been substantially better off. Instead, a growth suppression of about 27% had an effect similar to tax imposition on middle income Americans (Sommeiller, Price, and Wazeter 2016, 31). Additionally, worsening income inequality is self-perpetuating: countries with greater income inequality tend to also be those where economic advantages (or disadvantages) are passed on from parent to child in a long-term stratification phenomenon that economist Alan Krueger labeled the "Great Gatsby Curve" (Corak 2013, 80-81). Along the Great Gatsby Curve, which compares income inequality to intergenerational economic mobility, approximately 50 percent of economic advantage, or disadvantage, is bequeathed from generation to generation in the United States (Corak 2013, 81).

Income inequality is not solely a national problem; inequalities vary at state and even county, metropolitan area, and municipal levels. Policies at any of these levels can serve to alleviate – or exacerbate – some of the conditions contributing to inequality. Research reveals Florida to be a state with higher-than-average income inequality. Using a ratio of the income for the top 1% to the income of the bottom 99%, in 2013 Florida had the fifth highest income inequality in the United States (behind New York, Connecticut, Wyoming, and Nevada) according to Sommeiller, Price, and Wazeter (2016, 8). Several Florida counties and metropolitan areas also rank in the top 25 by this measure and study, representing a disproportionate number of the most unequal in the nation.

The purpose of this research was to determine the extent, possible causes and potential effects of changes in income inequality in the 67 Florida counties from 2000 to 2016. A Florida county-level analysis of income inequality over time will answer an important question: is income inequality growth happening at a rapid rate in only a few places, driving up Florida's overall numbers, or is this a widespread growth affecting a majority of Florida's residents?

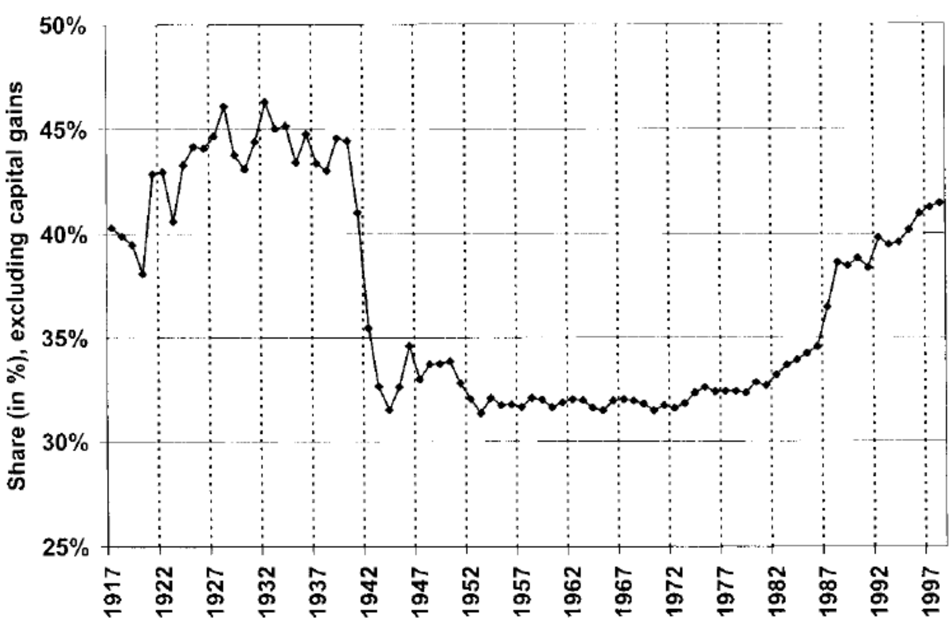
A broad array of research and studies are available, at global comparative, national, state, and local levels; the research covered in the literature review will focus on the U.S. and, to the extent available, Florida studies. Following the literature review are developed theories and hypotheses related to income inequality in Florida in 2000, 2016, and between these two points in time; definitions of income inequality and causal variables' measurements and methods; explorations of analysis and regression findings; and conclusions based on the findings, including potential policy proposals and areas for further research.

LITERATURE REVIEW

Income inequality studies exist on a scale from global to metropolitan; in order to keep the focus on Florida and U.S. inequality but maintain a broad enough basis of literature, this review focuses mainly on income inequality research at the United States national level while, as much as possible, encompassing research specific to the state of Florida and its metropolitan and county areas.

From 1928 to 1979, the income share of the top 1% fell in every state but one (Alaska); from 1979 to 2007, it increased in every state without exception, with current levels of inequality now near the peak seen in 1928 (Sommeiller, Price, and Wazeter 2016). Seminal historical income inequality research notes that the 20th century income inequality decline was over a specific and brief period of time (Piketty and Saez 2003) (see Figure 1).

Figure 1. Top Decile Income Share, 1917 - 1998



Source: Figure 1 in Thomas Piketty and Emmanuel Saez (2003)

Piketty and Saez noted that the top 1% income share is approaching its early 20th century levels: in 1915, the top 1% earned 400 times more than the average income, dropping to 50 times the average in 1970, and by 1998 were earning 250 times the average. Notably, while capital income accounted for most wealth held by the top 1%, the modern 1% accumulates its income via wage and entrepreneurial income, indicating that the contemporary top income distribution is somewhat less volatile than the capital income that declined as a result of diminishing gains once progressive income, estate and corporate income tax policies were implemented (2003).

Much research generally acknowledges a few key historical factors contributing to income inequality decline in the earlier era, pre-1979: rising minimum wage, low unemployment levels, and increases in labor union representation and collective bargaining in private industry (including Florida and Mellander 2016; Piketty and Saez 2003; Sommeiller, Price, and Wazeter 2016). Additionally, the cultural and political environments at the time would not have been friendly to a co-existence of high unemployment rates alongside executive compensation that could be perceived as excessive. This environment is exemplified by implementation of oversight institutions like the National War Labor Board, established in 1942 to review and approve all proposed wage changes (Piketty and Saez 2003, 29-30).

A temptation may arise to attribute the rise in income inequality to shifts in those same factors that had held inequality lower for five decades; much research exists to bolster such inclination. Private-industry unionization and collective bargaining are at historically low levels not approached since before 1928. This decline of organized labor in the private sector "affects the economic assimilation of recent immigrants and their offspring, widens black-white wage inequality among female workers, redistributes political power, and redefines the nature of strikes in modern America." (Rosenfeld 2010, 4)

The minimum wage, in relative dollars, buys fewer goods and services than it did in 1968 (Sommeiller, Price, and Wazeter 2016, 29). The post-bailout bonuses received by executives in the Great Recession period of the late 2000s and early 2010s were met with some degree of public consternation but little reversal, signaling a shift in the cultural and political environments from the earlier era. Gordon and Dew-Becker propose trade effects as a factor increasing inequality – the increase in import shares of U.S. GDP has pushed down the wages of unskilled workers in trades like manufacturing and suppressed domestic investment – but note that such effects have declined over time (2008, 12-13). Changes in skill-biased technical change (production technology advancements that favor skilled over unskilled labor), globalization of manufacturing, immigration, and productivity and efficiency improvements have also been demonstrated as factors contributing to the rise of inequality (Florida and Mellander 2016; Gordon and Dew-Becker 2008).

That rise has been substantial. Income growth for the top 1% from 2009 to 2013 was substantial, accounting for 85% of total income growth; in Florida, the top 1% of earners accounted for all income growth, while the remaining 99% experienced a fall in their share (Sommeiller, Price, and Wazeter 2016). This failure of the 1% income share to signal an increase in the share for the 99% is unsurprising given Thompson and Leight's research, which indicates that top share increases, especially for the top 1%, do not lead to rises in bottom and middle-income shares. Further, in their nationwide study, after a long "lagged effect," the bottom shares of low- and middle-income households instead fell while upper-income shares rose. Income growth for the middle share was found to be negatively associated with top incomes; however, at the low-income end, there was not a clear or consistent relationship between rising top share and income, once controlled for other factors. (Thompson and Leight 2012). Generally, wages for the overwhelming majority of Americans, including those with college degrees, have stalled or even declined since 1979, a year which coincides with the beginning of the upswing in income inequality; college graduates' hourly earnings increased a total of 4.4 percent from 2000 to 2013, with entry-level graduate wages falling over the same period (Bivens et al 2014, 4-5).

Social compact and societal fragmentation factors have been found to be significant, as have factors of enduring legacy. Tax rates favorable to lower and moderate-income workers, as well as unionization opportunities, can reduce income inequality growth, and historical context indicators like poverty levels and race are relevant in assessing income inequality (Florida and Mellander 2016; Glaeser, Resseger, and Tobio 2009). Some factors are harder to quantify but observable nonetheless, as noted by Piketty and Saez: "changing social norms regarding inequality and the acceptability of very high wages might partly explain the rise in U.S. top wage shares observed since the 1970s" (2016, 35). These factors would be of particular importance in policymaking considerations, as evidenced by van der Weide and Milanovic's argument that "income fragmentation … might promote social separatism" (2014, 22), by which high-income members of a community opt out of publicly-funded and publicly-provided education, health, and other services to utilize privatized equivalent services. This flight from public services by the rich could have detrimental effects for lower- and middle-income groups in particular; policies that enable or encourage a separation by classes perpetuate the breakdown of this social compact and hasten societal fragmentation. Additionally, some of these social and historical factors can have measurable effects on inequality for unexpected lengths of time; Glaeser, Resseger, and Tobio found 1850s levels of college enrollments, illiteracy rates, and slavery to be predictors of today's income inequality in cities (2009, 629).

The distinction between national income inequality and state income inequality is important, but much research done at the national and international comparative level has been shown to hold true for individual states. In his study, Mark W. Frank (2009) found state-level support for Piketty and Saez's conclusions about the income share of the top decile from 1945 to 2004. Negative effects may even appear to be exacerbated when the state level findings are compared to those nationally; Lochner et al. (2001) found that an increased mortality risk exists for individuals living in higher-inequality states compared to those in lower-inequality states. Updated research from Frank (2017) using Gini coefficient as a measure for income inequality ranked Florida at 7th nationally in 2000 (where 1 is most unequal and 50 is least unequal) and at 2nd nationally by 2015.

Florida's geographical characteristics and population density makeup could be explanatory of its income inequality changes and contributing variables – over 96% of Florida's population resides in metropolitan statistical areas (MSAs) (MacManus et al. 2015, 9). As costs of living in MSAs rise, populations "creep" further into the surrounding areas, leading to expansion of the MSA. This expanse has pricing effects, driving up the costs of housing in an area at the same time its population of low-wage workers expands due to their price-out in the central region of the MSA. Income inequality tends to be higher in large metro areas and their cities than in the nation broadly (Berube and Holmes 2016). Florida is disproportionately representative in income inequality rankings by metropolitan areas and counties, signaling the value in assessing Florida's income inequality at those levels. Sommeiller, Price, and Wazeter used the percentage of income share held by the top 1% of earners to rank United States metropolitan areas and counties; Florida was home to seven of the 25 most unequal metropolitan areas and nine of the 25 most unequal counties. Florida's relatively high housing cost might have significance relative to income inequality; however, Glaeser, Resseger, and Tobio found a weaker than expected link between income inequality and their calculated measure of housing consumption inequality (2009, 626).

Economic growth has been found to be significantly and positively related to income inequality: Mark W. Frank found the concentration of top income shares to be the primary driver of the link (2009). In a study determining the effect of income inequality on growth, van der Weide and Milanovic found that inequality has a positive effect on economic growth, beneficial solely to the top end of the income distribution and detrimental to the income growth of the poor; thus, the economic growth that inequality stimulates is of a type further advancing inequality (2014). Theirs and Frank's conclusion that the growth and inequality link is driven by the upper income share is compatible with Florida and Mellander's findings that income inequality more broadly is driven by lower income shares (2016), suggesting that policies addressing both ends of the spectrum would best address widening inequality. As a counterpoint: Glaeser, Resseger, and Tobio found a significant negative relationship between economic growth and income inequality when controlling for area-level differences, and hypothesized that at a national level, the link was due to inequality leading to "political strife" (2009, 640). Research findings indicate that policies encouraging economic growth should simultaneously consider how to enhance economic growth without continuing to deepen inequality, as growth may not "trickle down" to anyone, remaining in top shares, and in fact repressing bottom growth (Frank 2009; van der Weide and Milanovic 2014). However, Glaeser, Resseger, and Tobio found a positive rather than negative link between economic growth and income inequality after controlling for area-level differences; disparate research findings could indicate that localities experience growth impacts on income inequality differently.

Florida is an interesting state to study at the county level for many reasons, including its population, demographics, tax policies, metropolitan "sprawl", and variety of economic functions (tourist, agricultural, technological, etc.). Jongsup Kim (2004) analyzed Florida's counties for changes in income inequality from 1979 to 2000, focusing on the county's classification by primary economic function. In this time period, his findings indicated:

> a variety of factors explain the growth of county inequality including globalization, the shrinkage of manufacturing jobs caused by the rapid progress of an information-oriented society, and the expansion of low-wage service jobs, immigration, the weakening of labour market institutions, the proportion of the non-labour population, urbanization, and the approach index from the consumer market. (Kim 2004, 177).

County-level and other narrow-region analyses may be particularly important to the lower-income groups: in research related to income mobility – movement from one income bracket into another – Chetty et al. showed intergenerational income mobility outcomes varied more across regions for low-income families than for those of high-income families (2014, 1557). Additionally, middle-class erosion may have a more substantial detrimental effect on intergenerational mobility than upper income growth (*ibid*).

