The Ohio Migrant Effect:
An Introductory Analysis of the Impact of Immigration on Ohioan Income[1]

Joshua Luke Durell

Undergraduate Honors Thesis
Department of Economics
Wittenberg University

Under the Direction of Dr. David Wishart

April 13, 2018

Abstract:
The perceived costs and benefits of immigration take front stage for many U.S. political and policy debates, in both the public and private spheres. Various Ohio lawmakers seek to decrease immigration levels into the United States, both documented and undocumented, primarily by aligning Ohio state law with Federal law.[2] This raises the question: is there any measurable economic incentive to increase or decrease immigration levels in Ohio? One way to address this is to measure how immigration is correlated with income. If higher levels of immigration contribute to higher levels of income, increased immigration would be a beneficial policy, and vice versa. This study develops a model that quantifies the impact of immigration on incomes for native Ohioans. My study uses recent data from the US Census Bureau's American Community Survey (ACS) to develop and estimate an econometric model that suggests a more definitive answer to the question: "What effect does immigration have on per capita income in Ohio?" This study reports that across Ohio counties, a 1 percentage point increase in county immigrant population corresponds to a 0.0125 percent increase in county median income. The effect of immigration on county median income in Ohio suggested here is small but positive.

[1] This thesis was possible thanks to my advising committee, Dr. Wishart, Dr. Gwinn, and Dr. Hoff, my statistics professor, Dr. Andrews, and my proofreaders, Haley and Elise.
[2] See Ohio House Bill 179

1 Introduction

"It appears evidently from experience that a man is of all sorts of luggage the most difficult to be transported" (Smith, 1776). When Adam Smith wrote this in his famous 18th century economic treatise, *The Wealth of Nations*, immigrants seeking new lives in foreign countries faced months of overcrowded travel, limited access to food, disease, and high risk of loss. The incentives necessary to push people out of or pull people in from their native land to foreign soil had to be compelling. There had to be either too much danger or poverty in the sending country (push factors) or too irresistible a future in the receiving country (pull factors). Much remains the same in the 21st century. Despite the risk and cost of moving, in 2015, 244 million people around the world lived outside of their home country (UNFPA, 2015), experiencing, or at least hoping to experience, a better life than the one they left behind. Of these 244 million, in 2016, 43.7 million lived in the United States (Zong, Batalova, & Hallock, 2018). Political turmoil and war in the Middle East and North Africa has pushed hundreds of thousands of refugees into the United States alone. By 2016, the number of refugees in the United States from Middle Eastern/North African countries exceeded one million (Cumoletti & Batalova, 2018). Recently, for many in Central America, better economic prospects and the possibility of reunification with family members in the United States pulled (while violent crime in the home country pushed) large numbers of immigrants from El Salvador, Guatemala, and Honduras into the United States (Cohn, Passel, & Gonzalez-Barrera, 2017). Similarly, push factors like crime, illegal drug use, and political corruption continue to play a strong roll in Mexican immigration to the United States (Pew Research Center, 2009).

The prospect of the American Dream appears to be alive and well, as the United States continues to draw around one million immigrants every year (Haskins, 2016). The status of immigration in Ohio is no exception. Nearly 500,000 residents of Ohio were born outside of the United States (New American Economy, 2016), constituting over four percent of the current 11.5

million residents (Google Public Data, 2018). Additionally, as of 2014, roughly 95,000 undocumented immigrants live in Ohio (Pew Research Center Hispanic Trends, 2016). These immigrants are diverse, as Ohio is home to large numbers of Asian, Hispanic, and Somali immigrants. They are also, on average, very well educated. Among Ohio's adult immigrant population, 77 percent have a high school diploma and 38-42 percent have a college degree, far exceeding the 26 percent of native Ohioans with college degrees. The economic influence of immigrants in Ohio is notable. Immigrants in Ohio comprise around 5 percent of the workforce, most notably in life/physical/social sciences (16.5 percent), computer and mathematical sciences (14.1 percent) and farming/fishing/forestry (10.7 percent) (American Immigration Council, 2017). In 2014, Ohio immigrants paid $4.4 billion dollars in local, state, and federal taxes, and employed 122,404 Ohio residents (New American Economy, 2016).

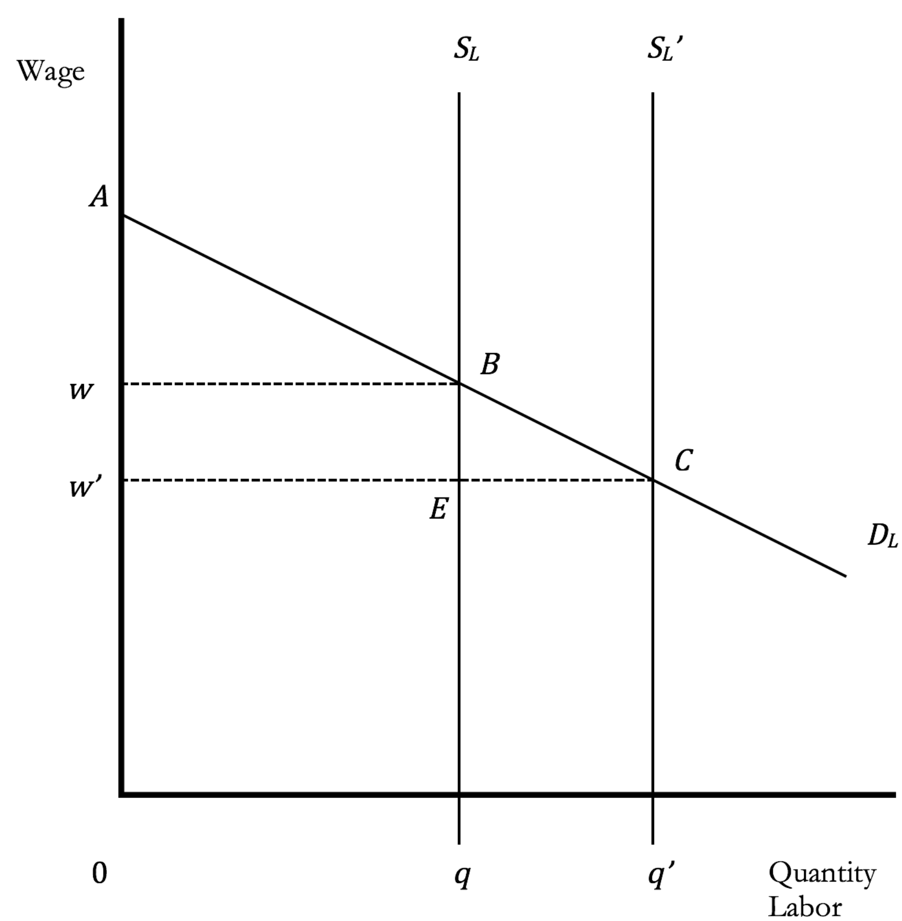
The social status of immigrants in the eyes of the United States public – as friends or foes - remains a question of heated debate. Over the last ten years, an increasing share of the American public has favored increased immigration. Of all American adults, a 2006 report revealed 55 percent of those polled thought that immigration hurt American workers, while a 2016 follow-up report saw the number drop to 45 percent. At the same time, the surveys also depict the increasing polarization of this debate between political parties. In 2006, 61 percent of Republicans and 54 percent of Democrats believed that immigration hurt American workers. By 2016, these percentages had risen to 67 percent among Republicans and dropped to 30 percent for Democrats (Rainie & Brown, 2016).

These party politics are reflected in global public opinion of the United States. For example, during the Obama administration, around 60% of Mexicans reported that they viewed the United States favorably, and around 40% reported that they were confident that the United States President would "do the right thing, regarding world affairs." During the first year of the Trump administration these numbers have fallen to 30% of Mexicans reporting a favorable view and 5% reporting confidence in decisions pertaining to world affairs. Interestingly, according to one study these opinions have held little sway in the desire Mexican nationals to move to the United States. As of 2009, one in three Mexicans reported that if they had all the necessary resources, they would move to the United States (Pew Research Center, 2009). Despite sharp drops in popularity, one third of Mexicans in Mexico still say they would move to the United States if afforded the resources and opportunity (Vice & Chwe, 2017). This statement does not tell the full story however, as studies also show that from 2009 to 2014, more Mexicans (both documented and undocumented) have left the United States than entered (Gonzalez-Barrera, 2015). This could be in response to 2013 and 2014 economic growth in Mexico or due to political tension in the United States.

Whether immigration has a positive impact on the United States economy, however, is the central question of this study. Economic theory can play a role in answering this question with no requirement of loyalty to a political party or a particular worldview. The general economic theory of immigration can be explained as follows (with reference to Figure 1 on the next page). The curve *S* represents the supply of labor, D_L represents the demand for labor, *w* is the wage paid at this quantity of labor, and *B* is the equilibrium point where the quantity demanded and quantity supplied of labor are equal. Under these conditions, the economy's GDP will be the area created by *ABq0*. The triangle above the wage line, *ABw*, is the portion of the GDP going to capital and the rectangle below the wage line, *wBq0*, is the portion of the GDP going to labor. Suppose the economy experiences an inelastic supply of labor and *q' – q* immigrants enter the country, causing *S* to shift to *S'*. This will move the economy's demand for labor down D_L to the new equilibrium *C*. This analysis shows that the immediate effect of immigration will be the addition to the economy's GDP of *BCq'q*. This addition will benefit capitalists and business owners by area *wBCw'* and hurt native laborers by area *wBEw'*. The net benefit from the immigration will be triangle *BCE*. Browning and

Zupan summarize that while this net gain *BCE* causes all Americans to benefit, the increase is offset by the initial low tax revenue gained from immigrants and their relatively high consumption of government services. It is important to mention that this is only a short-run analysis of the theory. In the long run, businesses in other regions will see that labor is cheaper in the region represented by Figure 1, and they will move their business into that region, increasing D_L and restoring equilibrium.

Figure 1: Economic Theory of Migration



Generally speaking, the economic theory proposes that immigration does indeed increase GDP, but a portion of that increase will be retained by the immigrants, and, in the short run (and as long as immigration levels remain constant), wages will necessarily fall in industries where immigrants compete with natives for positions, returning to equilibrium once new businesses access the cheap labor in the region in the long run.[3] The question that bubbles to the forefront is: How are native workers affected? Economists are divided concerning how immigration affects the native workers. This is the major point in need of resolution, as ultimately, the issue that drives immigration policy is whether natives' wages are harmed by immigration (Friedberg & Hunt, 1995).

Borjas outlines the current immigration debate that revolves around this idea of the harm caused to natives:

> Illegal immigration continues to vex the public and policymakers. Illegal immigrants have clearly benefited by living and working in the United States. Many business owners and users of immigrant labor have also benefited by having access to their labor. But some native-born Americans have also lost, and these losers likely include a disproportionate number of the poorest Americans (Borjas, 2013).

In hopes of clarifying this issue, economists have investigated the relationship between immigration and income in the United States, frustratingly, with mixed results. However, no studies exist that specifically address the impact of immigration on incomes in Ohio.[4] The purpose of this study is to apply tested econometric tools to county-level data for Ohio to examine the impact of immigration on Ohioans median household income by regressing income against immigration and other key independent variables.

It is important to mention that regardless of the impact of immigration on *natives*, there is no grounded argument that immigration is an economic bad. Any definition of perfect competition leading to economic efficiency will include the requirement of free entry and exit, both for firms and for labor. For a textbook example, when the Soviet Union fell, the 1992 immigration of Soviet

---

[3] There is debate among economists concerning whether immigration increases a country's or region's overall wealth. The Center for Immigration Studies contends that immigrants add to the cost of public services disproportionately to natives, and some studies suggest, at levels higher than they pay in taxes (Richwine, 2016) (Camarota, 2006) (Simcox, 1994), while the Cato Institute and others claim that immigrants use far less services than natives and the cost is balanced (Ku & Bruen, 2013) (Capps, Fix, & Henderson, 2011).

[4] There exists some scant work investigating Ohio migrant patterns, but none specific to income patterns. See (Venkatu & Fee, 2011) and (Otiso & Smith, 2005).

mathematicians into the United States rocked the American mathematical landscape. American mathematicians that published in the same fields as the Soviet émigrés were pushed into lower class institutions and became less likely to publish widespread, influential work (Borjas & Doran, 2012). While measuring the loss suffered by American mathematicians would be the immediate focus of many economists like Borjas, any unbiased review of the Soviet influx of quality mathematicians into the United States would maintain that America benefited at the expense of the former Soviet Union.

This idea of one country benefiting at the expense of another reflects how migration results in free human capital. Human capital is the concept that an individual's education, training, and health, while less separable from the actual person than financial assets, still result in income and economic outputs. The benefit of having educated workers immediately joining the labor force and utilizing modern technologies is a strong conceptual argument in favor of immigration. Becker, the economist who coined the term "human capital," attributes the recent growth of East Asian countries to nothing short of immense levels of human capital. He explains that as the "Asian tigers" like Japan and Taiwan have faced import discrimination from other developed countries they have successfully relied on their labor force to efficiently increase economic growth using existing technologies (Becker, 2007).

2 Literature Review

The National Academies of Sciences, Engineering, and Medicine determine that immigration both increases the host country's GDP and leaves the native population "better off" (National Academies of Sciences, 2017). Peri takes this one step further and argues that native-born workers without a college education do not suffer any wage loss due to immigration (Peri, 2017). However, Borjas claims just the opposite of Peri. He argues that while many studies posit that immigration benefits *all* native workers (those in complementary industries more than competing industries, but nonetheless, all native workers), the effects are miniscule and offset by multiple factors. Borjas estimates that in the United States the net benefit of immigration to natives is 0.2% of the GDP, and the benefit is disproportionate in a way that most poor, working class natives "lose" considerably in comparison to other classes (Borjas, 2013). Another study reiterates this statement, claiming that although recent academic research does not point to any significant long-run effect of immigration on U.S. wages, regions with low levels of education and income are subject to "significant net costs due to immigrants' use of public services" (Penn Wharton Budget Model, 2016).

It appears that the literature on the economic impact of immigration is clouded with uncertainty and inconsistency. Murray, Batalova, and Fix claim that:

> Researchers' findings on wage impacts have been divergent: large and negative, small and negative to non-existent, or positive. Thus, at least in the near-term, policy choices to reform immigration cannot and will not be based on reliable predictions of immigration's impact on native wages (Murray, Batalova, & Fix, 2006).

Additionally, in a current aggregation of 27 empirical studies, Peri states, "the wages of native workers, even workers with skills similar to those of the immigrants, do not change much in response to immigration." He shows that 19 of 27 reviewed influential studies conclude that the estimated effect on native wages for a 1% increase in immigration is between -0.1% and 0.1% and no study estimates that the effect exceeds 1% (Peri, 2014).

The Borjas-Peri relationship is a prototypical example of the differences between academic economists. In fact, Peri and Card review a graduate-level textbook on the economic impact of immigration by Borjas, arguing that it "presents a one-sided view of immigration, with little or no attention to the growing body of work that offers a more nuanced picture of how immigrants fit into the host country market and affect native workers" (Card & Peri, 2016). While admitting that Borjas is a leading scholar on immigration, Peri and Card critique both Borjas' modeling approach, as well as his focus on the *cost* of immigration. While a more thorough dive into the vast literature on the economics of migration is beyond the scope of this paper, the brief overview that I have presented clearly reveals that economists are deeply divided on the proper interpretation of the data related to immigration and income.

In describing the econometric standard for immigration studies, Borjas states: "[T]he typical study regresses a measure of native economic outcomes in the locality (or the change in that outcome) on the relative quantity of immigrants in that locality (or the change in the relative number)" (Borjas, 1999). Küng follows this approach, using a fixed-effects panel regression to estimate the impact of immigration on native wages in Switzerland (Küng, 2005). [5] The model developed in this study aligns closely with Küng's, as I draw liberally from his approach. The following balanced, panel, fixed-effects regression used to examine the impact of immigration on Ohio incomes is a model largely drawn from and dependent on the immigration literature concerning econometric regressions.

3 Data

Every year the American Community Survey (ACS) gathers extensive economic data on American communities. Random sampling techniques combined with paper/online options and interview follow-ups make this a trustworthy data set free from typical biases found in phone interviews and similar data collection methods (American Community Survey, 2017). This study uses one-year estimates for Ohio county data from the ACS from the years 2005 to 2016, all accessible on the U.S. Census Bureau's American Fact Finder. While the ACS does have varying types of studies examining all Ohio counties, the chosen data set is restricted to the 39 largest of the 88 Ohio counties, as the ACS only gathers yearly data for counties with populations over 65,000 residents (United States Census Bureau, 2016). However, the data still reaches around 80% the Ohio

[5] For additional examples of this approach in the literature see: (Altonji & Card, 1991), (Card, 2001), (LaLonde & Topel, 1991), (Jaeger, 2007), and (Schoeni, 1997).

population, as the population size of the counties included in the data swamps the size of those excluded (United States Census Bureau & American FactFinder, 2017). For this study's purposes, one-year estimates are more desirable than three-year or five-year because they show the most up-to-date, individual changes (United States Census Bureau, 2015).

Nearly thirty points of data are missing, shown below in Table 1. These data points are from counties representing relatively small populations. No county with missing data exceeds 110,000 in population. In contrast, the mean population across all counties and dates is 252,211 and the median population is 149,624.

Table 1: Missing Data

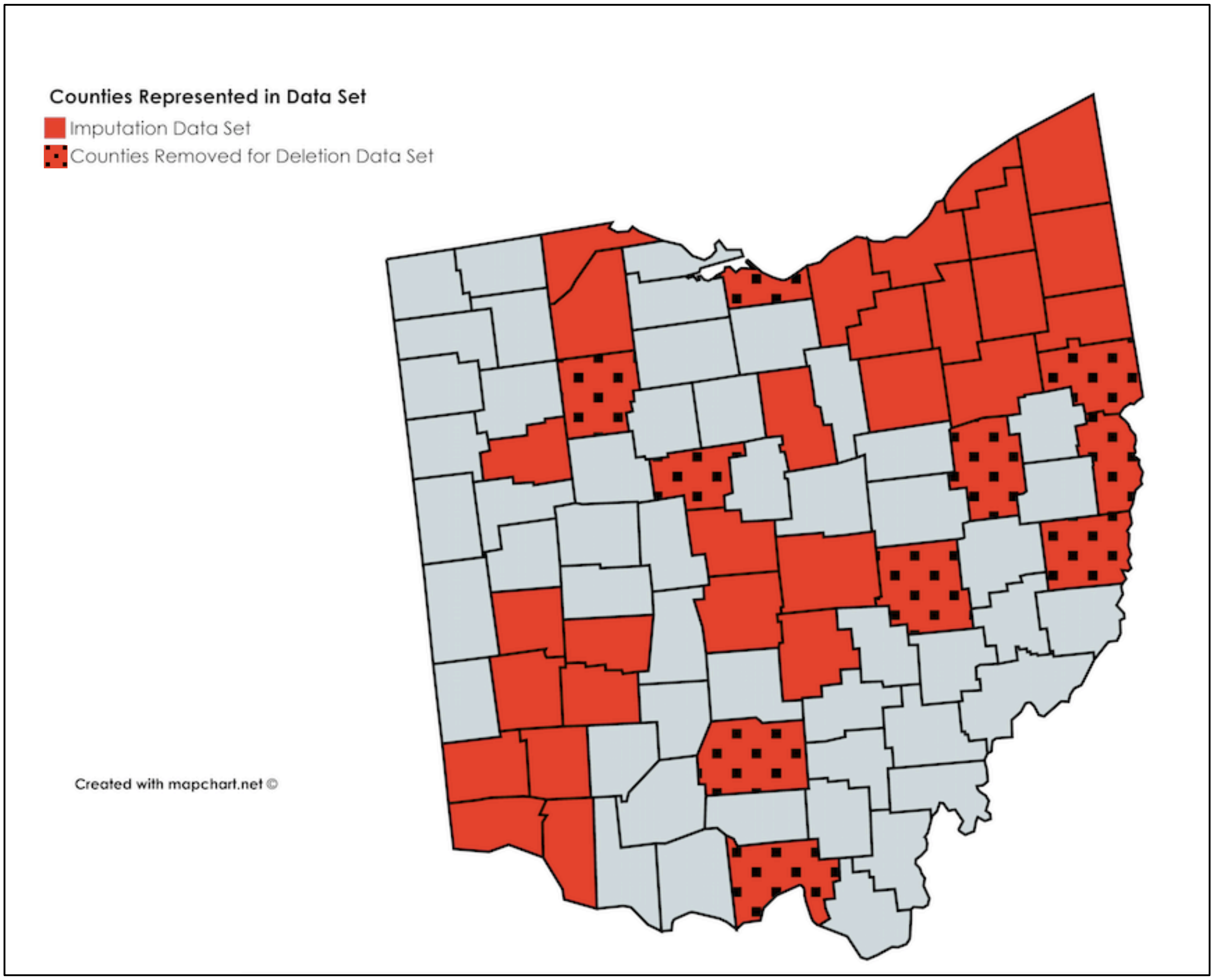
County	Factor	Year
Athens	All	('15,'16)
Belmont	Immigration	('09, '13, '15, '16)
Columbiana	Immigration	('05, '13)
Erie	Immigration	('08)
Hancock	Immigration	('08, '10)
Hancock	Unemployment	('05)
Jefferson	Immigration	('07, '10)
Marion	Immigration	('10, '14)
Marion	Unemployment	('05)
Muskingum	Immigration	('06, '07, '11, '13)
Ross	Immigration	('07, '13)
Scioto	Immigration	('05, '06, '07, '09, '11, '12)
Tuscarawas	Immigration	('06)

Based on this missing data, two distinct data sets are created for analysis. The first set, called the "Imputation Data Set" throughout this paper, uses a single imputation strategy, replacing data points with percentage means from the other counties. The second set, called the "Deletion Data Set" throughout this paper, uses a deletion strategy, removing all counties containing missing data sets. The complete data sets used can be viewed as one set in Table 11 at the end of the appendix, with the imputed values bold, italicized, and counties marked with an asterisk (*).[6] Athens County,

[6] This means that the Deletion Data Set contains none of the counties that have an asterisk (*) in Table 11

Ohio reached a high enough population level to be surveyed for the first time in 2015 and 2016. Because it was not represented in any data sets prior to 2015, it was removed from both the data sets prior to analysis. Figure 2 below shows a graphical representation of the counties included in both the imputation and the deletion data sets.

Figure 2: County Map



The gray counties are those counties that are not represented in the ACS data set. The red, dotted counties are the counties that had missing values. Thus, both the dotted and un-dotted counties comprise the imputation data set while only the red un-dotted counties comprise the deletion data set. I provide descriptive statistics of the data in Table 2 below.

Table 2: Descriptive Statistics for Data Sets

Variables & Description	Imputation Data Set		Deletion Data Set	
	min /max	mean	min/max	mean
Median Household Income:	28,342/101,693	49,013	36,015/101,693	51,704
Percent Immigration:	0.21/10.50	2.98	0.58/10.50	3.41
Age:	33.20/46.20	39.51	33.20/44.90	39.02
Education – high school	18.70/52.00	36.87	18.70/48.20	34.6
Education – two years:	4.60/13.60	8.05	4.90/13.60	7.94
Education – four years:	6.3/52.20	20.44	7.60/52.20	22.83
Education – graduate:	3.00/21.00	8.47	3.80/21.00	9.50
Unemployment:	2.30/18.60	7.86	2.30/16.40	7.63
Male-Female Ratio:	88.30/119.80	96.76	90.00/104.80	96.00
N: Observations in set	456		336	

Median household income has a large range in both data sets, with the minimum income in the imputation set Scioto County, the minimum income in the deletion set Ashtabula County, and the maximum in both sets Delaware County. Delaware County dwarfs the other counties in income levels, as the county with the next highest median family income is 2016 Warren County, at $80,207. Immigration, measured as the percent of population that is non-native, also has a wide range. The minimum value for the imputation set is 2005 Muskingum County, and the value reported is extremely low, even compared to other years for Muskingum County (the next lowest immigration value for Muskingum is 2015 at 0.72%). The minimum immigration value for the deletion data set is Ashtabula County. Immigration levels are highest by far in Franklin County, followed by Cuyahoga County. Median age of all residents in the county is less variable across counties, with the minimum of both sets being Franklin County and the maximum values from Erie and Geauga Counties for the imputation set and the deletion set, respectively.