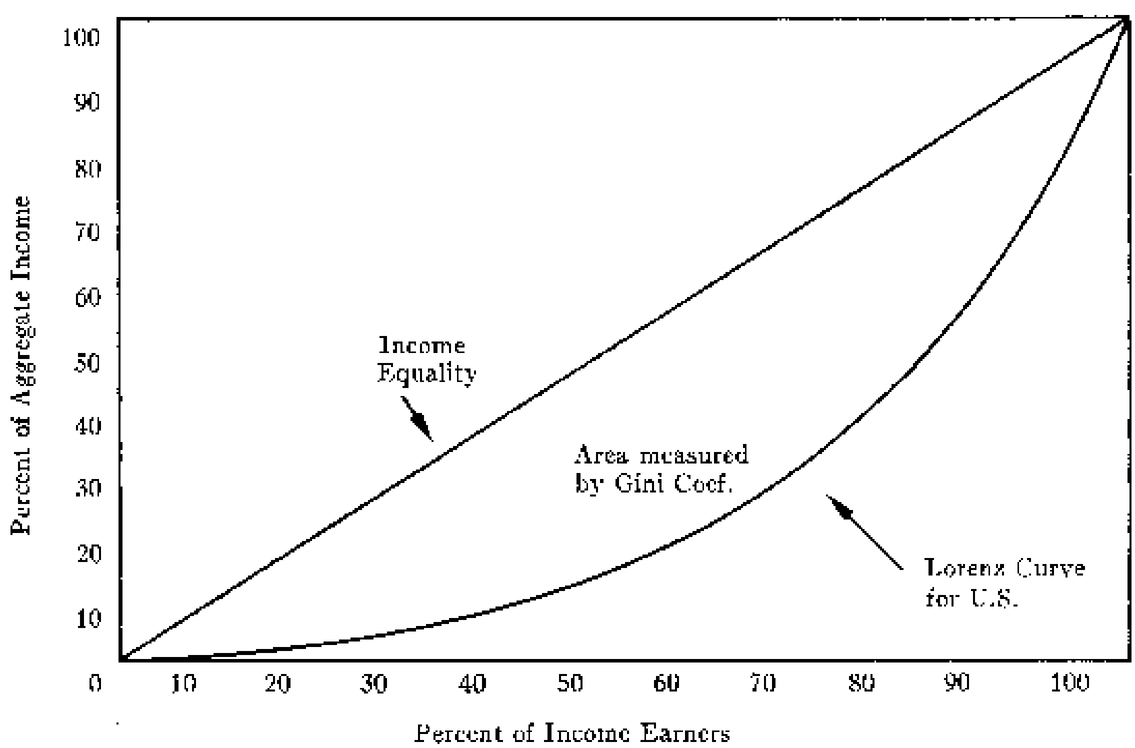
Why study income inequality, though, and why should Floridians be concerned about changes in income inequality in their county? As suggested by the studies related to a social compact, the impacts of income inequality have been shown to extend beyond structural and economic realms. Wilkinson and Pickett found evidence that unequal societies are more likely to bear the weight of social problems like mental illness, violence, imprisonment, lack of trust, teenage birth rates, obesity, drug use, and poor performance in schools; their research and evidence indicated that this connection likely reflects "sensitivity of health and social problems to the scale of social stratification and status competition, underpinned by societal differences in material inequality" (2009, 493). Glaeser, Resseger, and Tobio found a strong positive relationship between income inequality and murder rates in metropolitan areas, robust even upon controlling for average income and poverty rates, and hypothesized that "inequality breeds resentment," pointing to evidence that wealth-envy is strongly correlated to unhappiness (2009, 642). Gordon and Dew-Becker note a "startling divergence" in life expectancy changes over time, citing Singh and Siahpush's 2006 study that found that the top and bottom decile's gap in life expectancy had increased from 2.8 years in 1980 to 4.5 years in 2000 (2008, 35). Such findings indicate an increase in health welfare – such as positive health outcomes and increase in life expectancy – is about 1.5% faster for the rich than for the poor (*ibid*, 45).

Discussion is warranted of the actual measurement of income inequality. Methodologies to measure income inequality can result in varied findings and generate disparate rankings, making comparative analyses challenging. One common method for inequality calculation generates a comparative ratio of the top 1% of income holders to the bottom 99%, an approach used in numerous studies (Frank 2009; Piketty and Saez 2003; Sommeiller, Price, and Wazeter

2016). Other studies may use similar breakdowns, such as using incomes comparing the 95th percentile to the 20th percentile (Berube and Holmes 2016) or the 90th decile to the 10th decile (Gordon and Dew-Becker 2008). A substantial shortcoming of these comparative-ratio measures is that obtaining an accurate estimate of high-income shares can be problematic. The U.S. Census and American Community Survey (ACS) define a top income bracket as $200,000 or more; however, the threshold for the top 1% in the United States in 2013 was $389,436 (Sommeiller, Price, and Wazeter 2016). Using U.S. Census or ACS data, with its broad upper limit, would cause an overreporting of high-income share. An often-used alternative, using actual reported tax data, has two shortfalls: individuals earning less than threshold gross income levels may not file returns and are thus omitted from computation, possibly understating the lower-income range; further, such calculations at the level of the 67 counties may require an analysis of data that is outside the reasonable scope of this research.

Another method of measuring income inequality is with the Gini coefficient. Used in numerous studies (Dye 1969; Florida and Mellander 2016; Frank 2009), the Gini coefficient is the measure of the distance between theoretical perfect income equality (a value defined as 0) and a nation, state, or locality's proportion of aggregate income relative to population as demonstrated by the Lorenz curve (see Figure 2).

Figure 2: The Lorenz Curve of Income Inequality and Gini Coefficient



Source: Figure 1 in Thomas R. Dye (1969)

The Gini coefficient has its advantages: it is an invariable representative of inequality (it does not rely on population or production as part of its calculation); is easily applied for comparative study; and is independent of economic and population scale. The Gini coefficient also has noteworthy shortcomings: it does not take into consideration non-income benefits that may effectively move an earner up on the Lorenz curve; will give different results if applied to households or individuals; and can misstate inequality because it does not take into consideration the shape of the Lorenz curve. (In other words, an economy where one individual has half the wealth and the remaining individuals have the other half would have the same Gini coefficient as one where half of the individuals have zero income and the other half have perfectly equal income shares. This shortcoming could require careful consideration of a region's Lorenz curve when interpreting findings and making policy recommendations.)

Glaeser, Resseger, and Tobio's research is of note in making a determination on the selection of inequality measure, having found that these and other income measures have a "fairly high correlation" to each other (2009, 16) and alleviating some concern that any particular measurement would vastly differ from another.

THEORIES AND HYPOTHESES EXPLAINING INCOME INEQUALITY AND CHANGES IN INCOME INEQUALITY IN FLORIDA COUNTIES

Income inequality can be attributed to different factors across a spectrum of groupings. Explanatory variables could include poverty and high-income shares, employment rates, mean income, housing affordability, marital rates, race, educational attainment, average wage, percentage of employment that falls into high tech or creative class categories or, in the alternative, percentage of low-skill employment, urbanity, immigrant population percentage, and tax policies. Those variables that were ultimately selected for this regression are defined below; however, any of these variables may present opportunities for future study.

The selection of 2000 and 2016 as comparative years for study is intended to document a run-up to the Great Recession, which had considerable impacts on Florida. My expectation was that perhaps the recessionary effects minimized some of the expansion in income inequality and that 2016 inequality was not substantially greater than in the pre-Recession 2000 figures. (This expectation would turn out to be erroneous.) Additionally, Kim’s 2004 study spanning 1979 to 2000 at the Florida county level in combination with this study may allow future research the ability to extend findings back to 1979.

Economic Indicators

These indicators involve factors that engage or are derived from human capital and include two separate poverty measures, educational achievement levels, unemployment rates, cost-burdened housing rates, and per capita income figures.

Poverty. H1: There is a positive relationship between poverty measures and income inequality.

Poverty would seem to be closely related to income inequality, but some research signals that poverty may be a weaker indicator than expected. The correlation between poverty and income inequality has weakened over time due to the rapid earnings expansion experienced at the top of the income curve, leading income inequality impacts to be observable in both rich and poor metropolitan areas (Glaeser, Resseger, and Tobio 2009). Analyzing poverty in addition to inequality is important, because inequality may be poverty driven, or have a different primary driver, like top share or economic mobility. Thus, while inequality may be similar in two counties, the responses and policy measures best suited to address it may be very different. Research has used poverty to explain inequality, as with Glaeser, Resseger, and Tobio, and inequality to explain poverty (Bivens et al. 2014). Based on such research, I expect any measure of poverty and income inequality to be positively linked, though to a lesser degree than one might expect.

Cost Burdened Housing. H2: The rate of cost-burdened households is positively related to income inequality.

Florida ranks 49th in all states for affordable available housing, and over one-third of Florida households pay more than 30 percent of their incomes for housing (Golden 2016). This variable, if found to be significantly linked, is important at a county level because measures like inclusive housing policies can be implemented at a county level. As housing impacts driven by inequality are disproportionately detrimental to poor households, local governments may have greater control over affecting shifts in income inequality than they realize and can develop beneficial local housing policy recommendations, such as density concessions for inclusive housing. However, though affordable housing burdens show significant impacts on poverty (Golden 2016), the impact of these burdens on income inequality may or may not be significant. If a link exists, I expect it to be positive: more cost burdened households leading to greater income inequality.

Educational attainment. H3: There is a negative relationship between college-plus educational attainment and income inequality.

Educational attainment is important to both poverty rates and income inequality. In Florida, higher educational attainment levels generally contribute to lower poverty rates (Florida Legislature 2016). Research indicates that places with more college dropouts have been found to be more unequal over time (Glaeser, Resseger, and Tobio 2009, 630). One could hypothesize the relationship to be negative (higher educational attainment lowers poverty rates) or positive (higher educational attainment drives upper incomes higher, widening the divide). However, since educational attainment is likely to drive the lower, middle and lower-upper shares of income higher without impacting the very highest shares, I would expect an increase in education rates to contribute to a decrease in income inequality.

Unemployment rates. H4: There is a positive relationship between unemployment rates and income inequality.

Periods of lower inequality, such as the 1928 to 1979 era, were associated with rising minimum wages, strong union participation and collective bargaining successes, and lower levels of unemployment (Sommeiller, Price, and Wazeter 2016). Long periods of unemployment obviously and necessarily drive down household income, possibly contributing to downward mobility and impacting income inequality, so unemployment rates and income inequality would be positively associated, though the link is expected to be somewhat weak.

Income Per Capita. H5: There is a positive relationship between income per capita and income inequality.

Rather than attempt to estimate economic growth at a county level, such as with a county GDP measure, per capita income was selected to gauge the general expansion or contraction of a county population's overall income level and its relation to income inequality. While mean income levels may be viable for study, Florida and Mellander's findings indicate that more affluent metros were not necessarily more unequal. A hypothesis here is challenging, as per capita income rates can be driven from any range of the spectrum: negative, where an increase in per capita income propelled by an upward shift for the low- or middle-income range might tend to decrease inequality, or positive, where the same per capita increase driven from the high-income range would exacerbate inequality. Based on Florida's general economic demography and trends, lending a dash of pessimism, I expect per capita income and inequality to share a positive relationship.

Sociological Indicators

These indicators include demographic and sociologic factors: population density (as an indicator of a county's rurality/urbanity), marital rates, and race.

Population density. H6: There is a positive relationship between population density and income inequality.

While Florida and Mellander (2016) found county urbanity to be insignificant, other studies and literature such as that by Berube and Holmes (2016) have discussed a link between urbanity and income inequality. Following city and metropolitan inequality research, I expect to find that while counties with large metropolitan statistical areas (MSAs) may experience high levels of income inequality generally at the set points in time of 2000 and 2016, counties with substantial MSAs may indeed not show the most substantial inequality growth between 2000 and 2016, in that those counties were already experiencing substantial inequality by 2000. Population density is not necessarily the best estimate of rurality or urbanity – two counties with the same population density may feature very different scatter – and something like an index of relative rurality would be more accurate; however, at a county level, population density does give a reliable approximation of a county's rurality (Belk Jr., 2019). Population density, if significant, seems likely to be positively linked to income inequality: densely populated areas experience greater inequality.

Marital rates. H7: There is a negative relationship between marital rates and income inequality.

There is some consensus that the "disintegration of the traditional two-parent, two wage-earner family" (MacManus et al. 2015, 390) contributes substantially to poverty rates and evidence of "geographic intersection of race and poverty" (Florida and Mellander 2016, 81). Thus, the family structure of a county may be found to have impacts on income inequality: if a decline in marital rates means more single-earner households, which are more likely to be lower-income households, this contributes to inequality from a low-range expansion. The expectation is for a negative relationship in which inequality increases as marital rates decrease.

Race. H8: There is a positive relationship between race (as percentage non-white) and income inequality.

Like family structure, racial demography of a county may be found to have impacts on income inequality. While marital rates and race will be examined and regressed separately, there is some evidence that controlling for family structure cancels out race effects on income mobility (Chetty et al. 2014). Thus, in a bivariate regression, I hypothesize race (as measured by non-white population) to have a positive relationship with inequality due to systemic income effects on racial minorities; in a multivariate analysis, the significance or size of that relationship may be diminished.

Political / Policy Indicator

This category engages factors which are implemented politically through policy and governance and for this study includes a county's tax rate.

Tax rates. H9: There is a positive relationship between county tax rates and income inequality.

Florida and Mellander found that regional variation in income inequality was closely linked with indicators that signal a decline in the social compact, such as unionization and taxation rates (2016), and Chetty et al. found a modest correlation between upward income mobility and local tax policy (2014, 1558). Federal policy affects national inequality rates, but it is state and local tax policies that affect inequality at those levels (Florida and Mellander 2016). There may be a degree of variance between Florida counties in terms of taxation – property tax rates, local option sales taxes, etc. – but that degree may not be substantial enough to explain inequality differences and changes. If there is a link, however, I theorize it to be positive: property taxes may tend to be regressive, and thus higher property taxes affect low-income residents to a greater degree than high-income residents, exacerbating inequality.

Many more variables that may be significant to income inequality are not being explored in this study. Some, like technical change and job skills polarization, have been found to be necessary but not sufficiently explanatory factors (Florida and Mellander 2016). High income share has been used in various studies and found to be correlative to income inequality but is less predictive than poverty (Florida and Mellander 2016). Additionally, as noted with the 99-to-1 inequality ratio, an accurate estimate of the high-income share can be problematic to determine unless using actual reported tax data by county, which may require an analysis of data that is outside the reasonable scope of this research.

METHODOLOGY AND MEASUREMENT

The study analyzed the change in income inequality for each of Florida's 67 counties from 2000 to 2016. Additionally, variables determined to be possible contributing factors to income inequality were regressed to determine the extent to which they explained income inequality growth in each year and in the change between the two.

Income Inequality

While acknowledging its shortcomings as outlined in the literature review, this research will rely on the Gini coefficient to measure income inequality, due to its broad acceptance in literature and ubiquity as a measure that can be compared to other counties, localities, states, and even nations. The data used was derived by Mark L. Burkey from U.S. Census data for 2000 and reported by the American Community Survey (ACS) for 2016. (For this and all other variables that utilized ACS figures, the ACS five-year average was selected as a best measure.)

Population Weighting

While research indicates that cities and large metro areas tend to be more unequal (Berube and Holmes 2016; Florida and Mellander 2016; Glaeser, Resseger, and Tobio 2009), I might not expect population to have as much impact on the change over time; income inequality in higher population counties may have already been substantially higher than average in 2000. Rather than utilize population as an independent variable and examine it for impact, the results of regressions were instead weighted by population in order to control for the effects of the variance. Population was defined as the actual number of residents in a county according to Census/ACS reported data.

Independent Variables

Poverty - regressed using two separate measures. The U.S. Census Bureau's Official Poverty Measure (OPM) has been the uniform standard used for poverty statistical calculations since the 1960s. Based on analyst Mollie Orshansky's calculation of poverty threshold as three times the cost of a minimum food diet (U.S. Department of Commerce 2014), the measure is updated annually and used as a baseline figure for many means-tested programs and poverty rate calculations. The measure has come under fire by many researchers for defining income solely as pre-tax income, without incorporating tax liabilities, credits, and non-cash benefits, and for making no geographic adjustments or cost-of-living allowance in its calculation (see Meyer and Sullivan 2012). The U.S. Census Bureau developed the Supplemental Poverty Measure (SPM) in 2010 (U.S. Department of Commerce 2014) as a complement to the official measure. The SPM defines "income" differently than the OPM, accounting for tax credits and some noncash benefits and subtracting some expenses, which may more accurately account for antipoverty program effectiveness; calculates family units more flexibly, accounting for equivalence scale; and bases its thresholds on expenditures for housing, food, clothing, and utilities, which helps offset regional differences in cost of living (Meyer and Sullivan 2012). When using the OPM to measure poverty, Florida ranks 33rd in the nation among states and the District of Columbia, but falls to 47th using the SPM, on a scale at which 1 indicates the least poverty and 51 the most. (Collins 2017, 6). While arguably a better measure, the SPM could not be used for this study due to its non-existence in 2000; however, Florida's relatively high cost of living, and the variation of those expenses by county, are notable and thus a second poverty variable used a threshold of

150% of the Official Poverty Measure, to offset the understating effects of the OPM. Both measures were taken from U.S. Census/ACS data for 2000 and 2016.

Housing - the proportion of cost-burdened households per county. Golden (2016) sets different levels of cost-burden, and figures are reported by the University of Florida's Shimberg Center for Housing Studies; for this measure, the levels were combined to a single figure of those who pay greater than 30% of their average monthly income for housing costs. That figure was then divided by the ACS-reported five-year estimates for the total number of households in the county in 2016 to arrive at the percentage of cost-burdened households in a county. This data was not available for 2000 and would have been beyond the scope of this research to calculate; thus, only the 2016 model incorporates a housing-cost variable.

Educational attainment - the share of the county's adults with educational attainment of a four-year college degree or higher according to U.S. Census/ACS reported data for 2000 and 2016.

Unemployment rates – the official unemployment rates by county according to the U.S. Department of Labor's Bureau of Labor Statistics for 2000 and 2016. The monthly rates for each county in a given year were compiled and averaged in order to arrive at a mean unemployment rate by county year.

Income per capita - the mean income of county residents using Census/ACS reported data. In order to properly compare the two for the change model, the 2000 income figures were translated to 2016 dollars by multiplying the 2000 income by the average Consumer Price Index (CPI) for 2016 and dividing the result by the average CPI for 2000.

Population density - the actual number of residents in a county according to U.S. Census/ACS data divided by the county's land-only area in square mileage. As some counties are substantially wetland or bodies of water upon which no residences are established, the measure did not use total area.

Marital rates - the percentage of county population over the age of 15 that is married and not separated according to Census/ACS reported data for 2000 and 2016.

Race – the percentage of the county population that is racial-minority according to Census/ACS reported data; this racial-minority percentage was computed by subtracting from 100 that percentage of county residents who self-identified as white.

Tax policies – the county property tax rate, calculated as the county's total tax revenue divided by total property values as reported to the Florida Department of Revenue for 2000 and 2016. (Note: This measure does not account for municipal or special district tax rates, which may substantially affect residents within different areas of a county.)

DATA ANALYSIS

Explaining Income Inequality in Florida Counties – 2000

To test the hypotheses seeking to explain variance in Florida county inequality, a number of analyses are conducted. Three time frames are examined: 2000, 2016 and the difference between 2000 and 2016. For each time period descriptive statistics are examined, bivariate analysis is run for each independent variable, and a multivariate best model is run using weighted least squares. Finally, the values for the dependent variable are estimated based on the best model and compared to the actual values.

Univariate Analysis

Table 1 outlines the highest, lowest, and mean values, along with standard deviations, for income inequality (Gini coefficient) and each independent variable. For this and all univariate tables, it should be noted that the mean reported in the univariate table is the average of the 67 counties used in the data. These mean values differ from the statewide averages reported by the U.S. Census on applicable variables, which is based on individual survey data.

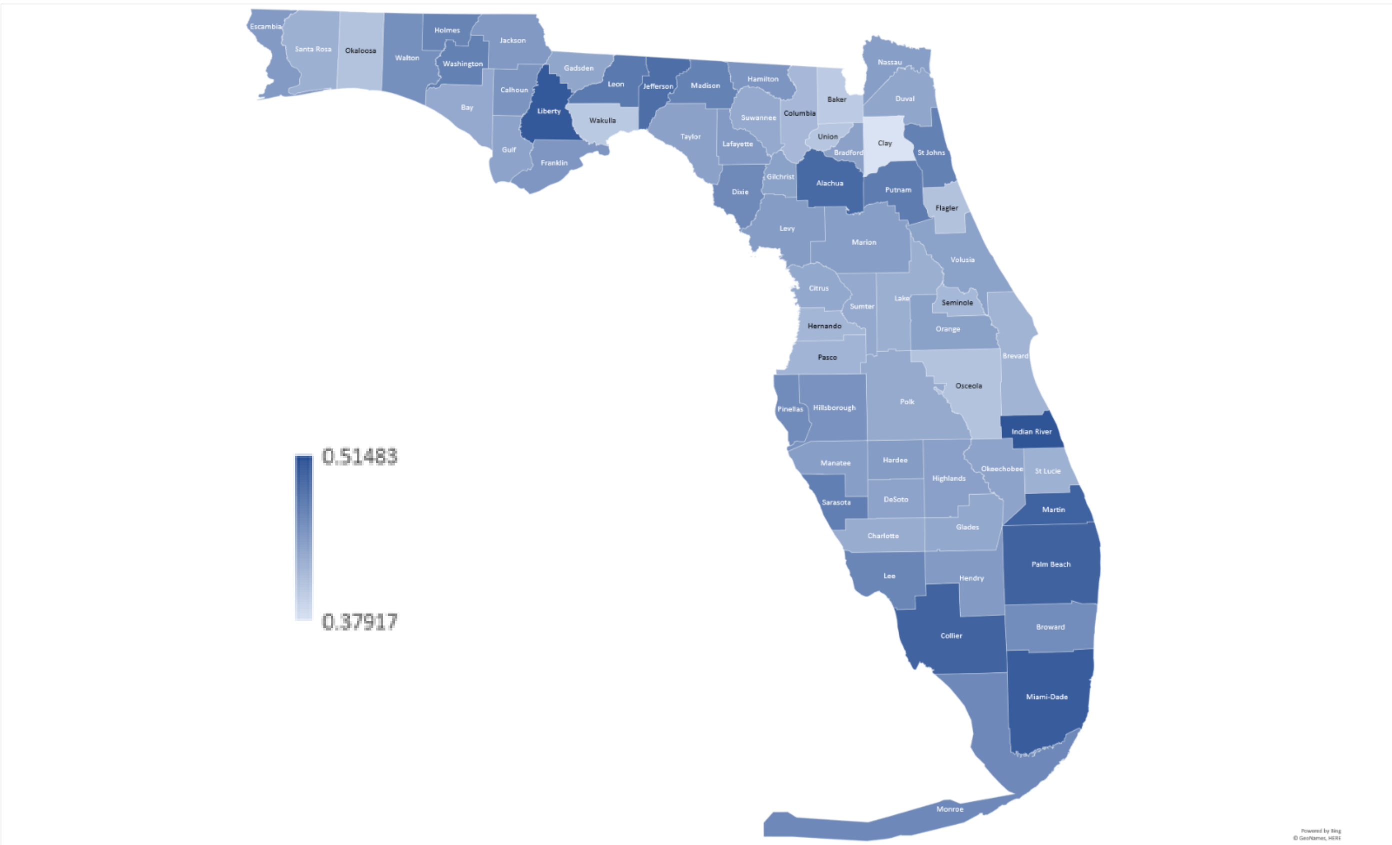
Table 1: Explaining Income Inequality in 2000 – Univariate Analysis

Dependent Variable	**Highest Value**	**Lowest Value**	**Mean Value**	**Standard Deviation**
Gini Coefficient	0.51483 (Indian River County)	0.37917 (Clay County)	0.44882	0.02808
Independent Variables	**Highest Value**	**Lowest Value**	**Mean Value**	**Standard Deviation**
Official Poverty Measure	26% (Hamilton County)	6.8% (Clay County)	14.35%	4.83%
150% of Official Poverty Measure	40.4% (Hardee County)	13.1% (Clay County)	25.06%	7.18%
Educational Attainment (College+)	41.7% (Leon County)	6.8% (Dixie County)	16.70%	8.10%
Unemployment Rate	7.3% (Hendry County)	2.9% (Monroe County)	4.04%	0.85%
Income Per Capita	$31,195 (Collier County)	$10,562 (Hamilton County)	$18,640.79	$4,773.21
Population Density	3,291.95 (Pinellas County)	8.4 (Liberty County)	287.43	487.00
Marital Rates	67.2% (Flagler County)	41.6% (Alachua County)	56.50%	5.09%
Race (% Non-White)	61.3% (Gadsden County)	5% (Citrus County)	19.70%	10.20%
County Tax Rate	2.90% (Highlands County)	1.08% (Monroe County)	1.75%	0.33%

Source: Collected by author from various sources listed in the Measurement section.

The mean Gini coefficient for Florida counties in 2000 was 0.44882, with a standard deviation of 0.02808. Indian River County had the highest inequality using this measure, at 0.51483, and Clay County experienced the lowest at 0.37917. Of the top and bottom five counties in this measure (see Appendix A), most of the counties with lowest inequality were located in the north of the state, and most of the highest-inequality counties were located along the southeastern shore. (Though oddly, one of the most equal and one of the most unequal – Liberty County and Wakulla County – are adjacent to each other in Florida's Panhandle.) Figure 3 demonstrates the range of income inequality by county using the Gini coefficient measurement; the darker a county is shaded, the higher its income inequality.

Figure 3: Income Inequality by County - 2000



The mean Official Poverty Measure (OPM) rate for Florida counties in 2000 was 14.35%, with a standard deviation of 4.83%. Hamilton County's highest rate of 26% contrasts with Clay County's, the lowest rate at 6.8%. The five highest-poverty counties were split between the northern and western Gulf portions of the state, whereas the lowest-poverty counties were somewhat spread out across the state.

The mean rate of poverty using the measure of 150% of OPM, unsurprisingly, is highly correlated with the OPM poverty rate, though at substantially higher proportions of the population. The mean rate for Florida counties in 2000 was 25.06%, with a standard deviation of 7.18%. Hardee County's 40.4% was the highest of this measure, with Clay County again at the lowest point with 13.1%. The top five counties in this measure were the same as in the OPM measure, though in a slightly different order, and four of the five lowest-OPM counties coincide with the lowest-five in this measure.

That Clay County, with the lowest income inequality, also experienced the lowest rates of both poverty measures in 2000 could suggest support for the correlation between poverty and income inequality, though none of the other counties in the top and bottom of these measures experienced positive correlations. In fact, Martin County experienced high levels of inequality but low levels of poverty at the 150% of OPM measure, which could indicate that Martin County's inequality is driven more by top shares than bottom.

The mean rate of educational attainment of a bachelor's degree or higher was 16.7%, with a standard deviation of 8.1%. Leon County had the highest rate at 41.7%, and Dixie County's rate of 6.8% was the lowest. As the county with the state capital and Florida State University, one of the state's largest colleges, Leon County's high educational attainment is unsurprising; the second-place county of Alachua is home to University of Florida and a large hospital system. The next three counties in the highest end share few geographical similarities; however, all of the lowest-attainment counties are again centered in Florida's northern Panhandle area.