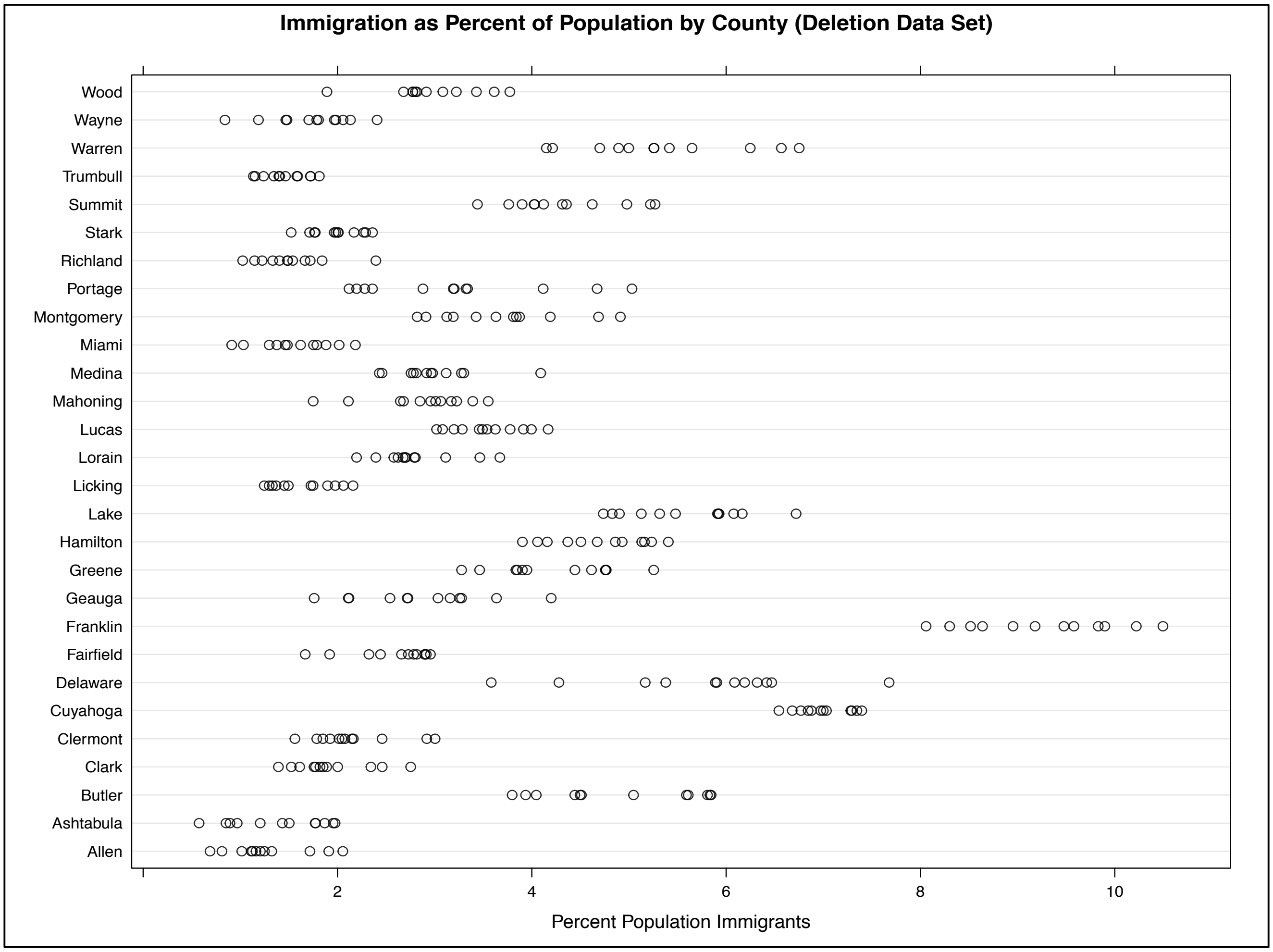
The education variables represent the highest degree held by the percent of the population over the age of 25. The graduate variable includes master's degrees, doctoral degrees, and professional degrees. A very high percentage for the high school variable corresponds with a low overall education level in the county. For instance, in the deletion data set Ashtabula County has the maximum value for the high school variable and has the minimum value for all three remaining education variables. For both data sets, Delaware County has the minimum percentage of population with a high school degree and the maximum value for four year degrees and graduate degrees.

Unemployment levels are lowest in Delaware County and highest in Ross County for the imputation set and highest in Lucas County for the deletion data set. Lastly, the male-female ratio is the number of males per 100 females. Interestingly, the mean value for both data sets shows that on average, Ohio has 100 women for every 96 men.

Figure 3 below shows a dot plot of immigrants as a percentage of county population, with years as distinct, unordered observations.[7] Generally, the spread of immigrants as percentages of county population is between one and three percent, except for Warren, Portage, and Delaware Counties, which have a wider spread. Trumbull, Stark, Licking, and Cuyahoga Counties all have very tight year-by-year spreads, all near 1%. At first glance, Franklin County appears to be an extreme outlier, its minimum percentage exceeding the maximum percentage of all other counties.

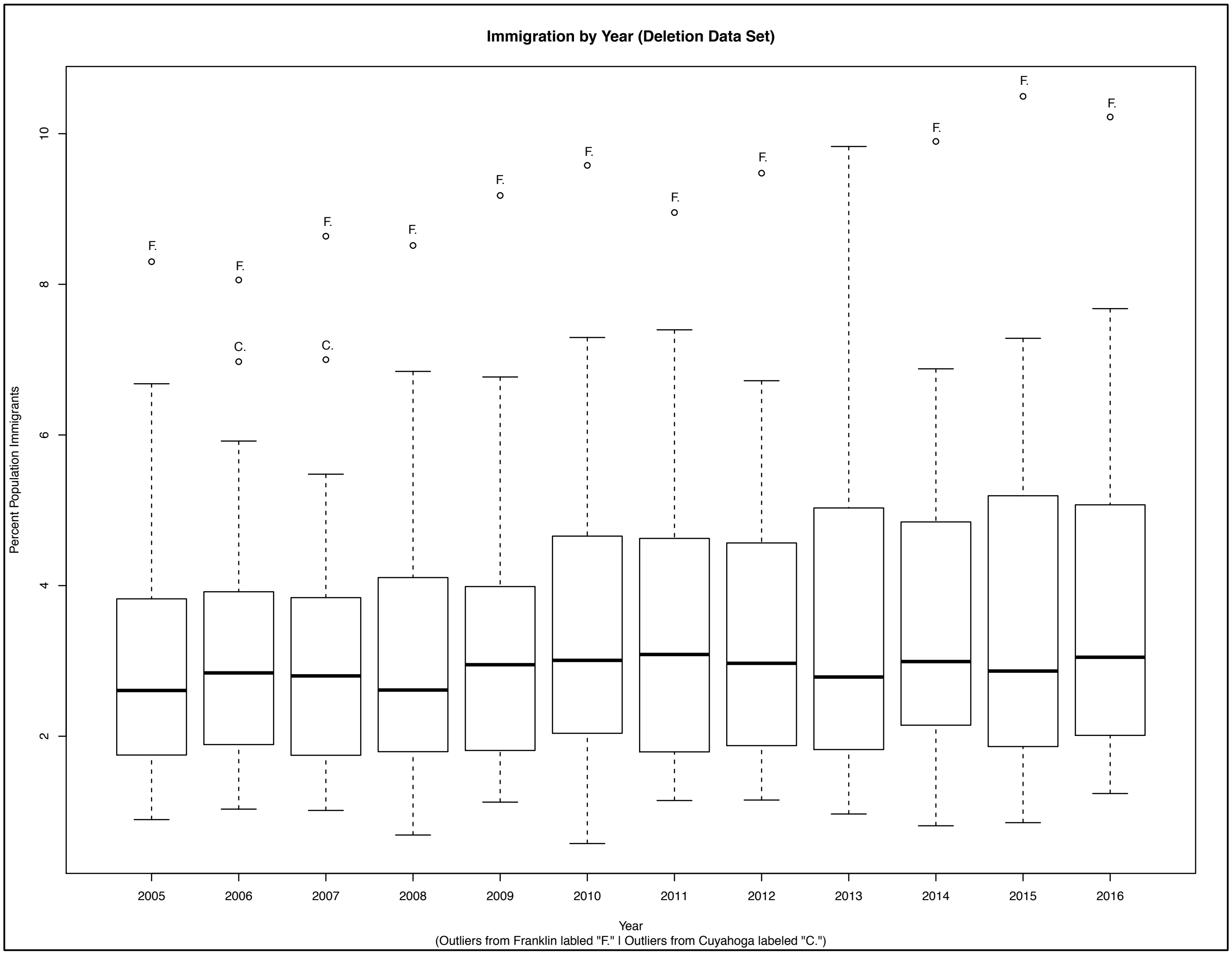
[7] The following figures only include counties that were used in the final deletion data set.

Figure 3: Dot Plot



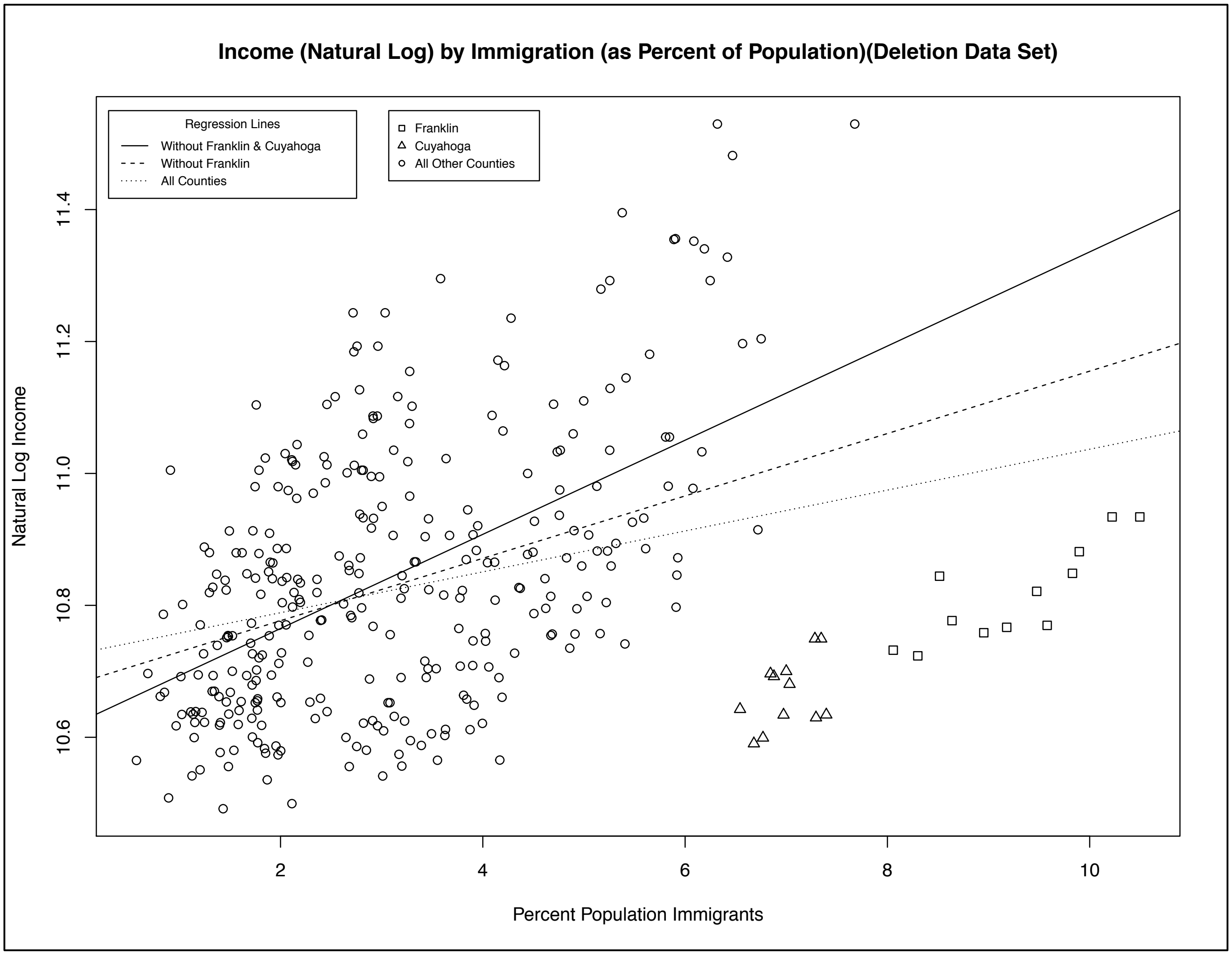
A more quantitative examination of outliers is performed with a Tukey box-whisker plot (a histogram-like plot where the box ends are drawn at the ends of the 1st and 3rd quarters, the dark line inside the box is the median value, and the "whiskers" are 1.5 times the interquartile range) below in Figure 4. This plot shows that the Franklin County outliers appear in almost every year, and percentages from Cuyahoga County appear twice. These outliers are expected, as Franklin and Cuyahoga Counties are home to Ohio's largest cities, Columbus and Cleveland, and large urban areas in America contain a disproportionately high number of immigrants (López & Bialik, 2017). Outlier label letters are explained at the bottom of the graph.