The county-level mean unemployment rate in 2000 was 4.04%, with a standard deviation of 0.85%. Hendry County's high rate of 7.3% contrasts with Monroe County's 2.9%, and Hendry's unemployment was substantially higher than the next-highest rate, Hardee County's 6%. Four of the five counties with the highest unemployment rates were located in the southern third of the state, while four of the five counties with the lowest unemployment rates were located in the northern third.

The mean income per capita by county was $18,640.79, with a standard deviation of $4,773.21. Collier County's high of $31,195 contrasts with Hamilton County's $10,562. The higher income-per-capita counties were somewhat regionally diverse, but correspond with counties/MSAs that a Florida resident would tend to recognize as being relatively affluent overall, and with one exception the counties on the low range were again located in the northern panhandle.

The mean population density in Florida counties is 287.43 residents per square mile, with a standard deviation of 487 residents. The standard deviation is higher than the mean; there is substantial variance in county population density, being widely dispersed across Florida's counties. The densest (and thus, one could roughly estimate, the most urban) county is Pinellas County with 3,292 residents per square mile; the least dense / most rural is Liberty County at 8.4 residents per square mile. Most of the five most-dense counties are within Florida's four largest metropolitan statistical areas (MSAs): Pinellas (Tampa-St. Petersburg-Clearwater), Broward (Miami-Fort Lauderdale-West Palm Beach), Seminole (Orlando-Kissimmee-Sanford), Miami-Dade (Miami-Fort Lauderdale-West Palm Beach), and Duval (Jacksonville). Once again, most of the counties on the lowest range are in the northern panhandle area; only Glades County is located to the south.

The mean percentage of married adult population was 56.5% in 2000, with a standard deviation of 5.09%. Flagler County was the "most married" at 67.2%, with Alachua County the "least married" at 41.6%. Alachua County contains the city of Gainesville, home to the University of Florida; the high percentage of students in this county likely accounts in large part for the low marital rates there. While geography does not appear to be a factor with this variable, age certainly does, as the Alachua County example suggests. At a glance, the counties with the highest and lowest percentage of married residents do appear to relate to data in counties with the most- and least-aged population as reported by Pew Research Center based on Census data (Kent 2015).

The mean percentage of non-white residents of a county in 2000 was 19.7%, with a standard deviation of 10.2%. The county with the most non-white residents (and Florida's only majority-non-white county) was Gadsden County at 61.3%, and Citrus County had the fewest at 5% of the county's population. The highest percentage counties were all centered in northern panhandle counties, and the lowest percentage counties were all located along the western Gulf coast.

The mean county property tax rate was 1.75%, with a standard deviation of 0.33%. Highlands County's 2.9% was highest, with Monroe County's 1.08% the lowest. There was not much of a noticeable regional or urban/rural trend in the high/low five counties on this measure.

Bivariate Regression

Initially, bivariate and multivariate regression analyses were run using two methods: unweighted, and a weighted least squares approach using county population. After a review of the results, it was determined that for all bivariate and multivariate models, the regression using weighted least squares was a preferable model in order to correct for substantial population differences. Due to the relatively low number of units (the 67 Florida counties), a threshold of .10 was utilized throughout for statistical significance. While .05 is the traditional significance upper-limit, the range can be expanded if the sample size is low. Table 2 displays the results of the separate regressions for all 67 counties in 2000.

Table 2: Explaining Income Inequality in 2000 – Bivariate Linear Regression

Independent Variables	B	Standard Error	Beta	Significance	R-Square
Official Poverty Measure	0.004	0.001	0.437	.000***	0.191
150% of Official Poverty Measure	0.002	0.001	0.381	.001***	0.145
Educational Attainment	0.002	0.001	0.363	.003***	0.132
Unemployment Rate	0.017	0.006	0.323	.008***	0.105
Income Per Capita	2.356 E-6	0.000	0.289	.018**	0.084
Population Density	8.221 E-6	0.000	0.199	0.106	0.040
Marital Rates	-0.003	0.001	-0.415	.000***	0.172
Race	0.001	0.000	0.297	.015**	0.088
County Tax Rate	-0.014	0.011	-0.158	0.203	0.025

Significance levels = ***.01, **.05, *.10

In the weighted bivariate regression, all but two of the variables hypothesized to have a relationship with income inequality displayed a statistically significant relationship at a .05 or greater level: both poverty measures, educational attainment, unemployment rate, income per capita, marital rates, and race. Only population density and county tax rate were found to be statistically insignificant. Two relationships were negative – county tax rate and marital rates, with marital rates being the only significant relationship of the two. As for the hypothesized relationships, only the positively-correlated educational attainment measure was counter to my expectation.

At this level of analysis, the two poverty and marital rates measures appear to be the most substantial indicators of income inequality, explaining about 19, 15, and 17 percent of income inequality respectively. The beta measures for these variables are all quite low, because of the small scale by which income inequality is measured when using the Gini coefficient.

For each percentage increase to a county's Official Poverty Measure, a .004 increase to the Gini coefficient for inequality could be expected. The relationship followed the hypothesized direction, as did the secondary poverty measure, for which a one percent increase would predict a slightly lower .002 inequality measure increase. Educational attainment ran counter to the hypothesized direction: a one-percent increase in educational attainment led to a .002 increase in income inequality. While not as expected, the relationship is explainable; as noted earlier, larger shares of population with higher educational attainment may drive higher-end incomes upward and widen inequality. The unemployment rate, as hypothesized, was positively related to income inequality, where a one-percent increase in unemployment would yield a 0.017 inequality increase. Income per capita was positive as hypothesized as well: a one-dollar increase in per capita income would yield a minute but measurable increase in inequality of 0.000002356. Population density was not statistically significant within this regression, nor was the county tax rate – though had they been significant, the direction of the relationships would have been as hypothesized. Marital rates were significant and negatively related; a one percent decrease in marital rates would yield a .003 increase in inequality. Finally, race was significant and positively related as expected, with a one percent increase in non-white population of a county yielding a .001 increase in income inequality.

Best Model – Multivariate Regression

In the initial regression model for 2000, better than 86 percent of income inequality was explained by the combined variables; however, several variables (poverty, educational attainment, income per capita, and especially marital rates) fell above a comfortable variance influence factor (VIF) statistic range (see Appendix B). Of these, marital rates had the highest VIF, correlating closely with race, population density, educational attainment, and poverty. Removing the marital rates variable from the regression eliminated all problematic VIF statistics and yielded a best model. It should also be noted that in every multivariate regression, only the Official Poverty Measure was utilized, as it was anticipated that the two poverty measures together would be far too closely correlated to generate an acceptable regression model.

Table 3 contains the results for the best-model multivariate regression analysis for income inequality in 67 Florida counties in 2000.

Table 3: Explaining Income Inequality in 2000 – Multivariate Linear Regression

Independent Variables	B	Standard Error	Beta	Significance	VIF
(Constant)	.141	.021		.000	
Official Poverty Measure	0.010	0.001	1.221	.000***	4.183
Educational Attainment	-0.001	0.000	-0.172	.071*	3.731
Unemployment Rate	0.005	0.004	0.088	0.221	2.129
Income Per Capita	9.473E-06	0.000	1.163	.000***	5.011
Population Density	7.683E-06	0.000	0.185	.001***	1.128
Race	0.000	0.000	-0.082	0.223	1.892
County Tax Rate	-0.007	0.004	-0.082	0.106	1.054

Significance levels = ***.01, **.05, *.10

R-Square: .861 Adjusted R-Square: .844 F Change: 52.196 Durbin-Watson: 1.644

In the multivariate best model, 86 percent of the variance in income inequality is explained by the measured independent variables. The F-change statistic supports significance of the model as a whole, and the Durbin-Watson score indicates a relatively low risk of multi-collinearity – though it should be noted that the VIF for income per capita is just slightly above a satisfactory range and was fairly strongly correlated to educational attainment and poverty level, though again these correlations should be unsurprising. This multi-collinearity is also demonstrated in the standardized coefficients of Beta for poverty and income per capita; the value greater than one suggests a collinearity between these predictors. Four of the seven tested variables were statistically significant: poverty, educational attainment, income per capita, and population density. Interestingly, this model supported all the variable's hypothesized directions, as educational attainment shifted from a positive to a negative relationship with income inequality.

In the multivariate regression model, a one percent increase in poverty would correspond with a .010 increase in income inequality. A one percent change in educational attainment leads to a .001 opposing shift in income inequality – now a relationship that supports the hypothesized direction, indicating that controlling for other measures yields the expected results. A one person per square mile increase in population density contributes to a 0.000007683 increase in income inequality. A one dollar increase in income per capita contributes to a 0.000009473 increase in income inequality, with the changes in both of these predictors being positive as hypothesized. Unemployment rate and race lost statistical significance in this multivariate model, and county tax rate continued to be statistically insignificant. This finding is particularly interesting to me in terms of race, as it seems that once controlled for poverty, educational, and per capita income factors, race is less of a predictor. (I continue to hypothesize that race in fact remains salient, in the sense of strong systemic impacts of the significant predictors upon many people of color.)

Predictive Model

Values from the best-model regression analysis were used to attempt to predict the Gini coefficient for each county and determine to what extent the model did in fact facilitate prediction of income inequality by county. Table 4 contains the results for the five largest underestimates and overestimates of predicted county income inequality in Florida in 2000.

Table 4: Predicting Income Inequality in 2000

Underestimates		**Actual Gini**	**Predicted Gini**	**Difference**	**Percentage**
1	Jefferson County	0.49108	0.45048	0.0406	8.27%
2	Indian River County	0.51483	0.47708	0.03775	7.33%
3	Miami-Dade County	0.5071	0.47112	0.03598	7.10%
4	Gilchrist County	0.44232	0.41644	0.02588	5.85%
5	Liberty County	0.51082	0.48448	0.02634	5.16%
Overestimates		**Actual Gini**	**Predicted Gini**	**Difference**	**Percentage**
1	DeSoto County	0.44009	0.48339	-0.0433	-9.84%
2	Clay County	0.37917	0.41086	-0.03169	-8.36%
3	Baker County	0.40289	0.43112	-0.02823	-7.01%
4	Hendry County	0.4488	0.47899	-0.03019	-6.73%
5	Hardee County	0.44639	0.47519	-0.0288	-6.45%

Twenty-eight of the counties' inequality levels were overestimated to varying degrees, and the remaining 39 counties were underestimated. All estimates fell within a ten-percent margin higher or lower than actual income inequality. Regionally, many of the counties that were over- or under-estimated were found in either the southern and northern parts of the state. Population seems to also be a factor, which may be a result of weighting the model: three of the five counties in both most underestimated and most overestimated are in the 20 lowest-population counties.

Explaining Income Inequality in Florida Counties - 2016

Univariate Analysis

Table 5 outlines the highest, lowest, and mean values, along with standard deviations, for income inequality (Gini coefficient) and each independent variable.

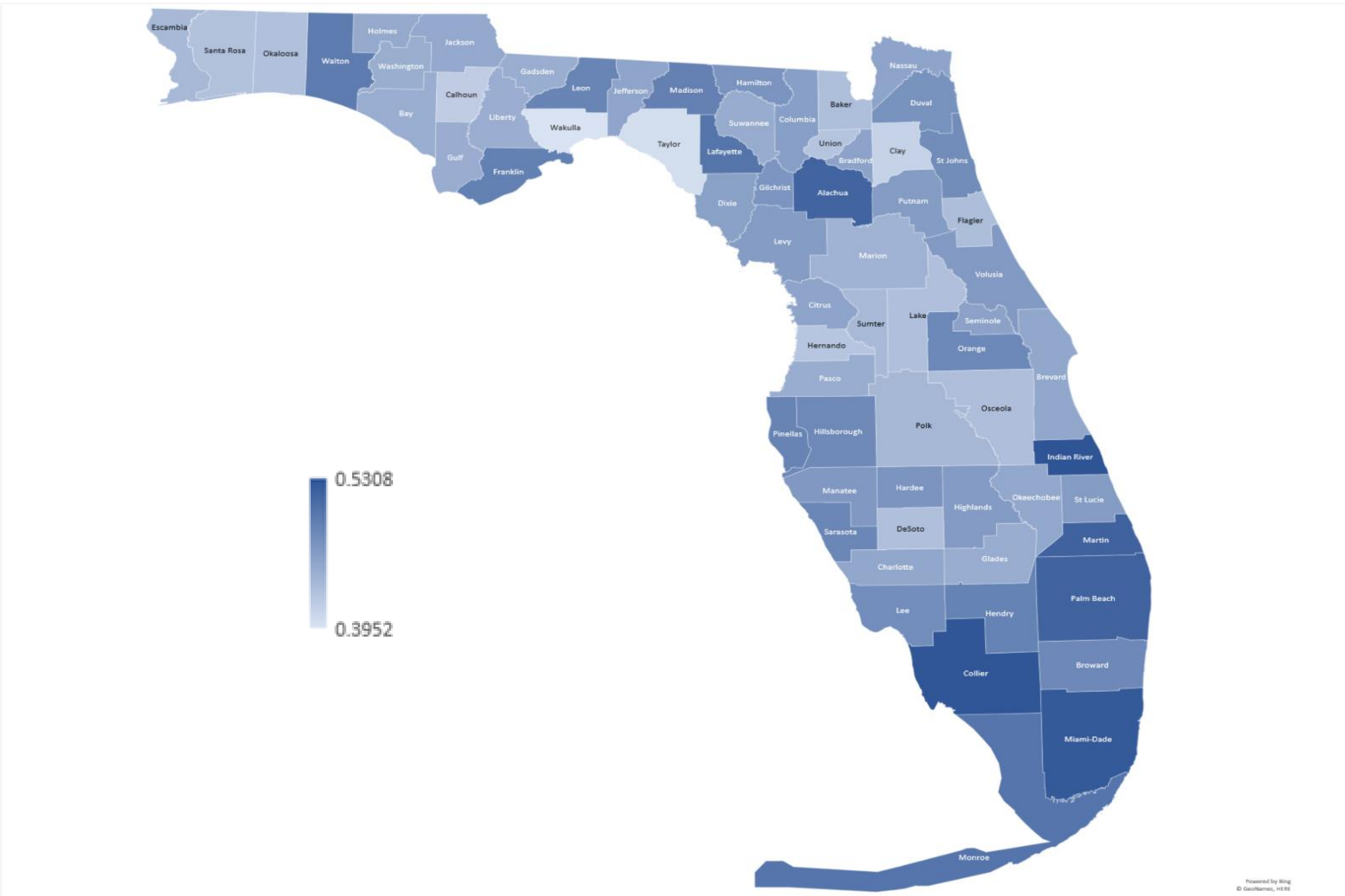
Table 5: Explaining Income Inequality in 2016 – Univariate Analysis