Figure 4: Box-Whisker Plot (1st-3rd quartiles, outliers specified)



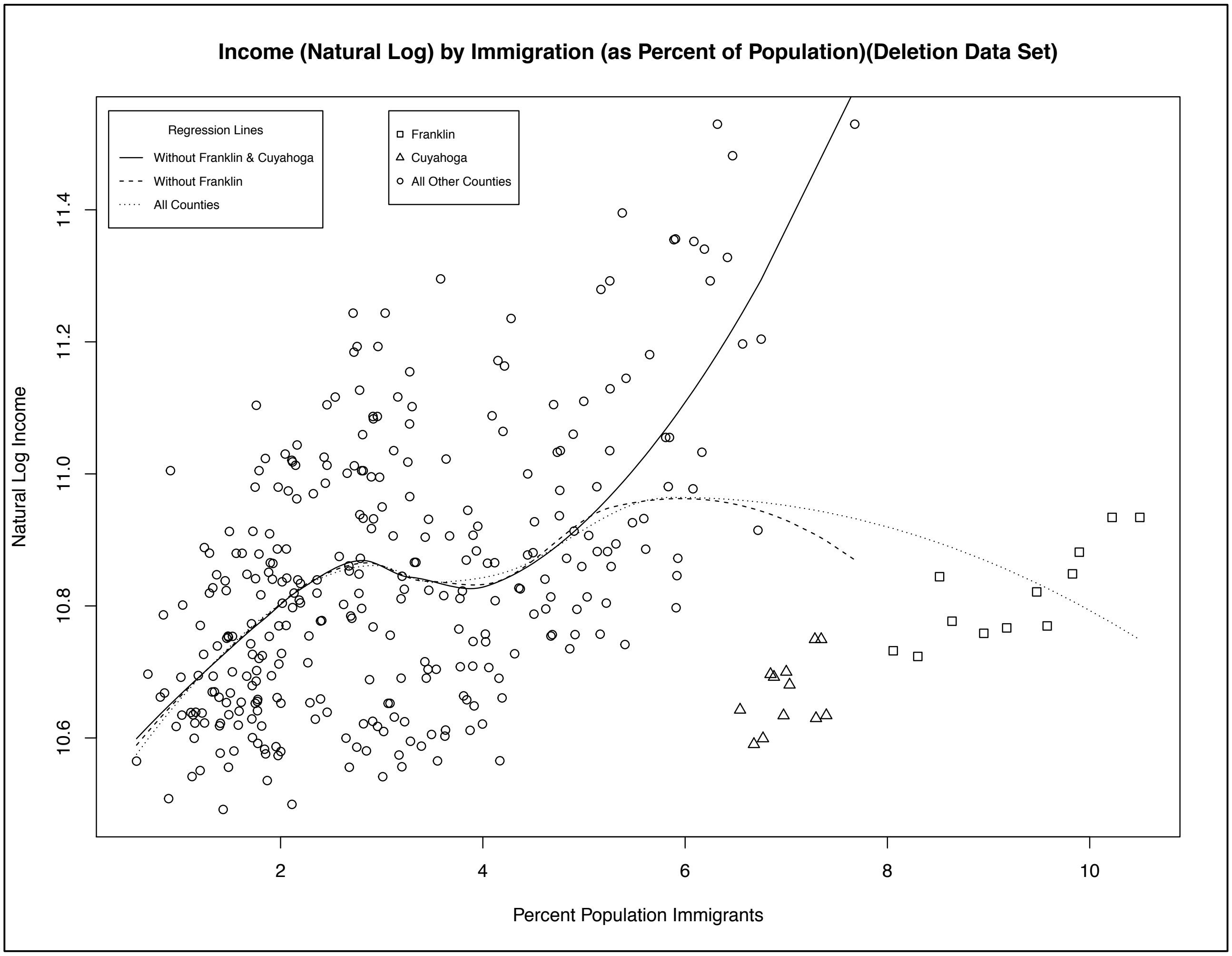
Further analysis of these outliers, illustrated below by the scatter plot in Figure 5, shows the apparent impact of Franklin and Cuyahoga counties on the slope of a regular ordinary least squares (OLS) regression line.

Figure 5: Scatter Plot – Linear Regression Lines



It appears from the scatterplot's linear lines that all counties display positive correlation between immigration and income. Franklin and Cuyahoga County appear to have strong outlying tendencies. The apparent effect of Franklin and Cuyahoga Counties appears significant enough to investigate further. To distinguish any sort of logarithmic or asymptotic relationship, a non-linear line of best fit (using the LOWESS method) is performed on top of the same scatter plot. The plot in Figure 6 below shows these LOWESS lines.

Figure 6: Scatter Plot – LOWESS lines



These lines reveal no consistent direction of the income-immigration relationship. This removes the possibility of arguing for a strong effect of the marginal effect of immigration, but highlights the potent effect of Franklin and Cuyahoga Counties. Ultimately, I conclude that there is no basis for removal of these counties from the main regression analysis. This is largely because I have strong evidence for why they exist, namely, urban areas draw immigrants. Furthermore, a log-transformation of immigration percentages that better conforms the data to normality reveals that the two counties do not represent statistically significant outliers.[8]

[8] Because of the apparent extreme nature exhibited by these outliers, I performed the regression with both counties removed and with only Franklin county removed. See Table 9 in the Appendix.

4 Model

The variables of the panel model are the following. **Income** is the natural log of the median, rather than mean, inflation-adjusted household income of a county. Median is used because large outlying incomes pull the mean higher than it should be as a representative measurement. For instance, the 2016 median household income for Delaware County was $94,234 while the mean household income was $128,117. This 36% increase in income is large enough to cause serious interpretation errors in the modeling phase. **Immigration** is simply the percent of non-citizens and non-native citizens living in the county and **Age** is the median age of all residents of the county (median is used here instead of the mean for the same reason the median was used for the Income variable). **Education** is the percentage of residents twenty-five years and older that have attained a certain level of education, broken down into four separate variables: high school, 2-year degree, 4-year degree, or a graduate degree (masters, doctorate or professional). Qualification-based categorizations like this typically only fail to demonstrate significant meaning when used across regions that exhibit different qualifications (for instance, if the model's regions were European countries, a four-year university degree from Malta may be significantly different than a four-year degree from the UK). Since data from the ACS on Ohio counties all demonstrate a uniform interpretation of "bachelor's degree," using qualification-based categorizations for cross-county data is a safe measurement of educational attainment (Connelly, Gayle, & Lambert, 2016).
Unemployment is simply the percentage of residents in Ohio counties that wish to work but are not employed. Finally, the **Male-Female Ratio** is the number of males per 100 females. As an aside, many similar studies include marital status as a typical factor in immigration-income models. It is excluded here as there was no consistent data in the ACS results. These factors constitute the following regression model:

$$I_{tc} = \gamma_0 + \gamma_1 M_{tc} + \gamma_2 A_{tc} + \gamma_3 E1_{tc} + \gamma_4 E2_{tc} + \gamma_5 E3_{tc} + \gamma_6 E4_{tc} + \gamma_7 U_{tc} + \gamma_8 F_{tc} + \epsilon_{tc}$$

Where I_{tc} is natural log of median income at time t in county c, M_{tc} is immigration level at time t in county c, A_{tc} is median age at time t in county c, $E1_{tc}$ is the percentage of adults with high school as their highest level of educational attainment at time t in county c, $E2_{tc}$ is the percentage of adults with a two-year degree as their highest level of educational attainment at time t in county c, $E3_{tc}$ is the percentage of adults with a four-year degree as their highest level of educational attainment at time t in county c, $E4_{tc}$ is the percentage of adults with a graduate degree as their highest level of educational attainment at time t in county c, U_{tc} is unemployment level at time t in county c, and finally, F_{tc} is the male-to-female ratio at time t in county c.

Panel regression models present unique problems with determining estimation techniques. Croissant and Milo suggest that when choosing models for panel regression, the standard pooled linear model starts as,

$$Y_{it} = A_{it} + B_{it} x_{it} + e_{it}$$

Where i is the individual (in this case, county), t is the time period (2005-2016), Y is the response variable, A and B are constants, set equal to A_{it} and B_{it} by assumption, x is the variable (or variables) of interest for individual i at time t, and e is the error term for individual i at time t.[9] In order to explain individual heterogeneity, the error term e can be split into two terms by introducing an error term corresponding to the individual and unchanging across time, u_i (Croissant & Millo, 2008). The model then becomes,

$$Y_{it} = A + Bx_{it} + u_i + e_{it}$$

[9] The parameter homogeneity assumption (that $A = A_{it}$ and $B = B_{it}$) is simply the assumption that for all individuals, at all times, A and B are the same. In a typical fixed effects model, all the "blocks" of the data are broken down to predict the dependent variable. I essentially assume that the "blocks" that are not related to individual error or individual values are the same. This is a rote, panel-specific assumption necessary to proceed with a panel analysis – comparable to normality and zero-centered assumptions about the OLS error term. If the parameters are not homogeneous across individuals and times, no legitimate, overarching conclusion about the nature of the variables could be inferred from the analysis results. Rather than saying, "It appears that immigration has a significant effect on income." I would have to say, "It appears that immigration in Delaware county had a specific effect on income in 2010."

Where u_i is the error term corresponding to the individual across time, and e_{it} is the idiosyncratic error and is assumed to be uncorrelated with other variables.[10]

At this point, the proper estimation method is determined based on correlation or independence among the individual error term and the other predictor variables. If the individual error terms are uncorrelated with the predictor variables, random-effects (RE), also known as OLS, is appropriate. If they *are* correlated, a fixed-effects (FE) estimation is appropriate. Torres-Reyna explains the FE estimator as a method to control for individual endogeneity that could affect the dependent variable and ultimately overthrow the validity of the model (Torres-Reyna, 2007). While it is known that the major problem with FE estimation is the inability to use time-invariant variables, this is not a problem for this model because all the variables are time-variant.

The correlation between individual error terms and predictor variables can be measured with a Hausman-type test, but Croissant and Milo propose two prior steps. First, a pooling test is required to establish the presence of coefficient homogeneity across individuals. Secondly, a Wooldridge test must be performed to determine the existence of unobserved effects, without which there would be no basis to assume that a FE model would be appropriate. A Hausman test can be performed with confidence only if the model first passes these two tests.

The Results section below discusses in detail the use of these tests, but it should come as no surprise that the FE estimation is appropriate for this study. A clear problem with studying the effect of immigration on county income is that there may be omitted variables related to income or predictors of income within counties that attract or dissuade immigrants, in which case, some latent variable would be the cause of an increase in income, even if immigration appears to be correlated. The use of FE estimators in the model removes the effect of time-invariant omitted variables that

[10] Croissant and Milo suggest further reading of this modeling technique can be found in econometric texts, specifically (Baltagi, 2013) or (Wooldridge, 2010).

appear within counties by adjusting for the individual county error. Because I use an FE estimator, the original proposed model technically becomes:

$$I_{tc} = \gamma_1 M_{tc} + \gamma_2 A_{tc} + \gamma_3 E_{tc} + \gamma_4 U_{tc} + \gamma_5 F_{tc} + \epsilon_{tc}$$

5 Results

First, determination of a proper estimation model (RE/OLS vs. FE) must be established by performing pooling, Woolridge, and Hausman tests.[11] These three tests are applied to the two data sets (single imputation and deletion). The Imputation Data Set fails the assumption of coefficient homogeneity, as determined by the pooling test. This is probably because using group means for counties with such small populations largely overestimates response variables. However, the Deletion Data Set passes this assumption for the pooling test. The deletion data set returns a p-value <2.2e-16 for the Hausman Test, indicating that the FE estimation is the proper approach. For this reason, the Deletion Data Set is retained while the Imputation Data Set is discarded for the remainder of the study. Because the form of Hausman test used in determination of FE estimators is robust against deviations from normality, there is no evidence of heteroscedasticity.[12]

While the Hausman test can be used to detect heteroscedasticity, it does not implement strategies to correct for any serial correlation (autocorrelation). Although the estimator (by definition) has within-county correlation (Croissant & Millo, 2008), I investigate correlation in the idiosyncratic errors. This step appears to be novel to this study within the broader literature of U.S. immigration panel analyses. It appears that the precedent in the literature reviewed is, at most, simply to perform a Hausman test and move on. For this study, the theoretical implications of autocorrelation seem severe enough to warrant a further analysis. A Breusch-Godfrey test reveals

[11] For both these tests and the regression model, I used R package 'plm' developed in (Croissant & Millo, 2008).
[12] See Tables 3-6 in the Appendix

the presence of serial correlation within the model.[13] To correctly account for this serial correlation, a robust covariance matrix estimation is performed (see the appendix for Table 10), consistent against autocorrelation and heteroscedasticity.[14, 15, 16] This correction widens the confidence interval of the original regression model. The new critical value of the factor of interest, immigration, is still significant with the widened confidence interval. Thus, the autocorrelation detected is determined to be ineffective in impacting the results of the model and I conclude that for this study's purpose there is no need to transform or change the data or model.

The regression results are shown below in Table 8.[17,18]

Table 8: Results for the Regression on log Income

Variables	FE, all counties		RE, all counties	
	coeff	p-value	coeff	p-value
Intercept	--	--	10.08424825	(< 2.2e-16) ***
Immigration	0.012167	(0.014036) *	0.00567568	(0.2382699)
Age	0.014060	(8.67e-07) ***	0.00857900	(0.0008178) ***
Ed: hs	-5.7489e-03	(0.002232) **	-0.00673321	(0.0004168) ***
Ed: 2 yr	1.7056e-03	(0.595237)	0.00138055	(0.6874159)
Ed: 4 yr	5.8958e-05	(0.921839)	0.00138137	(0.0370566) *
Ed: grad	1.0023e-02	(0.002132) **	0.01379298	(5.487e-05) ***
Unempl. Rate	-1.3148e-02	(< 2.2e-16) ***	-0.01577492	(< 2.2e-16) ***
Males:Females	1.4481e-03	(0.442114)	0.00598430	(0.0022743) **
R^2	0.54803		0.55396	
Adj. R^2	0.4953		0.54305	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The model's results (I focus only on the FE with all data) show that immigration, age, high school education, graduate education, and the unemployment rate are the variables that have a statistically significant impact on income at a 95 percent level confidence. More specifically, a 1

[13] See Table 7 in the Appendix
[14] See Table 10 in the Appendix
[15] more information and examples about how this type of estimation works can be seen in (Zeileis, 2004), (Haan & Levin), (Arai, 2015), and (Arellano, 1987).
[16] I used the technique proposed in (Millo, 2017)
[17] While I ultimately care about and will only consider the first regression (FE with all data) for discussion, I include the RE findings because most studies employ this estimation technique, and I include in table 9 (found in the appendix) the other two FE regressions as references to see how the slight outliers effected the results. The literature (see Küng, 2005) implies that some readers prefer to see both estimators.
[18] I used R package, "plm" (Croissant & Millo, 2008) for my regression and package "dplyr" (Wickham et al., 2017) for cleaning data.

percentage point increase in the immigrant share of total population corresponds to a 0.0125 percent increase in median income, a 1 percentage point increase in median age corresponds to a 1.41 percent increase in median income, a 1 percentage point increase in percent of population with high school degrees as their highest level of education corresponds to a 0.5 percent decrease in median income, a 1 percentage point increase in percent of population with graduate or professional degrees as their highest level of education corresponds to a 1 percent increase in median income, and a 1 percentage point increase in the unemployment rate corresponds to a 1.31 percent decrease in median income. Therefore, this study shows that I can say with 95 percent confidence that across Ohio counties, a 1 percentage point increase in county immigrant population corresponds to a 0.0125 percent increase in county median income. The effect of immigration on county median income in Ohio suggested here is small but positive.

The previously introduced concept of free human capital helps to explain these findings. As immigrants enter the state they bring with them education, knowledge, skills, and health. By attracting and recruiting workers that were raised and educated at the expense of another nation, Ohio has a free, increased pool of labor that can instantly be utilized in multiple industries. As immigrants with high education or relevant skills start working, they can pull median household income up. Additionally, immigrants with entrepreneurial skills bring new business to Ohio, increasing labor demand and decreasing unemployment.

The findings can also be supported with a return to the introductory explanation of the economic theory of immigration (Figure 1). The theory posits that an increase in immigration increases the supply of labor, decreases the wage level, and attracts industries that want to take advantage of lower wages, ultimately increasing economic performance, overall employment, and employee wages. In addition to the findings of this study, the economic status of both Ohio's wage structure and business growth corroborate this theory. Ohio only enforces a minimum wage above the federal standard for businesses grossing over $299,000 (NCSL, 2018). As regarding job growth, “Between 2011 and 2016, private employment in Ohio increased by 450,000 jobs, far outperforming the regional [Midwest] average of 261,000 jobs” (JobsOhio, 2018). It appears by the quantitative measures presented that both the concept of free human capital and the economic theory of immigration successfully explain the beneficial effect of immigration in Ohio.

6 Conclusion

The effect that immigration produces in respect to host country income is a widely-debated topic, both in the public and academic sector. This study builds on historical models of immigration to empirically evaluate the impact of immigration on the income of Ohio residents. Twelve years of data from the American Community Survey were used to build a literature-based, traditional econometric model to analyze this question. I determined that there were no significant outliers, and used a triad of tests to both determine the proper regression estimation technique for the data and to establish that the model was not heteroscedastic. I found the model to exhibit serial correlation, but an estimation of the regression coefficients robust against serial correlation revealed the findings to be accurate regardless. Finally, the study showed that at the margins, as the Ohio immigrant proportion of county populations increase by one percentage point, county median income increases by 0.0125%, supporting the general theoretical contention that immigration will increase income and wealth.

The study of economics is, in the perfect world, attached to the creation and implementation of policy. One appropriate federal policy recommendation that would capitalize on the benefits of immigration shown in this paper could be to implement a guest worker visa program with citizenship pathways, as determined by states. States that choose to extract the economic benefit of immigration can choose to issue visas specific to their state. This approach has been used both in Canada and Australia and has successfully stimulated regionalized benefits (Fuller & Rust, 2014). If such a policy were implemented in the United States, Ohio could offer its own guest worker visas, allowing more immigrants to enter the state workforce and subsequently accelerate positive economic growth.

A state-based policy recommendation involves Ohio's treatment of undocumented immigrants. Despite the internal political debates concerning the ethics of proper treatment of undocumented immigrants, Ohio's conduct towards these immigrants could be of great economic relevance. Forty percent of Hispanics say that "they have serious concerns about their place in America" and over half of foreign born Hispanics in the United States, documented and undocumented, are concerned that they or someone close to them could be deported under the current administration (Pew Research Center, 2017). If Ohio benefits from immigration, this kind of sentiment within American immigrant populations is bad news. Ohio lawmakers should be cautious about zealously aligning themselves with federal policy that could have a negative economic impact. One such example is Ohio House Bill 179, "Cooperate in enforcing federal immigration laws," where Representative Candice Keller has introduced a bill that would deny worker's compensation benefits for undocumented immigrants in Ohio. As this bill gains notoriety among groups like the ACLU, concern about Ohio's status as a friendly place for immigrants to live and work, regardless of legal status, will be propagated. Thus, the suggestion is that lawmakers should reject and work against this type of legislation that targets immigrant populations, and introduce legislation that encourages rather than limits immigration.

7 References

Altonji, J. G., & Card, D. (1991, January). The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives. In J. M. Abowd, & R. B. Freeman, *Immigration, Trade and the Labor Market* (pp. 201-234). Chicago, Illinois, USA: University of Chicago Press.

American Community Survey. (2017). *American Community Survey Information Guide*. Washington, D.C.: United States Census Bureau.

American Immigration Council. (2017). *Immigrants in Ohio*. Washington D.C.: American Immigration Council.

Arai, M. (2015). *Cluster-robust standard errors using R*. Stockholm University, Department of Economics. Stockholm: Stockholm University.

Arellano, M. (1987, November). Computing Robust Standard Errors for Within-Groups Estimators. *Oxford Bulletin of Economics and Statistics*, 49(4), 431-434.

Baltagi, B. H. (2013). *Econometric Analysis of Panel Data* (5 ed.). Chichester, West Sussex, England: John Wiley & Sons, Ltd.

Becker, G. (2007). Human Capital. In D. R. Henderson (Ed.), *Concise Encyclopedia of Economics* (2nd ed.).

Borjas, G. J. (1999). The Economic Analysis of Immigration. In O. Ashenfelter, & D. Card (Ed.), *Handbook of Labor Economcis* (pp. 1698-1757). Amsterdam: North Holland.

Borjas, G. J. (2013). *Immigration and the American Worker*. Washington D.C.: Center for Immigration Studies.

Borjas, G., & Doran, K. (2012, April 13). The Collapse of the Soviet Union and the Productivity of American Mathematicians. *The Quarterly Journal of Economics*, 1143-1203.

Browning, E. K., & Zupan, M. A. (2014). Microeconomics (12 ed.). Indianapolis, IN, USA: John Wiley & Sons.

Camarota, S. A. (2006). *Immigration's Impact on Public Coffers*. Washington, D.C.: Center for Immigration Studies.

Capps, R., Fix, M., & Henderson, E. (2011). Trends in immigrants' use of public assistance after welfare reform. *Immigrants and Welfare: The Impact of Welfare Reform on America's Newcomers*, 123-152.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Market Impacts of Higher Immigration. *Journal of Labor Economics*, 22-64.

Card, D., & Peri, G. (2016). Immigration Economics: A Review. UC Davis, UC Berkely, NBER.

Cohn, D., Passel, J., & Gonzalez-Barrera, A. (2017). *Rise in U.S. Immigrants From El Salvador, Guatemala and Honduras Outpaces Growth From Elsewhere*. Washington D.C.: Pew Research Center.

Connelly, R., Gayle, V., & Lambert, P. S. (2016). A review of educational attainment measures for social survey research. *Methodological Innovations*, 9, 1-11.

Croissant, Y., & Millo, G. (2008, July). Panel Data Econometrics in R: The plm Package. *Journal of Statistical Software*, 27(2), pp. 1-43. doi: 10.18637/jss.v027.i02 (URL: http://doi.org/10.18637/jss.v027.i02).

Cumoletti, M., & Batalova, J. (2018). *Middle Eastern and North African Immigrants in the United States*. Washington D.C.: Migration Policy Institute.

Dawson, R. (2011). How Significant Is a Boxplot Outlier? *Journal of Statistics Education*, 19(2).

Friedberg, R., & Hunt, J. (1995). The Impact of Immigrants on Host Country Wages, Employment and Growth. *American Economic Association*, 9(2), 23-44.

Fuller, B., & Rust, S. (2014, April 23). State-Based Visas - A Federalist Approach to Reforming U.S. Immigration Policy. *Policy Analysis*, 748.

Gonzalez-Barrera, A. (2015). *More Mexicans Leaving Than Coming to the U.S*. Washington D.C.: Pew Research Center.

Google Public Data. (2018, January 12). *Google Public Data*. Retrieved February 18, 2018, from Google: https://www.google.com/publicdata/explore?ds=kf7tgg1uo9ude_&met_y=population&hl=en&dl=en

Haan, W. J., & Levin, A. (n.d.). *A Practitioner's Guide to Robust Covariance Matrix Estimation*. San Diego: National Science Foundation.

Haskins, R. (2016). Economic Mobility of Immigrants in the United States. Washington D.C.: Economic Mobility Project.

Jaeger, D. A. (2007). *Skill Differences and the Effect of Immigrants on the Wages of Natives*. College of William and Mary. Williamsburg: Institute for the Study of Labor (IZA).

JobsOhio. (2018). Business Climate. Retrieved 03 22, 2018, from JobsOhio: http://jobs-ohio.com/why-ohio/business-climate/

Küng, L. (2005). *The Impact of Immigration on Swiss Wages: A Fixed Effects Two Stage Least Squares Analysis*. University of Fribourg, Department of Economics. Fribourg: University of Fribourg.

Ku, L., & Bruen, B. (2013). *Poor Immigrants Use Public Benefits at a Lower Rate than Poor Native-Born Citizens*. Washington, D.C.: Cato Institute.