Dependent Variable	Highest Value	Lowest Value	Mean Value	Standard Deviation
Gini Coefficient	0.5308 (Indian River County)	0.3952 (Wakulla County)	0.46054	0.03024
Independent Variables	**Highest Value**	**Lowest Value**	**Mean Value**	**Standard Deviation**
Official Poverty Measure	29.9% (DeSoto County)	9% (St. Johns County)	17.80%	5.10%
150% of Official Poverty Measure	44.3% (Hardee County)	15.4% (St. Johns County)	29.30%	6.90%
Cost-Burdened Households	59.6% (Miami-Dade County)	15.9% (Gilchrist County)	37.50%	8.20%
Educational Attainment (College+)	45.2% (Leon County)	6.4% (Dixie County)	21.00%	9.30%
Unemployment Rate	8.5% (Hendry County)	3.2% (Monroe County)	5.10%	90.00%
Income Per Capita	$39,616 (Collier County)	$12,943 (Union County)	$24,164.46	$6,156.74
Population Density	3,431.51 (Pinellas County)	9.92 (Liberty County)	356.50	546.64
Marital Rates	61.7% (Sumter County)	35.9% (Union County)	47.10%	5.30%
Race (% Non-White)	59.1% (Gadsden County)	6.7% (Citrus County)	20.70%	9.80%
County Tax Rate	1.27% (Duval County)	0.33% (Walton County)	0.76%	0.20%

Source: Collected by author from various sources listed in the Measurement section.

The mean Gini coefficient for Florida counties in 2016 increased to 0.46054, with an increased standard deviation of 0.03024. Indian River County again had the highest inequality using this measure, at 0.5308, and Wakulla County experienced the lowest at 0.3952. Of the top and bottom five counties in this measure (see Appendix A), four of the five counties in the top were unchanged from 2000; only Collier County was a new entry in the five most unequal counties, replacing Liberty County. Though not all the same as in 2000, once again, most of the counties with the lowest inequality were located in the north of the state. Figure 4 demonstrates the range of income inequality by county using the Gini coefficient measurement.

Figure 4: Income Inequality by County - 2016



The mean Official Poverty Measure (OPM) rate for Florida counties in 2016 increased to 17.8%, with a standard deviation of 5.1%. DeSoto County's highest rate of 29.9% contrasts with that of St. Johns County, the lowest rate at 9%. The five highest-poverty counties were largely the same as in 2000 and again split between the northern and western Gulf portions of the state, whereas the lowest-poverty counties saw two new entries and remained somewhat spread out across the state.

The mean secondary poverty measure rate for Florida counties in 2016 was 29.3%, with a standard deviation of 6.9% (a lower deviation than in 2000). Hardee County's 44.3% was the highest of this measure, with St. Johns County again at the lowest point with 15.4%. In 2016 only three of the top five counties in this measure were the same as in the OPM measure, though in a slightly different order, but again four of the five lowest-OPM counties coincide with the lowest-five in this measure.

More than one-third of Florida's residents on average spend greater than 30% of their income on housing: the mean rate of cost-burden by county was 37.5%, with a standard deviation of 8.2%. Miami-Dade residents are the most likely to experience cost-burden, at 59.6%, and Gilchrist County residents the least likely, at 15.9%. In the top five counties, over 50% of their residents are cost-burdened and most are in densely populated MSAs (with the exception of Monroe, a tourism-centered county comprising the Florida Keys and surrounding areas, which are heavy on higher-priced and water-proximate properties).

The mean rate of educational attainment of a bachelor's degree or higher increased to 21%, with a standard deviation of 9.3%. Leon County again boasts the highest rate at 45.2%, and Dixie County's rate remained lowest, declining to 6.4%. The counties with highest attainment rates vary little from 2000; however, the lowest-attainment counties are more dispersed throughout Florida in 2016 than in 2000.

The county-level mean unemployment rate in 2000 was 4.04%, with a standard deviation of 0.85%. Hendry County again held the highest rate at 8.5%, contrasting once more with Monroe County's 3.2%. Hendry's unemployment also remained substantially higher than the next-highest rate, Sumter County's 7.1%. In 2016, both the high- and low-unemployment counties were more dispersed throughout the state than in 2000.

The mean income per capita by county was $24,164.46, with a standard deviation of $6,156.74. Collier County maintained the top spot with $39,616, contrasted with Union County's $12,943. Four of the five highest and lowest income-per-capita counties remained the same as in 2000.

The mean population density in Florida counties in 2016 increased to 356.5 residents per square mile, with a standard deviation of 546.6 residents. The densest (and thus ostensibly the most urban) county remains Pinellas County with 3,431.5 residents per square mile; the least dense / most rural is Liberty County at 9.9 residents per square mile. Most of the five most-dense counties are largely unchanged, though Orange County, within the Orlando-Kissimmee-Sanford MSA, supplanted Duval County on density. Once again, all counties on the lowest range are in the northern panhandle area, with the exception of Glades County.

The mean percentage of married adult population declined to 47.1% in 2016, with a standard deviation of 5.30%. Sumter County was the "most married" at 61.7%, with Union County the "least married" at 35.9%. While the counties on the highest/lowest margins shifted somewhat, it remained the case that the counties seemed correlated to the most- and least-aged population (Kent 2015).

The mean percentage of non-white residents of a county in 2016 increased one point to 20.7%, with a standard deviation of 9.8%. Florida's only majority-non-white county continued to be Gadsden County at 59.1%, slightly lower than in 2000, and Citrus had the fewest – but more than in 2000 – at 6.7% of the county's population. The highest percentage counties remained the same, and in the same order, as in 2000, though the lowest percentage counties changed and were no longer regionally concentrated.

County tax rates declined substantially from 2000 across the entire state. The mean county property tax rate was down nearly a full percent, to 0.76%, with a standard deviation of 0.20%. Duval County's 1.27% was highest, with Walton County's 0.33% the lowest. There remained not much of a noticeable regional or urban/rural trend in the low five counties on this measure, but four of five high-rate counties were in the north of the state. The counties also shuffled from 2000, with only Alachua appearing in the top five for both years, and only Okaloosa and Collier counties remaining for 2016's lowest end.

Bivariate Regression

Table 6 displays the results of the separate regressions for all 67 counties in 2016.

Table 6: Explaining Income Inequality in 2016 – Bivariate Linear Regression

Independent Variables	B	Standard Error	Beta	Significance	R-Square
Official Poverty Measure	0.002	0.001	0.246	0.045**	0.061
150% of Official Poverty Measure	0.002	0.001	0.239	.051*	0.057
Cost Burdened Housing	0.003	0.000	0.700	.000***	0.490
Educational Attainment	0.002	0.001	0.496	.000***	0.246
Unemployment Rate	-0.004	0.007	-0.066	0.594	0.004
Income Per Capita	2.664E-06	0.000	0.376	.002***	0.142
Population Density	1.511E-05	0.000	0.358	.003***	0.128
Marital Rate	-0.003	0.001	-0.449	.000***	0.201
Race	0.001	0.000	0.172	0.163	0.030
County Tax Rate	-0.009	0.020	-0.055	0.661	0.003

Significance levels = ***.01, **.05, *.10

In the weighted bivariate regression, all but three of the variables hypothesized to have a relationship with income inequality displayed a statistically significant relationship at a .05 or greater level: both poverty measures, cost-burdened housing, educational attainment, income per capita, population density, and marital rates. Interestingly, unemployment rates and race lost significance in 2016 where it was present in 2000; additionally, county tax rate continued to be statistically insignificant. Three relationships were negative – unemployment rate, marital rates, and county tax rate, with marital rates being the only significant relationship of the two. As for the hypothesized relationships, again only the positively-correlated educational attainment measure was counter to my expectation.

In 2016 as compared to 2000, the two poverty measures lost some of their substantive impact and all variables were dwarfed in this sense by cost-burdened housing, which explained 49% of income inequality. Educational attainment and marital rates measures were the next most substantial indicators of income inequality, explaining about 25 and 20 percent of income inequality respectively.

For each percentage increase to either a county's Official Poverty Measure or the secondary poverty measure, a .002 increase to the Gini coefficient for inequality could be expected. The relationship followed the hypothesized direction as in 2000. The additional variable of cost-burdened housing, unique to the 2016 analysis, was positively correlated as hypothesized; a one-percent increase in the number of residents who lived in cost-burden circumstances would result in a .003 increase in the Gini coefficient. Educational attainment again ran counter to the hypothesized direction: a one-percent increase in educational attainment led to a .002 increase in income inequality. Running counter to the findings from 2000, the unemployment rate was not statistically significant, and once again neither was the county tax rate. Income per capita was as hypothesized as well, with a positive link in which a one-dollar increase in per capita income would yield a minute but measurable increase in inequality of 0.000002664. Population density was statistically significant within the 2016 regression, unlike in 2000; a one person per square mile increase in population density would lead to a 0.00001511 increase in income inequality. Marital rates were significant and negatively related and duplicative of 2016; a one percent decrease in marital rates would yield a .003 increase in inequality. Unlike in 2000, race was not statistically significant in this regression.

Best Model – Multivariate Regression

The initial regression of the 2016 variables had some problematic correlations (see Appendix B); while the model appeared to explain approximately 89 percent of income inequality variance, two variables – income per capita and marital rates – had a VIF well over 5, indicating a too-proximate correlation. The marital rates variable was also substantially correlated to poverty and population density measures, unsurprisingly – additional adults in a household will naturally increase density, and additional earners in a household decreases the likelihood of that household being below a poverty line – but because of these multiple close correlations, marital rate was removed from the model. Removing marital rates from the model retained the 89 percent explanatory rate, but income per capita remained problematic based on the VIF statistic, too closely correlated to educational attainment, and so the income per capita variable was also removed from the regression. The resultant regression model was deemed the best model for this analysis.

Table 7 contains the results for the best-model multivariate regression analysis for income inequality in 67 Florida counties in 2016.

Table 7: Explaining Income Inequality in 2016 – Multivariate Linear Regression

Independent Variables	B	Standard Error	Beta	Significance	VIF
(Constant)	0.216	0.034		.000	
Official Poverty Measure	0.003	0.001	0.259	.007***	1.853
Cost-Burdened Housing	0.002	0.000	0.531	.000***	1.715
Educational Attainment	0.003	0.000	0.626	.000***	2.096
Unemployment Rate	0.012	0.005	0.212	.031**	1.956
Population Density	5.986E-06	0.000	0.142	.076*	1.317
Race	-0.001	0.000	-0.326	.000***	1.553
County Tax Rate	0.008	0.012	0.052	0.504	1.267

Significance levels = ***.01, **.05, *.10

R-Square: .724 Adjusted R-Square: .691 F Change: 22.094 Durbin-Watson: 2.254

The removal of two variables did appear to impact the R-square, and the best model's predictive measure dropped to about 72 percent; however, the Durbin-Watson of 2.254 combined with the predictors' VIF rates all near or below 2.0 indicates a lower multicollinearity risk than in the 2000 model. The standardized coefficients of beta further support this low multicollinearity to a stronger degree than in the 2000 model. The F-statistic of the model is sufficient for statistical significance. Once again, the directions of a few relationships shifted; county tax rate and educational attainment were again positively correlated with income inequality, though only educational attainment was statistically significant in this model. The number of statistically significant predictors increased compared to 2000, up to six of seven in this regression; only county tax rates remained statistically insignificant.

In the multivariate regression model, a one percent increase in poverty would correspond with a .003 increase in the Gini coefficient of income inequality. A one percent increase in county residents in a cost-burdened housing situation would result in a .002 increase in the Gini coefficient of income inequality, supporting the hypothesis. A one percent increase in educational attainment would link to a .003 increase in income inequality – no longer a relationship that supports the hypothesized direction and back in line with the bivariate regression results. Unemployment rate regains its statistical significance and hypothesis support in this model, with a one percent increase in unemployment leading to a .012 increase to inequality. A one person per square mile increase in population density contributes to a 0.000005986 increase in income inequality as hypothesized. Race returned to significance in this model, for the first time in an opposite direction as hypothesized: according to this regression, a one percent increase in percentage of non-white residents in a county would predict a .001 decrease in income inequality. County tax rate continued to be statistically insignificant (though had it been significant, it would have been opposite the hypothesized direction). The strongest predictors of income inequality in this model, according to the standardized coefficients of beta, were educational attainment levels and cost-burdened housing populations.

Predictive Model

As with 2000, values from the best-model regression analysis were used to attempt to predict the Gini coefficient for each county and determine to what extent the model did in fact enable a research to predict income inequality by county. Table 8 contains the results for the five largest underestimates and overestimates of predicted county income inequality in Florida in 2016.

Table 8: Predicting Income Inequality in 2016

Underestimates		Actual Gini	Predicted Gini	Difference	Percentage
1	Lafayette County	0.5006	0.39262	0.10798	21.57%
2	Madison County	0.4883	0.41686	0.07144	14.63%
3	Liberty County	0.4455	0.38293	0.06257	14.04%
4	Gilchrist County	0.4695	0.40406	0.06544	13.94%
5	Franklin County	0.4886	0.4238	0.0648	13.26%
Overestimates		**Actual Gini**	**Predicted Gini**	**Difference**	**Percentage**
1	Osceola County	0.4304	0.48117	-0.05077	-11.80%
2	Leon County	0.4848	0.52396	-0.03916	-8.08%
3	Flagler County	0.4306	0.46383	-0.03323	-7.72%
4	Sumter County	0.4344	0.46724	-0.03284	-7.56%
5	Hernando County	0.4236	0.44961	-0.02601	-6.14%

Thirty-nine of the counties' inequality levels were overestimated to varying degrees, and the remaining 28 counties were underestimated. In this analysis, while all but one overestimate fell within a ten-percent margin of the actual number, nine counties were underestimated by greater than 10 percent, and the model underestimated one county – Lafayette – by over 20 percent. Regionally, all five underestimated counties were in the northern portion of the state, and the counties that were overestimated were found in the central and northern parts of the state. Population again seems to also be a factor at the underestimated end, which may be a result of weighting the model: all five underestimated counties are in the 20 lowest-population counties, though none of the overestimated counties are in that selection of counties.

Explaining Change in Income Inequality in Florida Counties – 2000 to 2016

Univariate Analysis

Table 9 outlines the highest, lowest, and mean values, along with standard deviations, for income inequality (Gini coefficient) and each independent variable.

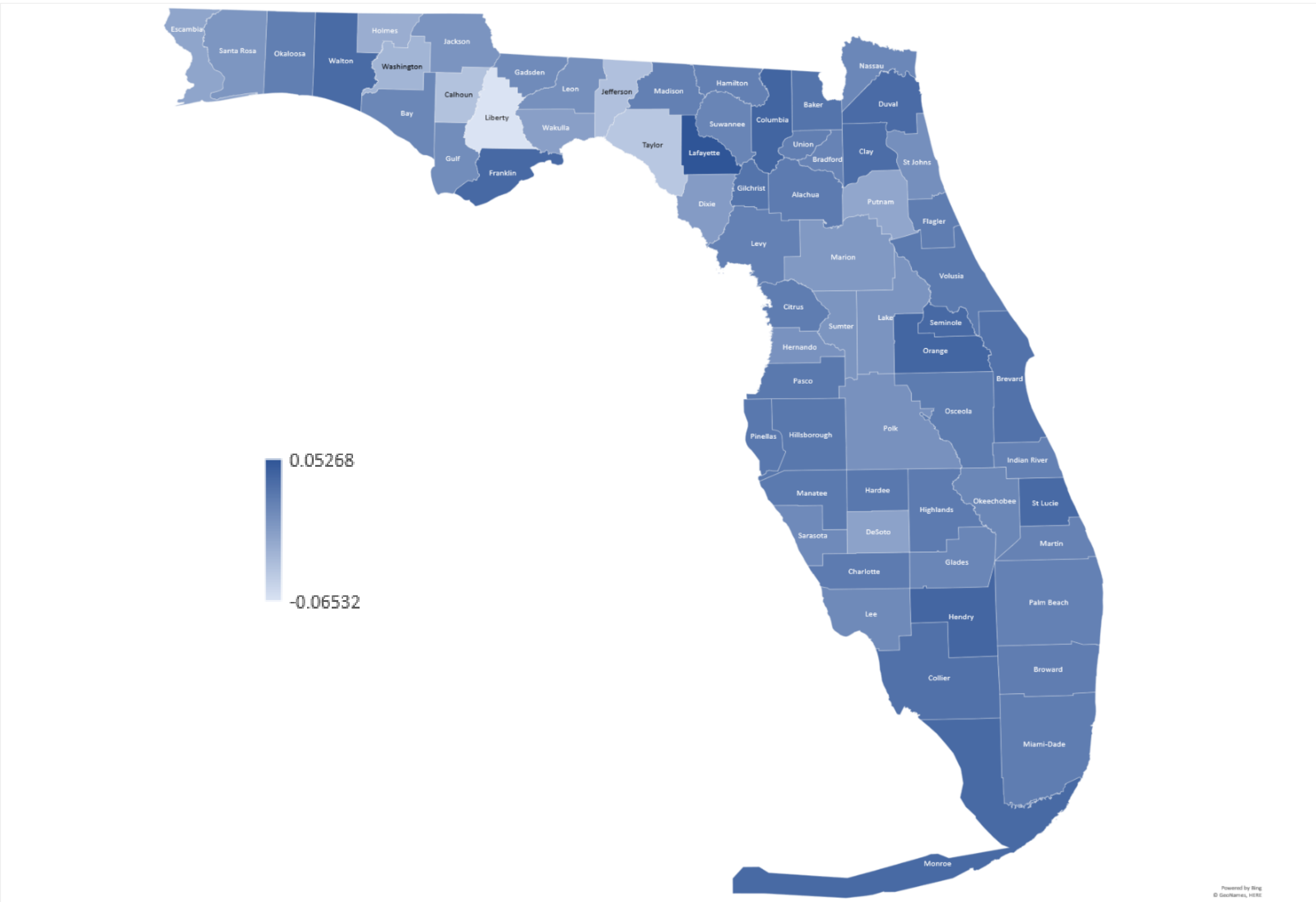
Table 9: Explaining Change in Income Inequality, 2000 to 2016 – Univariate Analysis

Dependent Variable	**Highest Value**	**Lowest Value**	**Mean Value**	**Standard Deviation**
Gini Coefficient	.05268 (Lafayette County)	-.06532 (Liberty County)	0.0117	0.02139
Independent Variables	**Highest Value**	**Lowest Value**	**Mean Value**	**Standard Deviation**
Official Poverty Measure	9.7% (Gilchrist County)	-6.9% (Calhoun County)	3.43%	2.90%
150% of Official Poverty Measure	11.5% (Osceola County)	-6.6% (Franklin County)	4.25%	3.66%
Educational Attainment (College+)	17.6% (Sumter County)	-0.9% (Glades County)	4.28%	2.80%
Unemployment Rate	2.8% (Sumter County)	-1.4% (Gulf County)	1.04%	0.66%
Income Per Capita	$8,133.86 (Sumter County)	-6,789.67 (Liberty County)	($1,816.49)	2344.55
Population Density	402.56 (Orange County)	-1.37 (Monroe County)	69.07	90.50
Marital Rates	-0.7% (Franklin County)	-19.3% (Glades County)	-9.38%	3.13%
Race (% Non-White)	8.7% (Broward County)	-11.6% (Hardee County)	0.96%	3.81%
County Tax Rate	-0.54% (Charlotte County)	-2.08% (Highlands County)	-0.99%	0.28%

Source: Collected by author from various sources listed in the Measurement section.

The mean Gini coefficient change in income inequality from 2000 to 20016 was 0.0117, with a standard deviation of 0.02139; the county with the largest increase in inequality from 2000 to 2016 was Lafayette (a .05268 change) and the greatest decline in inequality was in Liberty County (a -.06532 change). Only 14 of Florida's 67 counties saw a decline in inequality. Of those 14, all were located in the northern and panhandle area, with the exception of DeSoto County and northern-adjacent Sumter and Marion counties. Figure 5 demonstrates the range of income inequality change by county using the Gini coefficient measurement.

Figure 5: Income Inequality Change by County - 2000 to 2016



The mean Official Poverty Measure (OPM) change for Florida counties in 2000 was 3.43%, with a standard deviation of 2.90%. Gilchrist County had the largest increase from 2000 to 2016 (9.7%), and Calhoun County the largest decline (6.9%).

The mean secondary poverty measurement rate change for Florida counties was 4.25% with a standard deviation of change of 3.66%. Osceola County's 11.5% jump in this poverty measure makes it the highest, and Franklin County saw the greatest decline at 6.6%.

The mean rate of educational attainment of a bachelor's degree or higher changed by a mean of 5.6%, with a standard deviation change of 2.80%. Sumter County's 17.6% leap made it by far the greatest gain in attainment from 2000, and only two counties, Dixie and Glades, registered a decline in attainment, Glades County's being the greater at -0.9%.

The county-level mean unemployment rate change from 2000 to 2016 was 1.04%, with a standard deviation in change of 0.66%. Sumter County had the largest shift, a 2.8% increase, and once again the number of counties who experienced a decline was quite small – only Union (-0.1%), Okeechobee (-0.3%) and Gulf counties (-1.4%).

Income per capita by county also declined in the period between 2000 and 2016, by a mean of $-1,816.49, with a standard deviation of $2,344.55. After adjusting for inflation, only 14 counties had an increase in per capita income; Sumter County's $8,134 increase dwarfed the next highest increase, Walton County's $3,111. Most counties saw a fairly substantial decrease, the greatest of which was Liberty County's decline of $-6,790 per capita. With the exception of Monroe County, all counties with a per capita income increase were northern or northern-adjacent; notable, as this was the same case for the only counties to experience a decline in income inequality.

The mean population density in Florida counties increased between 2000 and 2016 by a mean of 174.31 residents per square mile, with a standard deviation in density of 90.50 residents. Orange County had the greatest increase in density with a 402.5 jump. Density only declined, by very small degree, in two counties, Madison and Monroe; Monroe County's was the greatest at -1.37.

The mean percentage of married adult population also declined between 2000 and 2016, by a mean of -9.38%, with a standard deviation of 3.13% of change. Every county experienced a decline in married population, but Franklin County had the smallest decrease at -0.7%. Glades County's decline of -19.3% was greatest.

The percentage of non-white residents of a county between 2000 and 2016 increased by a mean of 0.96%, with a standard deviation of 3.81%. Broward County's increase of 8.7% was the largest by a wide margin (Clay County's second-place shift was three points lower); Hardee County had an 11.6% decline in non-white residents. (The counties of Okeechobee, DeSoto, Hendry, and Hardee, the four with the largest declines, are all in close proximity.)

County tax rates declined substantially from 2000 to 2016 by a mean of 0.99%, with a standard deviation of 0.28% of change. While no county saw an increase, Charlotte County's tax rate declined the least at -0.54%, and Highlands County had the greatest decrease at -2.08%.

Of particular note in the univariate change model between 2000 and 2016 is Sumter County. Sumter appeared on none of the high/low five counties for any variables in 2000, but features prominently in several measures for 2016, including the two poverty measures (low), cost-burdened housing (low, but cannot be compared to 2000), unemployment (high), and marital rates (highest). Sumter and Marion Counties were also two of the only 14 counties that experienced a decline in income inequality. I am ascribing these sizable shifts to what I would call, "The Villages Effect." The Villages, a massive rapid-growth retirement community that spans portions of Lake, Marion, and especially Sumter Counties, might well warrant its own deeper analysis within these measures. The Villages Effect appears profound even at a glance. Sumter County experienced huge surges in educational attainment and per capita income, the second-largest decline in both poverty measures, and while every county experienced a drop in marital rates, Sumter experienced the second-lowest drop. It also homogenized: there was a substantial decrease in non-white population. It has the highest unemployment rate increase, however, which is intriguing. Retirement is not a factor in unemployment rates, so one theory is that some retirees are looking for full- or part-time work, or simply that economic growth and business development in the area has not quite kept pace with explosive population growth.

Bivariate Regression

Table 10 displays the results of the separate regressions for the change in variables between 2000 and 2016 for all 67 counties.

Table 10: Explaining Change in Income Inequality, 2000 to 2016 – Bivariate Linear Regression

Independent Variables	B	Standard Error	Beta	Significance	R-Square
Official Poverty Measure	0.002	0.001	0.294	.016**	0.087
150% of Official Poverty Measure	0.002	0.001	0.291	.017**	0.085
Educational Attainment	0.001	0.001	0.154	0.213	0.024
Unemployment Rate	-2.014E-05	0.004	-0.001	0.995	0.000
Income Per Capita	6.317E-07	0.000	0.091	0.464	0.008
Population Density	4.964E-05	0.000	0.447	.000***	0.199
Marital Rates	0.002	0.001	0.202	0.101	0.041
Race	0.000	0.000	0.122	0.324	0.015
County Tax Rate	0.003	0.005	0.069	0.581	0.005

Significance levels = ***.01, **.05, *.10

In the weighted bivariate regression, only three of the variables hypothesized to have a relationship with income inequality displayed a statistically significant relationship at a .10 or stronger level: both poverty measures and population density. The relationships were in the hypothesized direction. Educational attainment, unemployment rate, income per capita, marital rates, race, and county tax rates were all not statistically significant (though marital rates were extremely close, at .101).

When explaining the change in income inequality over time, as opposed to the level of income inequality at a given point in time, of the three statistically significant predictors, population density appears to be the strongest, accounting for nearly 20 percent of the fluctuation. The poverty measures have a lower impact, around nine percent each.

Each percentage increase to either a county's Official Poverty Measure or the secondary poverty measure predicted a .002 increase to the Gini coefficient for inequality. The relationship followed the hypothesized direction as in 2000 and 2016. Population density was statistically significant within the change predictive model; a one person per square mile increase in population density would lead to a 0.00004964 increase in income inequality. Had they been significant, then the relationship between income inequality and educational attainment, unemployment rate, marital rates, and county tax rates would have been opposite the hypothesized direction; however, all of these, along with per capita income and race, were not statistically significant.

Full Model – Multivariate Regression

The initial full-model regression of the change from 2000 to 2016 was also deemed the best model for this analysis; with no evident multi-collinearity problems, all the independent variables were retained for the analysis (with the exception of the secondary poverty measure removed from all multivariate regressions).

Table 11 contains the results for the best-model multivariate regression analysis for change in income inequality in 67 Florida counties between 2000 and 2016.