LaLonde, R. J., & Topel, R. H. (1991). Labor Market Adjustments to Increased Immigration. In J. M. Abowd, & R. B. Freeman*, Immigration, Trade and the Labor Market* (pp. 167-199). Chicago, Illinois, USA: University of Chicago Press.

López, G., & Bialik, K. (2017). *Key findings about U.S. immigrants*. Washington D.C.: Pew Research Center.

Map Chart. Retrieved April 12, 2018 from Map Chart: https://www.mapchart.net/

Millo, G. (2017). Robust Standard Error Estimators for Panel Models: A Unifying Approach. *Journal of Statistical Software*, 82(3), 1-27. doi: 10.18637/jss.v082.i03 (URL: http://doi.org/10.18637/jss.v082.i03).

Murray, J., Batalova, J., & Fix, M. (2006). *The Impact of Immigration on Native Workers: A Fresh Look at the Evidence*. Washington, D.C.: Migration Policy Institute.

NCSL. (2018). State Minimum Wages. Washington D.C.: National Conferences of State Legislature.

New American Economy. (2016). *The Contribution of New Americans in Ohio*. New York: New American Economy.

Otiso, K. M., & Smith, B. W. (2005, December). Immigration and Economic Restructuring in Ohio's Cities, 1940-2000. *The Ohio Journal of Science*, 105(5), 133-137.

Penn Wharton Budget Model. (2016). *The Effects of Immigration on the United States' Economy*. University of Pennsylvania. Philadelphia: Penn Wharton Budget Model.

Peri, G. (2014). *Do immigrant workers depress the wages of native workers*? Davis, California & Bonn, Germany: IZA World of Labor.

Peri, G. (2017). *The Impact of Immigration on Wages of Unskilled Workers*. Washington, D.C.: Cato Institute.

Pew Hispanic Center. (2006). *The State of American Public Opinion on Immigration in Spring 2006: A Review of Major Surveys*. Washington, D.C.: Pew Research Center.

Pew Research Center. (2009). *Most Mexicans See Better Life in U.S. - One-In-Three Would Migrate*. Washington D.C.: Pew Research Center.

Pew Research Center. (2017). *Latinos and the New Trump Administration*. Washington D.C.: Pew Research Center.

Pew Research Center Hispanic Trends. (2016). *U.S. unauthorized immigration population estimates*. Washington, D.C.: Pew Research Center.

Rainie, L., & Brown, A. (2016). *Americans less concerned than a decade ago over immigrants' impact on workforce*. Fact Tank. Washington D.C.: Pew Research Center.

Richwine, J. (2016). *The Cost of Welfare Use by Immigrant and Native Households*. Washington, D.C.: Center for Immigration Studies.

Schoeni, R. F. (1997). *The Effects of Immigration on the Employment and Wages of Native Workers: Evidence from the 1970s and 1980s*. Santa Monica: RAND.

The National Academies of Sciences (2017). *The Economic and Fiscal Consequences of Immigration.* (F. D. Blau, & C. Mackie, Eds.) Washington, D.C.: The National Academies Press.

Simcox, D. (1994). *The Costs of Immigration.* Washington, D.C.: Center for Immigration Studies.

Smith, A. (1776). *The Wealth of Nations.* London: Metheun & Co.

Torres-Reyna, O. (2007). *Panel Data Analysis Fixed and Random Effects using Stata.* Princeton: Princeton University.

UNFPA. (2015, December 23). Migration. Retrieved March 21, 2018, from United Nations Population Fund: https://www.unfpa.org/migration

United States Census Bureau / American FactFinder. (2017). *Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2016.* Washington D.C.: United States Census Bureau. Retrieved from Ohio Demographics: https://www.ohio-demographics.com/counties_by_population

United States Census Bureau. (2015). *American Community Survey (ACS) When to Use 1-year, 3-year, or 5-year Estimates.* Retrieved February 18, 2018, from United States Census Bureau: https://www.census.gov/programs-surveys/acs/guidance/estimates.html

United States Census Bureau. (2016). *American Community Survey Data Suppression.* Washington, D.C.: United states Census Bureau.

Venkatu, G., & Fee, K. (2011). *Domestic Migration and its Impact on Ohio.* Cleveland: Federal Reserve Bank of Cleveland.

Vice, M., & Chwe, H. (2017). *Mexican Views of the U.S. Turn Sharply Negative.* Washington D.C.: Pew Research Center.

Wickham, H., Francois, R., Henry, L., and Müller, K. (2017). dplyr: A Grammar of Data Manipulation. R package version 0.7.4. https://CRAN.R-project.org/package=dplyr

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2 ed.). Cambridge, Massachusetts, USA: The MIT Press.

Zeileis, A. (2004, November). Econometric Computing with HC and HAC Covariance Matrix Estimators. *Journal of Statistical Software*, 11(10).

Zong, J., Batalova, J., & Hallock, J. (2018). *Frequently Requested Statistics on Immigrants and Immigration in the United States.* Washington, D.C.: Migration Policy Institute.

8 Appendix

Table 3: Pooling Test for Coefficient Homogeneity

H_o = stable, H_a = unstable

Statistic	Imputation Data Set	Deletion Data Set
F	1.2507	0.88737
degrees freedom 1	296	216
degrees freedom 2	114	84
p-value	0.08296	0.7543
reject H_o?	yes	no

Table 4: Wooldridge Test for Unobserved Effects

H_o = observed effect, H_a = unobserved effects

Statistic	Imp. Data Set <removed>	Deletion Data Set
Z	--	3.7873
p-value	--	1.523e4
reject H_o?	--	yes

Table 5: Hausman Test for Estimation Determination

H_o = Either Model is Consistent, H_a = RE is Inconsistent

Statistic	Imp. Data Set <removed>	Deletion Data Set
χ^2	--	152.79
degrees freedom	--	8
p-value	--	<2.2e-16
reject H_o?	--	yes

Table 6: Regression-Based Robust Hausman Test for Estimation Determination

H_o = Either Model is Consistent, H_a = RE is Inconsistent

Statistic	Imp. Data Set <removed>	Deletion Data Set
χ^2	--	302.36
degrees freedom	--	8
p-value	--	<2.2e-16
reject H_o?	--	yes

Table 7: Breusch-Godfrey Test for Panel Models

H_o = No Serial Correlation in Idiosyncratic Errors, H_a = Serial Correlation in Idiosyncratic Errors

Statistic	Result
χ^2	86.076
degrees freedom	12
p-value	<2.815e-12
reject H_o?	yes

Table 9: Supplementary Results for the Regression on log Income

Variables	FE, w/o Franklin		FE, w/o Franklin/Cuyahoga	
	coeff	p-value	coeff	p-value
Immigration	8.4705e-03	(0.097091) .	8.2235e-03	(0.114011)
Age	1.5148e-02	(2.031e-07) ***	1.5235e-02	(2.86e-07)***
Ed: hs	-5.3998e-03	(0.004306) **	-5.5449e-03	(0.004088) **
Ed: 2 yr	1.2356e-03	(0.701929)	9.0740e-04	(0.782861)
Ed: 4 yr	1.8059e-05	(0.976877)	-4.3091e-05	(0.946959)
Ed: grad	9.9030e-03	(0.002557) **	9.7501e-03	(0.003697) **
Unempl. Rate	-1.3157e-02	(< 2.2e-16) ***	-1.2944e-02	(< 2.2e-16) ***
Males:Females	1.7878e-03	(0.344996)	1.7292e-03	(0.367903)
R^2	0.54357		0.53717	
Adj. R^2	0.48988		0.48223	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 10: Covariance Matrix Estimation

Variables	FE, all counties	
	coeff	p-value
Immigration	1.2167e-02	0.083475 .
Age	1.4060e-02	1.623e-10 ***
Ed: hs	-5.7489e-03	0.007866 **
Ed: 2 yr	1.7056e-03	0.596396
Ed: 4 yr	5.8958e-05	0.902083
Ed: grad	1.0023e-02	0.001182 **
Unempl. Rate	-1.3148e-02	< 2.2e-16 ***
Males:Females	1.4481e-03	0.375513

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 11: Full Data Set
(note: missing values replaced by year means are bolded and italicized, and the county represented is followed by an asterisk (*). This data set includes all deleted counties. The final set removed all counties listed in Appendix 1.)

county	date	inc	imm	age	hs	2 yr	4 yr	grad	emp	m:f	pop
Allen	2005	41712	1.11	37.3	42.5	9.2	11.1	5.8	7.8	94.8	101619
Allen	2006	44100	1.91	37.4	42.1	9.4	10.4	6.8	7.7	98.1	105788
Allen	2007	44002	1.01	37.3	43.9	8.6	14.3	5.0	8.6	98.1	105233
Allen	2008	44210	0.69	37.6	44.4	8.9	13.6	5.3	8.6	97.3	105168
Allen	2009	37855	1.12	38.1	41.4	7.6	15.5	4.7	13.0	100.0	104357
Allen	2010	41057	1.25	38.6	41.6	9.2	16.4	6.5	12.7	98.3	106205
Allen	2011	41307	1.72	37.5	42.1	8.8	17.1	7.4	13.3	101.6	106094
Allen	2012	41729	1.16	38.2	40.9	9.6	17.9	7.3	7.9	100.9	105141
Allen	2013	43030	1.32	37.7	38.3	9.0	17.1	7.0	9.7	100.3	105298

Allen	2014	42701	0.81	38.3	40.0	12.5	14.2	5.9	9.5	101.5	105040
Allen	2015	47592	1.21	38.8	38.9	11.0	11.2	8.2	6.7	100.3	104425
Allen	2016	47592	2.06	38.2	37.8	13.6	10.0	6.7	6.7	98.4	103742
Ashtabula	2005	36611	0.89	39.2	40.7	5.7	7.6	5.3	6.7	94.0	101082
Ashtabula	2006	37628	1.87	38.6	45.5	7.5	8.4	3.9	6.4	95.8	102703
Ashtabula	2007	39806	1.77	40.0	48.2	6.8	13.1	4.4	9.2	95.9	101141
Ashtabula	2008	42417	1.77	38.8	46.5	5.5	13.7	4.1	8.3	94.1	100648
Ashtabula	2009	39610	1.96	41.0	45.1	4.9	11.2	3.8	13.8	100.3	100767
Ashtabula	2010	38751	0.58	41.8	45.6	7.7	12.5	4.6	12.0	99.2	101429
Ashtabula	2011	38204	1.20	41.2	46.4	7.3	13.8	4.1	12.3	101.7	101345
Ashtabula	2012	36015	1.43	41.9	44.7	5.5	12.8	4.1	10.2	99.5	100389
Ashtabula	2013	40839	0.97	42.3	43.1	8.0	12.5	4.4	8.3	97.1	99811
Ashtabula	2014	39079	1.98	41.8	44.8	7.9	13.0	4.7	6.2	102.2	99175
Ashtabula	2015	42965	0.85	42.2	44.5	6.7	8.5	4.0	6.6	97.4	98632
Ashtabula	2016	42965	1.50	43.4	42.6	8.0	8.2	5.4	6.6	102.8	98231
Belmont	2005	34628	0.86	42.7	47.2	8.6	7.5	5.5	10.1	93.2	65833
Belmont	2006	37760	1.08	41.2	43.7	8.8	11.9	4.2	6.3	96.3	68771
Belmont	2007	35732	1.13	42.5	48.1	8.7	14.9	5.9	6.4	98.3	67908
Belmont	2008	39549	0.88	42.7	45.6	9.3	12.8	3.6	4.6	98.8	67975
Belmont*	2009	38256	***2.85***	43.2	41.5	8.2	14.5	3.9	8.3	100.7	68066
Belmont	2010	38548	0.92	43.6	44.7	11.5	14.9	4.3	7.9	101.4	70319
Belmont	2011	40981	0.98	43.4	46.1	7.9	11.8	4.7	11.6	101.8	70151
Belmont	2012	44245	1.03	44.0	43.9	10.7	15.3	4.7	8.8	105.4	69671
Belmont*	2013	38224	***3.20***	43.9	42.9	11.1	15.0	5.8	6.7	103.9	69571
Belmont	2014	42079	1.71	44.1	45.3	7.4	16.2	6.5	9.0	103.4	69461
Belmont*	2015	48220	***1.59***	44.4	39.6	12.0	11.2	6.3	6.3	106.2	69154
Belmont*	2016	48220	***3.31***	44.5	39.4	11.8	12.3	6.7	6.3	105.4	68673
Butler	2005	50140	3.80	35.4	37.8	6.0	15.5	8.0	6.2	96.3	339309
Butler	2006	53278	3.94	35.0	35.8	6.9	16.2	9.1	6.4	95.7	354992
Butler	2007	52955	4.44	35.2	36.1	6.8	25.3	9.2	5.6	96.1	357888
Butler	2008	52297	4.05	35.2	35.4	6.8	25.0	8.6	5.8	96.0	360765
Butler	2009	53421	5.61	35.7	34.4	6.3	25.6	9.5	11.4	96.7	363184
Butler	2010	54541	5.05	36.0	33.8	6.8	27.7	10.3	10.9	96.8	368630
Butler	2011	53138	4.50	36.3	34.4	7.2	26.8	9.8	9.9	96.1	369999
Butler	2012	55687	4.51	37.1	34.8	8.0	26.8	8.3	7.9	96.2	370589
Butler	2013	55958	5.59	36.5	34.3	8.2	28.9	9.8	7.1	95.9	371272
Butler	2014	58730	5.83	36.1	33.3	7.2	29.8	11.5	6.4	96.0	374158
Butler	2015	63273	5.81	36.6	32.8	8.1	18.8	10.2	5.2	95.9	376353
Butler	2016	63273	5.85	36.5	32.1	7.1	19.3	10.4	5.2	96.7	377537
Clark	2005	39319	2.00	38.2	41.5	8.3	10.3	6.5	9.6	95.4	139053