Table 11: Explaining Change in Income Inequality, 2000 to 2016 – Multivariate Linear Regression

Independent Variables	B	Standard Error	Beta	Significance	VIF
(Constant)	0.032	0.012		.008	
Official Poverty Measure	0.004	0.001	0.519	.000***	1.880
Educational Attainment	-7.671E-05	0.001	-0.011	0.930	1.630
Unemployment Rate	-0.006	0.003	-0.211	.053*	1.252
Income Per Capita	2.974E-06	0.000	0.428	.002***	1.843
Population Density	4.977E-05	0.000	0.448	.000***	1.307
Marital rates	0.001	0.001	0.186	0.143	1.712
Race	0.001	0.000	0.189	0.121	1.590
County Tax Rate	0.011	0.004	0.281	.012**	1.296

Significance levels = ***.01, **.05, *.10

R-Square: .470 Adjusted R-Square: .397 F Change: 6.429 Durbin-Watson: 1.807

According to the R-square, the model's predictive measure for change was substantially lower than for the point-in-time models, at 47 percent. The Durbin-Watson of 1.807 combined with the predictors' VIF rates all below 2.0 indicates a low multicollinearity risk. The F-statistic of the model is sufficient for statistical significance. The model contains five statistically significant predictors: poverty, unemployment rate, income per capita, population density, and county tax rate. (Cost burdened housing could not be assessed for impact over time due to its omission from the 2000 model.)

In the multivariate regression model, a one percent increase in poverty would correspond with a .004 increase in the Gini coefficient of income inequality. Unemployment rate again holds statistical significance but loses its support of the hypothesized direction in this model, with a -.006 increase to inequality tied to a one percent change in unemployment. Per capita income was statistically significant in the hypothesized direction, with a one dollar increase in per capita income leading to a 0.000002974 increase in the Gini coefficient. A one person per square mile increase in population density contributes to a 0.00004977 increase in income inequality in the direction hypothesized. County tax rate finally achieves significance in this final model, though opposite the hypothesized direction, and a one percent increase in county tax rate corresponds with a .011 increase in income inequality. Within this model, educational attainment, marital rates, and race were not statistically significant predictors of a change over time in income inequality. The strongest predictors of income inequality in this model, according to the standardized coefficients of beta, were poverty, per capita income, and population density.

Predictive Model

As the 2000-2016 change model was substantially less explanatory of variance than either the 2000 or 2016 models, the predictive capabilities of this model were, understandably, less astute, as demonstrated in Table 12.

Table 12: Predicting Change in Income Inequality, 2000 to 2016

Underestimates		**Actual Gini**	**Predicted Gini**	**Difference**
1	Lafayette County	0.05268	0.01133	0.04135
2	Hendry County	0.03820	-0.00098	0.03918
3	Baker County	0.02711	-0.00001	0.02712
4	Highlands County	0.02078	-0.00232	0.02310
5	Hardee County	0.02381	0.00214	0.02167
Overestimates				
1	Liberty County	-0.06532	-0.02732	-0.03800
2	Holmes County	-0.02084	0.01696	-0.03780
3	Washington County	-0.02679	0.00210	-0.02889
4	Jefferson County	-0.03658	-0.01021	-0.02637
5	DeSoto County	-0.01139	0.01203	-0.02342

Regionally, the counties that were most underestimated and overestimated were found in the northern and southwestern portions of the state and tended to be lower-population counties. This finding appears consistent with both 2000 and 2016 models in that these regions and less populous areas, particularly the northern panhandle, are some of the most difficult in which to predict income inequality.

Discussion of Results

The two predictors that shared statistical significance in all three models, poverty and population density, maintained a positive relationship to income inequality throughout, as hypothesized. Only one predictor, marital rates, either never achieved significance (the change model) or had to be removed from the analysis due to multicollinearity issues (2000 and 2016). Educational attainment had significance in the 2000 and 2016 models, but not the change model, and its relationship to income inequality changed direction from negative as hypothesized in 2000 to positive in 2016. This may support findings by researchers like Bivens et al. who noted the stall or decline in wages for all including college graduates, preventing those with an education from substantially impacting the inequality curve. Educational attainment was difficult to hypothesize because of such competing theories, so the inconsistent findings are somewhat unsurprising. Unemployment rates were significant only in the 2016 and change models, but changed direction there as well: positively correlated to income inequality in 2016, as hypothesized, and negatively correlated in the change model. County tax rates only gained significance in the change model, and in being positively correlated to income inequality, ran counter to the hypothesized direction. One possibility is that tax rate achieved significance in the change model due to how substantially the rate changed in the time span. Nonetheless, it is noteworthy that in 2016, four of the five highest-tax-rate counties were in the north of the state, where poverty rates tended to run high and inequality was more difficult to predict. Race was only statistically significant in the 2016 model and there too disproved the hypothesis by being negatively correlated with income inequality, which perhaps indicates a tendency for race to be less impactful as a factor on income inequality when controlling for other factors like poverty and educational attainment. Population density was a challenging factor with regard to predictive capacity: more rural counties as defined by population density were less predictable in terms of income inequality projections. Possibly a different measure for density would be more predictive; this leaves room for future study.

CONCLUSIONS

Potential Impacts – Policy

Understanding the drivers of income inequality is important; while inequality may be similar in two cities or metro areas, the responses and policy measures best suited to address it may be very different. Looking at poverty or high income shares in addition to inequality is important, because the problem may be, among other factors, poverty driven, or top-income driven, or economic mobility driven. For income inequality to be addressed at all ends of the spectrum, the explosive rise of top income shares and accurately-measured poverty and lower-income levels must both be examined.

As housing impacts driven by inequality are disproportionately detrimental to poor households, local (city/county) governments may have greater control over effecting shifts in income inequality than they realize. Governments "should consider monitoring the relationship between income and rental costs at different points in the distribution – not just at the low end, but in the middle as well – to ensure their efforts respond adequately to those affordability challenges and preserve housing opportunities for a wide range of workers and families." (Berube and Holmes 2016). Density concessions for inclusive housing policies are one of many options available to counties; this concession increases the maximum number of allowable units in a multi-family structure if some are designated as affordable housing and encourage developers to include these options within their planned communities.

Tax rates were not statistically significant in most regressions; they may not vary enough county by county for marked significance, but the low overall taxation rates in the state may contribute to its high standing in terms of nationwide inequality, particularly given that Florida has a general overall regressive approach to taxation, with most taxes based on some ownership of property. Another consideration is how these regressive property-based taxes impact lower-income residents, who frequently rent their residences; while increased homestead exemptions may put money back in the pockets of Florida's homeowners, these exemptions do not trickle down to renters. However, any departure from this mostly property-based taxation by proposing statewide taxation policy would be likely doomed. Florida's constitution bars a state income tax (article VII), voters must approve any constitutionally imposed new tax by a two-thirds majority (article XI), and as of the 2018 election, a supermajority would be needed for tax changes proposed by the legislature. Local-level tax policies and redistributive measures such that might counter inequality at a national level might just drive a flight of the wealthy at a local metropolitan or county level, and thus not address income inequality directly.

If a state income tax would be difficult to achieve, broad-level changes to capitalism and the free markets seem even less likely; however, much evidence suggests that encouraging a broad expansion of wage levels overall, which have stagnated or declined for most Americans, would decrease inequality. The Economic Policy Institute suggests policy decisions are more important in explaining the slowing of wage growth than many oft-cited factors like skill change and technical bias (Bivens et al. 2014, 6). Support has grown for minimum wage increases over the years, and if Florida were to vote to pass the $15 minimum wage amendment proposed to the 2020 ballot (and the Legislature were to implement it thereafter), the impact on those at the low end of the income scale could be substantial. Though the proposal implements the shift gradually, arriving at $15 per hour by 2026 (State of Florida 2019), moving wage-earners further up the income scale and closer to a middle-income range would likely reduce poverty and thus may reduce income inequality from a bottom-shares aspect.

However, Dye (1969) noted that his “admittedly rough calculations suggest that the *distribution* of social and economic resources within a state may be more important politically than the *level* of social and economic resources.” If his assessment was correct, policy solutions need not be expensive ones; a shift in the appropriation of tax dollars may be as or more effective than an increase in them. The Florida Legislature in 1992 passed the William E. Sadowski Affordable Housing Act, which created two new trust funds, one local and one statewide, fueled by a small increase in documentary stamp taxes. The local fund distributes funds to counties and cities for flexible use in production and preservation of affordable housing, mostly home construction but also rental housing to a lesser extent; the state funds are more heavily applied toward construction and rehabilitation of multi-family rental housing. Unfortunately, in many legislative years between 2006-07 and 2013-14, the program’s funds were swept into general revenues and not fully appropriated as designed (Florida Housing Coalition 2018). Addressing both poverty and cost-burdened housing by ensuring that Sadowski Trust Fund monies are appropriated as intended to counties for affordable housing assistance could lift more families out of poverty and decrease inequality.

Education’s impact on income inequality was somewhat inconsistent in these results, but if education – either a via formal university or vocational training – is impactful on either income inequality or poverty, or both, then the facilitation of attaining such education is an important goal. Particularly in counties where costs of living and housing cost burden is high, governments and institutions both can smooth the path for residents seeking to inch up the income ladder and effect economic mobility. Many cities and counties (and homeowners associations) have regulations on the number of unrelated adults who can legally reside in a single residence – for example, in University of Florida's home town of Gainesville the limit is three, with some areas of the city permitting up to five (Knee 2019). College-adjacent areas can keep costs of living lower while attending college for students by eliminating or increasing limits on the number of unrelated adult roommates who can reside in a single residence, facilitating their ability to successfully complete their education and move into higher-paying jobs and up the income scale. Policies can be implemented by school boards and universities to encourage attendance and completion at secondary institutions (colleges and vocational schools alike). School boards could implement courses and workshops on life skills after high school: work-school-life balance, budgeting, time management, etc. Colleges, universities, and vocational schools could relax some of their mandates, particularly those tied to financial aid, governing time frames for completion and maintenance of grades. These institutions might offer additional assistance to those students struggling to complete school while juggling the work load required to cover sometimes substantial living expenses.

As noted in Piketty and Saez (2003), "changing social norms regarding inequality and the acceptability of very high wages might partly explain the rise in U.S. top wage shares observed since the 1970s." (35) This normative shift could itself be problematic in addressing inequality – one can rarely use policy recommendations to address societal norms.

There may be a sort of silver lining at the county level: some degree of local income inequality (though notably not poverty, per se) is not always a bad thing. Studies suggest there are communitarian effects of income inequality, with an important caveat: if people at income levels do not stratify and isolate into homogenous communities in which their own private institutions replace their use of public ones, inequality can benefit lower income groups (Glaeser, Resseger, and Tobio 2009, 640).

Potential Impacts – Areas for Further Study

The most obvious area for improvement in this study, and one I would incorporate if extending this study further, is the inclusion of high-income shares as an independent variable. As noted previously, research has found high-income shares to be highly correlated to income inequality. The predictive models in my findings particularly lead me to believe this would be an important factor in explaining county income inequality: northern panhandle counties, which I would hypothesize to have fewer index-skewing extremely high-income individuals and households, were the most likely counties to be overstated in terms of inequality. If high-income shares were incorporated, the predictive capability of these models may put these counties closer to their actual inequality levels.

Incorporation of other explanatory variables could inform the models further, by including factors such as percentage of employment that falls into high tech or creative class categories or, in the alternative, percentage of low-skill employment; immigrant population percentage; average wage rates; and further stratification of the race variable used here. As this research shows that population density was unreliable in terms of predicting income inequality in counties measured as more rural by density, I would also encourage the application of other more exacting measures of urbanity/rurality, such as index of relative rurality, which might lead to more accurate predictive capabilities in the model. A simplified binary dummy variable for rural/non-rural might also provide better insight. The results of this study show that population density and income inequality's relationship is both significant and inconsistent on predictive abilities; a question remains, however, whether income inequality and population density are in fact linked or if there is simply a link between poverty and rurality that makes population density look more significant than it is.

Further, there are differences between income inequality and wealth inequality – which is even higher in the US than income inequality – and there is space for further studies on wealth inequalities in Florida's counties.

APPENDIX A: Top and Bottom Five Counties Independent and Dependent Variable Measurements (2000, 2016, Change)

Table A: Top and Bottom Five Counties – Gini Coefficient of Income Inequality

2000		County	Gini
High	**1**	Indian River County	0.51483
	2	Liberty County	0.51082
	3	Miami-Dade County	0.50710
	4	Martin County	0.50202
	5	Palm Beach County	0.50110
Low	**5**	Osceola County	0.40975
	4	Union County	0.40719
	3	Wakulla County	0.40432
	2	Baker County	0.40289
	1	Clay County	0.37917
2016		**County**	**Gini**
High	**1**	Indian River County	0.53080
	2	Collier County	0.52980
	3	Miami-Dade County	0.52640
	4	Martin County	0.51700
	5	Palm Beach County	0.51690
Low	**5**	Hernando County	0.42360
	4	Calhoun County	0.41670
	3	Clay County	0.41150
	2	Taylor County	0.40040
	1	Wakulla County	0.39520
Change		**County**	**Gini**
High	**1**	Lafayette County	0.05268
	2	Columbia County	0.03972
	3	Orange County	0.03879
	4	Hendry County	0.03820
	5	Seminole County	0.03646
Low	**5**	Washington County	-0.02679
	4	Jefferson County	-0.03658
	3	Calhoun County	-0.03764
	2	Taylor County	-0.04174
	1	Liberty County	-0.06532

Table B: Top and Bottom Five Counties – Official Poverty Measure

(% of county residents at or below)

2000		County	OPM
High	**1**	Hamilton County	26
	2	Hardee County	24.6
	3	Hendry County	24.1
	4	DeSoto County	23.6
	5	Madison County	23.1
Low	**5**	Charlotte County	8.2
	4	St. Johns County	8
	3	Sarasota County	7.8
	2	Seminole County	7.4
	1	Clay County	6.8
2016		**County**	**OPM**
High	**1**	DeSoto County	29.9
	2	Madison County	28.5
	3	Hamilton County	27.0
	4	Putnam County	27.0
	5	Hardee County	26.4
Low	**5**	Martin County	11.8
	4	Sarasota County	11.0
	3	Clay County	10.2
	2	Sumter County	9.9
	1	St. Johns County	9.0
Change		**County**	**OPM**
High	**1**	Gilchrist County	9.7
	2	Okeechobee County	9.3
	3	Union County	8.4
	4	Osceola County	8.0
	5	Holmes County	6.9
Low	**5**	Gulf County	-1.4
	4	Liberty County	-3.0
	3	Taylor County	-3.2
	2	Sumter County	-3.8
	1	Calhoun County	-6.9

Table C: Top and Bottom Five Counties – 150% of Official Poverty Measure

(% of county residents at or below)

2000		**County**	**150PM**
High	**1**	Hardee County	40.4
	2	Hamilton County	39.4
	3	Hendry County	38.1
	4	Madison County	37.1
	5	DeSoto County	36.4
Low	**5**	Martin County	16.1
	4	St. Johns County	14.6
	3	Sarasota County	14.5
	2	Seminole County	13.8
	1	Clay County	13.1
2016		**County**	**150PM**
High	**1**	Hardee County	44.3
	2	DeSoto County	43.2
	3	Madison County	42.3
	4	Hendry County	42.2
	5	Okeechobee County	40.9
Low	**5**	Santa Rosa County	20.2
	4	Clay County	19.8
	3	Sarasota County	19.4
	2	Sumter County	17.3
	1	St. Johns County	15.4
Change		**County**	**150PM**
High	**1**	Osceola County	11.5
	2	Okeechobee County	10.1
	3	Union County	9.2
	4	DeSoto County	8.9
	5	Lee County	8.1
Low	**5**	Calhoun County	-1.6
	4	Taylor County	-2.4
	3	Hamilton County	-3.1
	2	Sumter County	-6.3
	1	Franklin County	-6.6

Table D: Top and Bottom Five Counties – Cost-Burdened Housing (2016)

(% of county residents spending 30+% of income for housing costs)

2016		County	CBH
High	**1**	Miami-Dade County	59.6
	2	Osceola County	58.9
	3	Monroe County	57.6
	4	Broward County	53.0
	5	Orange County	50.3
Low	**5**	Sumter County	27.9
	4	Washington County	27.4
	3	Lafayette County	26.6
	2	Liberty County	21.7
	1	Gilchrist County	15.9

Table E: Top and Bottom Five Counties – Educational Attainment

(% of county residents with 4+ years of college)

2000		County	EdAttain+4
High	**1**	Leon County	41.7
	2	Alachua County	38.7
	3	St. Johns County	33.1
	4	Seminole County	31
	5	Collier County	27.9
Low	**5**	Union County	7.5
	4	Liberty County	7.4
	3	Hamilton County	7.3
	2	Lafayette County	7.2
	1	Dixie County	6.8
2016		**County**	**EdAttain+4**
High	**1**	Leon County	45.2
	2	St. Johns County	42.5
	3	Alachua County	41.5
	4	Seminole County	35.8
	5	Palm Beach County	34.2
Low	**5**	Hardee County	9.6
	4	Hendry County	9.1
	3	Glades County	8.9
	2	Union County	7.6
	1	Dixie County	6.4
Change		**County**	**EdAttain+4**
High	**1**	Sumter County	17.6
	2	Walton County	10.1
	3	Pasco County	9.4
	4	St. Johns County	9.4
	5	Manatee County	7.1
Low	**5**	Jackson County	0.9
	4	Levy County	0.6
	3	Union County	0.1
	2	Dixie County	-0.4
	1	Glades County	-0.9

Table F: Top and Bottom Five Counties – County Population Density

2000		**County**	**PopDensity**
High	**1**	Pinellas County	3291.95
	2	Broward County	1346.46
	3	Seminole County	1184.93
	4	Miami-Dade County	1157.91
	5	Duval County	1006.73
Low	**5**	Dixie County	19.64
	4	Taylor County	18.48
	3	Glades County	13.67
	2	Lafayette County	12.94
	1	Liberty County	8.40
2016		**County**	**PopDensity**
High	**1**	Pinellas County	3431.51
	2	Broward County	1540.58
	3	Seminole County	1432.33
	4	Miami-Dade County	1404.01
	5	Orange County	1390.32
Low	**5**	Franklin County	21.89
	4	Taylor County	21.64
	3	Glades County	16.65
	2	Lafayette County	16.09
	1	Liberty County	9.92
Change		**County**	**PopDensity**
High	**1**	Orange County	402.56
	2	Hillsborough County	346.29
	3	Lee County	319.40
	4	Seminole County	247.40
	5	Miami-Dade County	246.10
Low	**5**	Franklin County	1.58
	4	Liberty County	1.52
	3	Hardee County	0.54
	2	Madison County	-0.41
	1	Monroe County	-1.37

Table G: Top and Bottom Five Counties – County Unemployment Rate

2000		County	Unemployment
High	1	Hendry County	7.3
	2	Hardee County	6.0
	3	Gulf County	6.0
	4	St. Lucie County	5.8
	5	Okeechobee County	5.4
Low	5	Alachua County	3.0
	4	Clay County	3.0
	3	St. Johns County	3.0
	2	Baker County	3.0
	1	Monroe County	2.9
2016		**County**	**Unemployment**
High	1	Hendry County	8.5
	2	Sumter County	7.1
	3	Citrus County	6.7
	4	Hardee County	6.7
	5	Highlands County	6.5
Low	5	Orange County	4.3
	4	Wakulla County	4.1
	3	Okaloosa County	4
	2	St. Johns County	3.8
	1	Monroe County	3.2
Change		**County**	**Unemployment**
High	1	Sumter County	2.8
	2	Gadsden County	2.2
	3	Citrus County	2
	4	Putnam County	2
	5	Baker County	1.9
Low	5	Bay County	0.1
	4	St. Lucie County	0
	3	Union County	-0.1
	2	Okeechobee County	-0.3
	1	Gulf County	-1.4

Table H: Top and Bottom Five Counties – County Tax Rate

2000		County	Tax Rate
High	1	Highlands County	2.90
	2	Holmes County	2.77
	3	Hillsborough County	2.72
	4	Hernando County	2.18
	5	Alachua County	2.15
Low	5	Charlotte County	1.36
	4	Gadsden County	1.32
	3	Okaloosa County	1.27
	2	Collier County	1.19
	1	Monroe County	1.08
2016		**County**	**Tax Rate**
High	1	Duval County	1.27
	2	Gulf County	1.13
	3	Escambia County	1.06
	4	Glades County	1.04
	5	Alachua County	1.03
Low	5	Collier County	0.38
	4	Sarasota County	0.35
	3	Monroe County	0.35
	2	Okaloosa County	0.34
	1	Walton County	0.33
Change		**County**	**Tax Rate**
High	1	Charlotte County	-0.54
	2	Indian River County	-0.63
	3	Calhoun County	-0.63
	4	Hamilton County	-0.63
	5	Duval County	-0.65
Low	5	Hernando County	-1.34
	4	Baker County	-1.42
	3	Hillsborough County	-1.89
	2	Holmes County	-1.94
	1	Highlands County	-2.08

Table I: Top and Bottom Five Counties – County Per Capita Income, Average

2000		County	PCI
High	1	Collier County	31195
	2	Martin County	29584
	3	Palm Beach County	28801
	4	St. Johns County	28674
	5	Sarasota County	28326
Low	5	Madison County	12511
	4	Hardee County	12445
	3	Calhoun County	12379
	2	Union County	12333
	1	Hamilton County	10562
2016		**County**	**PCI**
High	1	Collier County	39616
	2	St. Johns County	38362
	3	Monroe County	36771
	4	Martin County	35892
	5	Sarasota County	35210
Low	5	Calhoun County	16560
	4	Madison County	16486
	3	Taylor County	16081
	2	Hamilton County	15970
	1	Union County	12943
Change		**County**	**PCI**
High	1	Sumter County	8133.87
	2	Walton County	3111.19
	3	Gilchrist County	2128.14
	4	Columbia County	1528.76
	5	Hamilton County	1249.01
Low	5	Lee County	-5256.88
	4	Palm Beach County	-5295.94
	3	Martin County	-5341.26
	2	Indian River County	-5740.15
	1	Liberty County	-6789.67

Table J: Top and Bottom Five Counties – Marital Rate

(% of county residents who are married)

2000		County	Marital Rate
High	1	Flagler County	67.2
	2	Charlotte County	64.8
	3	Nassau County	63.6
	4	Citrus County	63.5
	5	Hernando County	63.5
Low	5	Miami-Dade County	49.2
	4	Liberty County	48.2
	3	Gadsden County	48
	2	Leon County	43.7
	1	Alachua County	41.6
2016		**County**	**Marital Rate**
High	1	Sumter County	61.7
	2	St. Johns County	56.3
	3	Nassau County	55.4
	4	Charlotte County	55.3
	5	Collier County	54.9
Low	5	Glades County	40.2
	4	Hamilton County	39.8
	3	Leon County	37.9
	2	Alachua County	37
	1	Union County	35.9
Change		**County**	**Marital Rate**
High	1	Franklin County	-0.7
	2	Sumter County	-1.4
	3	St. Johns County	-3.6
	4	Alachua County	-4.6
	5	Leon County	-5.8
Low	5	Baker County	-14.5
	4	Hamilton County	-14.8
	3	Union County	-15.6
	2	Bradford County	-18.2
	1	Glades County	-19.3

Table K: Top and Bottom Five Counties – Race

(% of county residents who self-identify as non-white)

2000		**County**	**RaceNW**
High	**1**	Gadsden County	61.3
	2	Madison County	42.5
	3	Hamilton County	41.2
	4	Jefferson County	40.7
	5	Duval County	34.2
Low	**5**	Charlotte County	7.4
	4	Sarasota County	7.4
	3	Hernando County	7.1
	2	Pasco County	6.3
	1	Citrus County	5
2016		**County**	**RaceNW**
High	**1**	Gadsden County	59.1
	2	Madison County	42.1
	3	Hamilton County	40
	4	Jefferson County	39
	5	Duval County	38.8
Low	**5**	Charlotte County	9.9
	4	Nassau County	9.6
	3	Sarasota County	8.8
	2	Gilchrist County	8.1
	1	Citrus County	6.7
Change		**County**	**RaceNW**
High	**1**	Broward County	8.7
	2	Clay County	5.7
	3	Flagler County	5.5
	4	St. Lucie County	5.4
	5	Pasco County	5.2
Low	**5**	Sumter County	-6.1
	4	Okeechobee County	-7.6
	3	DeSoto County	-9.4
	2	Hendry County	-10.1
	1	Hardee County	-11.6

APPENDIX B: Imperfect Multivariate Regression Models (2000, 2016)

Table A: Imperfect Multivariate Regression Model – 2000

Independent Variables	B	Standard Error	Beta	Significance	VIF
Constant	0.202	0.072		0.007	
Official Poverty Measure	0.01	0.001	1.164	.000***	5.983
Educational Attainment	-0.001	0.001	-0.224	.048**	5.190
Unemployment Rate	0.005	0.004	0.104	0.162	2.272
Income Per Capita	9.661E-06	0.000	1.186	.000***	5.300
Population Density	5.562E-06	0.000	0.135	.085*	2.512
Marital Rates	-0.001	0.001	-0.146	0.383	11.621
Race	0	0.000	-0.140	0.141	3.715
County Tax Rate	-0.008	0.004	-0.085	.096*	1.058

Significance levels = ***.01, **.05, *.10

R-Square: .863 Adjusted R-Square: .844 F Change: 45.593 Durbin-Watson: 1.699

Table B: Imperfect Multivariate Regression Model A – 2016

Independent Variables	B	Standard Error	Beta	Significance	VIF
Constant	0.194	0.054		0.001	
Official Poverty Measure	0.005	0.001	0.548	.000***	4.320
Cost-Burdened Housing	0.002	0.000	0.428	.000***	1.952
Educational Attainment	0	0.000	-0.058	0.515	4.684
Unemployment Rate	0.011	0.003	0.195	.002***	2.050
Income Per Capita	7.228E-06	0.000	1.021	.000***	5.767
Population Density	1.784E-06	0.000	0.042	0.457	1.915
Marital Rates	-0.002	0.001	-0.355	.003***	7.636
Race	-0.001	0.000	-0.246	.000***	2.518
County Tax Rate	0.011	0.003	0.072	0.132	1.345

Significance levels = ***.01, **.05, *.10

R-Square: .905 Adjusted R-Square: .890 F Change: 60.504 Durbin-Watson: 2.158

Table C: Imperfect Multivariate Regression Model B – 2016

Independent Variables	B	Standard Error	Beta	Significance	VIF
Constant	0.047	0.028		0.1	
Official Poverty Measure	0.007	0.001	0.695	.000***	3.008
Cost-Burdened Housing	0.002	0.000	0.489	.000***	1.726
Educational Attainment	8.11E-05	0.000	0.016	0.860	4.352
Unemployment Rate	0.009	0.003	0.159	.012**	1.973
Income Per Capita	6.699E-06	0.000	0.946	.000***	5.429
Population Density	5.971E-06	0.000	0.142	.007***	1.317
Race	0	0.000	-0.135	.024**	1.774
County Tax Rate	0.016	0.008	0.104	.040**	1.283

Significance levels = ***.01, **.05, *.10

R-Square: .889 Adjusted R-Square: .873 F Change: 57.930 Durbin-Watson: 2.105

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