Clark	2006	42546	1.77	39.3	41.4	8.7	10.3	4.7	7.9	93.0	141872
Clark	2007	42687	1.39	39.5	39.8	8.1	16.9	6.8	9.2	91.5	140477
Clark	2008	45467	1.82	39.8	38.9	8.2	15.9	6.3	6.5	92.5	139859
Clark	2009	42367	1.61	39.9	37.8	7.7	15.1	5.1	12.3	93.8	139671
Clark	2010	39580	2.75	40.6	38.2	8.0	17.1	6.1	11.5	91.6	138193
Clark	2011	41292	2.34	40.2	35.9	7.6	18.1	5.8	12.5	93.6	137691
Clark	2012	39178	1.85	41.5	39.3	6.9	17.3	6.2	13.3	94.3	137206
Clark	2013	43742	1.76	41.8	36.8	8.7	18.9	7.1	8.6	94.1	136167
Clark	2014	41729	2.46	40.8	35.4	9.9	16.5	6.1	8.9	94.9	136554
Clark	2015	46811	1.52	40.5	37.4	9.7	10.9	6.8	6.9	93.4	135959
Clark	2016	46811	1.89	41.9	38.8	8.5	11.6	6.3	6.9	91.8	134786
Clermont	2005	50845	2.02	36.1	36.0	6.8	15.8	8.0	6.8	96.2	189124
Clermont	2006	52279	1.92	35.6	37.4	7.8	15.9	6.8	6.5	95.2	192706
Clermont	2007	53029	1.79	36.3	35.5	7.4	23.4	6.7	5.2	96.5	193490
Clermont	2008	61288	1.85	36.8	35.1	7.8	25.9	9.8	5.1	97.5	195385
Clermont	2009	58348	2.08	38.4	37.7	5.9	23.1	7.3	10.1	97.6	196364
Clermont	2010	56952	3.00	38.9	35.6	7.1	25.9	9.0	9.0	96.3	197604
Clermont	2011	55934	2.92	39.2	34.4	8.3	25.5	8.4	6.5	98.3	199139
Clermont	2012	53087	1.56	38.8	36.2	9.1	24.5	8.4	7.8	96.3	199085
Clermont	2013	61702	2.05	40.5	33.5	9.7	27.7	9.5	4.2	98.1	200218
Clermont	2014	62554	2.16	39.3	34.6	9.2	27.3	8.4	5.5	98.2	201560
Clermont	2015	60661	2.46	39.9	31.6	10.9	19.3	9.0	3.8	96.4	201973
Clermont	2016	60661	2.15	39.7	31.3	8.9	17.9	10.2	3.8	97.9	203022
Columbiana*	2005	36969	***2.60***	40.3	44.4	8.4	7.3	4.5	9.3	95.9	107164
Columbiana	2006	37791	1.42	39.6	47.6	9.6	7.2	3.1	7.7	100.8	110542
Columbiana	2007	39605	0.88	40.2	48.7	7.5	13.0	4.6	8.3	99.1	108698
Columbiana	2008	40941	0.89	40.8	45.1	7.1	14.2	3.8	7.9	99.0	107873
Columbiana	2009	37595	0.73	43.1	47.1	9.9	10.9	3.7	13.1	100.6	107722
Columbiana	2010	35909	1.98	41.7	46.4	9.5	13.6	4.6	12.6	102.6	107800
Columbiana	2011	43975	0.74	42.9	48.4	6.9	13.0	4.3	11.6	99.4	107570
Columbiana	2012	44210	1.18	42.5	45.5	9.3	13.0	3.7	8.6	100.0	106507
Columbiana*	2013	42100	***3.20***	42.8	45.9	8.6	14.3	5.7	7.9	98.6	105893
Columbiana	2014	42640	0.68	43.4	47.0	9.3	14.9	4.7	8.8	99.5	105686
Columbiana	2015	47864	3.14	44.2	44.3	8.4	10.3	4.1	8.4	100.8	104806
Columbiana	2016	47864	1.76	44.2	43.5	11.3	8.4	4.7	8.4	103.4	103685
Cuyahoga	2005	39752	6.68	39.3	31.0	6.0	16.6	10.9	9.6	90.1	1305166
Cuyahoga	2006	41522	6.97	39.9	31.4	6.7	15.9	11.1	9.4	90.2	1314241
Cuyahoga	2007	44358	7.00	40.1	31.5	7.0	27.8	11.5	8.7	90.3	1295958
Cuyahoga	2008	44199	6.84	40.6	29.4	6.5	28.3	10.9	8.9	90.2	1283925
Cuyahoga	2009	40101	6.77	39.7	29.7	6.6	27.9	11.5	13.6	90.0	1275709

Cuyahoga	2010	41347	7.29	40.2	29.0	7.4	29.1	11.6	13.0	90.3	1278208
Cuyahoga	2011	41530	7.40	40.3	29.1	6.3	29.2	11.7	12.1	90.3	1270294
Cuyahoga	2012	41880	6.54	40.6	28.4	6.9	29.9	12.1	11.3	90.5	1265111
Cuyahoga	2013	43501	7.03	40.7	27.8	7.2	31.4	12.8	10.6	90.7	1263154
Cuyahoga	2014	44016	6.88	40.3	27.9	7.3	31.0	13.0	10.0	90.9	1259828
Cuyahoga	2015	46601	7.28	40.3	28.3	8.0	17.7	12.8	7.6	90.8	1255921
Cuyahoga	2016	46601	7.35	40.2	29.0	7.5	18.2	13.0	7.6	91.0	1249352
Delaware	2005	75767	4.28	34.2	20.7	8.4	32.7	15.8	5.0	97.9	147601
Delaware	2006	79173	5.17	33.5	20.8	7.9	31.5	17.1	3.5	97.7	156697
Delaware	2007	80448	3.58	33.4	20.3	6.9	49.2	17.0	4.0	97.7	160865
Delaware	2008	88899	5.38	33.4	20.8	7.1	49.0	16.5	3.8	97.0	165026
Delaware	2009	83106	6.42	36.8	22.1	8.0	47.5	16.5	4.9	99.5	168708
Delaware	2010	85146	6.09	37.4	18.7	8.1	50.0	16.7	6.8	94.2	175250
Delaware	2011	85365	5.89	37.8	20.5	6.6	50.5	18.4	4.3	97.2	178341
Delaware	2012	85470	5.90	37.7	22.1	6.4	49.2	18.4	3.2	98.2	181061
Delaware	2013	84159	6.19	37.8	21.5	7.4	51.8	17.2	3.1	98.1	184979
Delaware	2014	96949	6.47	38.0	20.0	7.0	52.2	21.0	2.7	98.8	189113
Delaware	2015	101693	6.32	38.2	19.7	6.3	36.1	18.1	2.3	98.8	193013
Delaware	2016	101693	7.68	38.1	20.1	6.0	34.3	20.6	2.3	98.6	196463
Erie	2005	40627	1.68	40.5	40.0	6.1	12.7	5.4	7.2	93.0	76797
Erie	2006	45549	1.61	41.2	42.5	8.0	13.4	6.3	6.1	95.3	78116
Erie	2007	48654	3.52	41.8	40.7	8.2	19.0	7.3	7.3	97.4	77323
Erie*	2008	46385	***2.73***	42.0	40.8	10.6	18.1	5.2	6.1	93.3	77062
Erie	2009	43099	1.07	43.9	38.8	7.3	21.1	9.0	8.2	95.8	76963
Erie	2010	42246	1.98	43.8	42.7	7.0	19.3	7.4	12.0	97.8	77070
Erie	2011	46949	1.71	43.5	41.2	8.3	20.4	7.5	9.6	94.8	76751
Erie	2012	44694	1.31	44.2	37.7	8.2	21.3	7.9	8.8	92.6	76398
Erie	2013	46073	1.82	44.6	35.3	9.6	22.6	7.7	8.1	94.6	76048
Erie	2014	48734	1.92	44.4	40.6	9.3	22.2	7.5	6.3	97.6	75828
Erie	2015	48949	1.61	44.4	43.7	7.8	13.3	7.2	7.5	95.1	75550
Erie	2016	48949	2.95	46.2	37.5	9.9	13.5	8.2	7.5	95.5	75107
Fairfield	2005	51044	1.92	36.5	36.8	8.7	15.2	8.0	6.3	98.7	135828
Fairfield	2006	55113	2.90	36.0	40.5	8.4	15.3	7.3	4.1	98.0	140591
Fairfield	2007	59033	2.44	36.0	38.5	8.0	22.6	7.1	5.6	97.4	141318
Fairfield	2008	58104	2.32	36.7	37.7	7.2	23.7	7.4	5.7	100.7	142223
Fairfield	2009	51427	1.67	37.7	35.7	8.5	25.8	8.0	10.1	99.5	143712
Fairfield	2010	55981	2.82	39.3	35.8	8.8	26.6	9.5	8.7	96.2	146351
Fairfield	2011	59607	2.90	39.1	36.4	8.7	25.2	9.7	9.1	102.1	147066
Fairfield	2012	60615	2.73	39.2	33.7	10.3	25.7	8.1	8.1	99.8	147474
Fairfield	2013	56286	2.78	39.2	33.2	9.7	26.1	7.9	6.1	98.4	148867

Fairfield	2014	59933	2.66	39.6	33.6	10.5	27.3	8.6	4.6	100.3	150381
Fairfield	2015	65316	2.91	38.5	36.1	9.1	17.4	8.3	3.9	99.0	151408
Fairfield	2016	65316	2.96	40.2	32.4	10.4	17.1	10.1	3.9	99.8	152597
Franklin	2005	45410	8.30	34.1	27.5	6.0	22.0	12.5	7.0	96.3	1068080
Franklin	2006	45803	8.06	34.5	29.3	5.6	21.8	12.2	7.2	96.1	1095662
Franklin	2007	47900	8.64	34.5	27.7	6.4	35.3	12.5	6.2	96.5	1118107
Franklin	2008	51238	8.52	34.6	25.7	6.5	35.8	12.9	5.8	96.4	1129067
Franklin	2009	47416	9.18	33.2	25.9	6.4	36.0	11.9	8.9	95.7	1150122
Franklin	2010	47557	9.58	33.5	26.9	6.6	34.9	12.1	11.2	94.7	1165897
Franklin	2011	47029	8.95	33.5	26.0	6.7	34.9	12.5	9.3	94.9	1178799
Franklin	2012	50074	9.48	33.7	25.3	7.2	37.2	13.5	7.7	95.1	1195537
Franklin	2013	51460	9.83	33.9	25.4	6.2	37.4	13.9	6.6	95.0	1212263
Franklin	2014	53180	9.90	34.0	24.6	6.6	38.0	14.2	6.0	95.0	1231393
Franklin	2015	56055	10.50	34.0	25.0	7.0	24.6	13.9	5.5	95.2	1251722
Franklin	2016	56055	10.22	34.0	25.5	7.0	25.1	14.0	5.5	95.5	1264518
Geauga	2005	69890	3.28	39.8	25.5	6.1	24.8	14.1	4.0	97.4	94171
Geauga	2006	61120	2.11	40.9	29.6	5.6	19.2	13.1	5.6	99.9	95676
Geauga	2007	67276	3.16	41.0	28.0	7.9	32.2	13.1	4.5	95.6	95029
Geauga	2008	60969	2.12	42.6	27.6	7.3	32.7	12.3	5.4	98.2	94753
Geauga	2009	60957	3.26	42.9	25.5	6.7	35.4	10.6	9.4	95.3	99060
Geauga	2010	61236	3.64	43.2	28.2	8.9	34.5	13.9	7.4	98.0	93408
Geauga	2011	63855	4.20	44.4	29.1	8.2	34.5	14.6	4.3	94.0	93228
Geauga	2012	67264	2.54	44.1	32.2	7.3	33.4	12.3	6.5	97.3	93680
Geauga	2013	66428	1.76	43.5	26.8	7.8	36.6	12.3	4.5	96.0	93972
Geauga	2014	72001	2.73	44.1	26.4	9.2	36.4	12.4	4.3	97.3	94295
Geauga	2015	76384	2.72	44.6	25.3	8.7	25.6	11.8	3.3	99.1	94102
Geauga	2016	76384	3.03	44.9	26.1	7.6	23.3	12.8	3.3	97.4	94060
Greene	2005	56659	3.85	38.2	27.0	9.4	16.6	16.5	5.5	97.8	143218
Greene	2006	55895	3.46	36.5	30.6	9.4	18.6	14.2	5.5	94.8	152298
Greene	2007	54560	3.90	36.5	27.8	8.2	35.3	17.1	5.6	95.2	154656
Greene	2008	57849	3.28	36.7	26.0	9.6	33.6	14.4	5.5	93.8	159190
Greene	2009	55310	3.95	37.3	28.9	9.3	33.6	16.5	8.3	94.9	159823
Greene	2010	51048	4.61	37.1	28.3	8.6	34.6	15.4	8.9	97.0	161605
Greene	2011	56194	4.76	36.5	27.5	9.2	35.1	16.9	9.8	95.6	162846
Greene	2012	52544	3.84	36.9	25.9	7.6	35.9	17.2	8.5	95.7	163587
Greene	2013	59872	4.44	37.9	24.1	9.0	37.9	18.3	8.1	94.2	163204
Greene	2014	58396	4.76	37.9	24.6	9.7	37.5	16.3	6.4	97.6	163820
Greene	2015	62018	5.25	37.8	28.1	8.0	19.5	16.5	3.9	98.1	164427
Greene	2016	62018	4.77	38.6	24.6	8.6	19.8	17.2	3.9	95.3	164765
Hamilton	2005	43933	4.16	37.6	31.0	6.7	19.3	11.6	7.2	92.1	786982

Hamilton	2006	44652	4.06	37.8	30.0	7.5	19.0	11.7	6.8	91.8	822596
Hamilton	2007	48416	4.51	38.0	30.1	6.7	32.2	12.0	6.9	92.0	842369
Hamilton	2008	50301	4.37	38.6	28.0	8.2	31.8	12.1	6.3	92.5	851494
Hamilton	2009	46451	3.90	36.8	27.3	7.0	32.4	12.3	9.3	91.9	855062
Hamilton	2010	46236	5.41	37.1	27.7	7.5	33.1	12.5	10.7	92.3	802252
Hamilton	2011	45940	4.86	37.3	27.0	7.4	33.4	12.8	11.8	92.7	800362
Hamilton	2012	46837	4.67	37.3	27.9	7.5	33.4	12.9	9.3	92.7	802038
Hamilton	2013	46967	5.16	37.4	27.0	7.7	34.4	13.6	8.5	92.6	804520
Hamilton	2014	48770	4.93	36.7	27.2	8.5	35.6	13.8	8.4	93.0	806631
Hamilton	2015	53229	5.13	37.0	27.3	8.1	22.9	13.7	6.5	92.8	807598
Hamilton	2016	53229	5.23	37.0	26.7	8.1	21.7	15.2	6.5	93.1	809099
Hancock*	2005	45117	2.21	37.2	37.6	7.5	14.3	9.9	***7.2***	99.8	71503
Hancock	2006	44433	3.02	36.9	36.6	9.3	15.0	8.8	4.9	91.5	73824
Hancock	2007	48567	3.15	37.0	40.0	8.6	22.3	8.5	5.1	94.9	74204
Hancock*	2008	51386	***2.73***	38.1	39.2	7.1	24.2	9.0	2.5	96.6	74273
Hancock	2009	47556	3.21	38.3	34.5	10.3	28.4	8.8	7.0	94.1	74538
Hancock*	2010	50150	***3.08***	38.6	37.9	6.5	23.5	8.3	9.2	93.0	74727
Hancock	2011	46742	2.72	38.4	38.6	8.5	22.3	10.7	12.0	95.2	75056
Hancock	2012	47947	2.29	39.1	38.3	10.3	24.2	6.7	8.2	93.4	75671
Hancock	2013	46382	2.66	37.4	33.6	7.7	28.0	11.5	5.7	101.6	75773
Hancock	2014	50898	4.10	39.6	36.5	10.4	25.4	8.2	5.3	93.9	75337
Hancock	2015	52810	2.95	39.3	36.7	7.9	16.0	10.7	3.7	95.9	75573
Hancock	2016	52810	4.02	38.2	36.0	10.8	16.3	9.4	3.7	96.5	75872
Jefferson	2005	34442	1.45	43.1	44.3	8.2	8.7	4.5	5.7	92.1	68436
Jefferson	2006	31741	1.26	44.0	47.5	8.5	9.3	3.5	6.0	90.9	70125
Jefferson*	2007	38499	***2.88***	43.9	47.8	7.0	14.9	5.2	4.6	88.3	68730
Jefferson	2008	36492	2.56	43.9	40.2	11.3	15.8	4.7	7.6	89.1	68526
Jefferson	2009	36978	0.72	44.0	41.7	11.2	13.1	3.9	10.4	92.3	67691
Jefferson*	2010	36008	***3.08***	44.3	47.4	11.5	14.9	6.3	10.0	92.3	69614
Jefferson	2011	42075	1.22	44.5	44.8	12.0	14.8	6.1	7.8	93.8	68828
Jefferson	2012	40566	1.25	44.3	43.6	10.0	16.6	5.2	8.3	92.0	68389
Jefferson	2013	37012	1.20	44.1	43.3	13.1	13.2	4.5	6.6	91.9	67964
Jefferson	2014	40293	0.86	44.6	39.3	13.6	15.5	5.7	13.3	96.8	67694
Jefferson	2015	44257	1.55	44.7	42.8	11.2	8.8	6.5	4.9	91.9	67347
Jefferson	2016	44257	0.73	44.6	44.1	10.5	11.4	5.1	4.9	94.3	66704
Lake	2005	48885	5.91	40.1	36.8	7.6	15.8	7.8	6.3	95.1	229566
Lake	2006	51322	5.92	40.7	37.3	8.0	14.8	7.8	4.5	95.7	232892
Lake	2007	55607	5.48	41.2	34.8	7.6	26.7	7.9	4.8	95.5	233392
Lake	2008	58536	6.08	41.2	35.2	8.4	24.0	8.6	5.7	94.6	234030
Lake	2009	53849	5.32	42.4	34.8	8.0	23.7	7.4	7.8	97.4	236775

Lake	2010	52685	4.83	42.4	34.3	8.0	23.9	8.0	9.6	94.2	230101
Lake	2011	52690	5.93	42.5	33.9	8.2	25.9	8.2	8.9	96.1	229885
Lake	2012	54973	6.72	43.2	33.2	8.7	26.0	9.0	7.1	94.9	229582
Lake	2013	54906	4.90	42.7	36.1	9.1	25.7	8.5	6.1	95.9	229857
Lake	2014	58721	5.13	43.8	32.9	9.6	27.0	9.3	5.3	94.6	229230
Lake	2015	61870	6.17	43.9	34.7	9.8	16.5	8.9	3.9	96.8	229245
Lake	2016	61870	4.74	43.7	31.9	9.1	17.5	11.1	3.9	94.0	228614
Licking	2005	49980	1.30	38.1	40.1	6.3	14.4	7.0	8.2	96.3	151499
Licking	2006	50386	1.33	37.8	40.6	6.9	14.6	5.9	6.4	95.1	156287
Licking	2007	53551	1.25	36.9	38.8	6.3	23.0	7.7	7.2	94.2	156985
Licking	2008	51392	1.37	37.7	39.5	6.1	21.6	6.8	6.5	96.0	157721
Licking	2009	50922	1.45	38.9	40.7	7.1	21.0	6.5	8.5	96.9	158488
Licking	2010	51132	2.06	39.3	36.9	9.0	21.9	6.6	9.6	95.2	166701
Licking	2011	54887	1.73	39.8	38.6	7.4	22.8	7.2	6.9	95.6	167248
Licking	2012	52331	1.90	39.4	37.6	8.2	21.0	7.0	8.0	97.0	167537
Licking	2013	54875	1.49	40.3	39.1	8.5	21.4	8.2	7.7	95.3	168375
Licking	2014	57654	2.16	40.7	35.4	7.5	26.9	10.0	4.8	96.0	169390
Licking	2015	58685	1.98	39.0	34.7	10.0	15.1	7.9	4.3	96.1	170570
Licking	2016	58685	1.75	40.0	34.2	10.4	16.7	8.3	4.3	95.3	172198
Lorain	2005	47913	2.39	37.7	36.8	8.0	12.6	6.9	6.6	94.5	287985
Lorain	2006	48838	2.80	38.0	37.0	8.2	12.2	7.2	6.8	97.1	301993
Lorain	2007	50718	2.20	37.8	37.7	8.1	20.0	7.6	10.2	95.9	302260
Lorain	2008	52834	2.58	38.4	36.4	9.1	20.0	7.0	7.1	98.0	304373
Lorain	2009	48110	2.70	39.4	36.9	8.0	20.2	7.4	12.3	96.7	305707
Lorain	2010	50200	3.47	40.3	36.6	8.5	21.7	7.6	10.7	96.8	301449
Lorain	2011	48280	2.69	40.1	35.6	9.2	21.0	7.7	10.4	96.9	301614
Lorain	2012	49131	2.62	41.0	32.2	9.4	22.2	8.1	10.3	96.9	301478
Lorain	2013	52687	2.79	41.2	31.9	8.9	24.5	9.5	8.3	96.9	302827
Lorain	2014	52082	2.68	41.5	34.2	8.9	21.7	8.7	7.8	97.5	304216
Lorain	2015	54504	3.11	41.3	32.6	9.7	14.5	8.7	7.2	97.9	305147
Lorain	2016	54504	3.67	41.3	30.3	12.2	14.9	9.7	7.2	97.0	306365
Lucas	2005	40348	3.49	35.9	33.6	7.4	14.5	8.7	9.2	94.4	437901
Lucas	2006	42296	3.08	36.2	34.5	7.8	14.5	8.0	9.4	94.0	445281
Lucas	2007	44704	3.78	36.7	32.1	8.8	23.4	8.2	11.0	93.9	441910
Lucas	2008	40990	4.00	37.0	32.9	8.9	22.1	8.3	9.7	93.8	440456
Lucas	2009	39934	3.28	36.7	32.8	7.8	21.5	7.7	16.4	93.4	463493
Lucas	2010	38773	4.17	37.0	33.1	7.9	24.3	8.7	14.4	93.5	441468
Lucas	2011	38421	3.20	37.1	31.5	9.2	22.0	9.2	14.6	93.7	440005
Lucas	2012	40529	3.02	37.7	32.4	8.9	23.6	9.0	13.8	94.4	437998
Lucas	2013	40245	3.62	37.8	31.1	9.1	24.3	9.2	11.2	94.0	436393

Lucas	2014	42132	3.91	38.3	30.5	9.2	26.4	10.6	8.1	94.4	435286
Lucas	2015	44534	3.46	37.8	30.6	10.2	15.2	9.3	7.1	94.2	433689
Lucas	2016	44534	3.54	38.0	28.2	10.4	16.2	9.9	7.1	94.3	432488
Mahoning	2005	36294	2.11	41.3	41.9	5.6	12.7	6.1	7.7	90.2	240774
Mahoning	2006	38393	2.68	41.0	39.4	8.0	13.2	6.0	8.9	92.2	251026
Mahoning	2007	38763	3.55	41.3	41.4	5.5	21.4	6.7	7.1	93.0	240420
Mahoning	2008	40125	2.65	42.0	38.6	6.0	22.0	8.2	8.0	92.7	237978
Mahoning	2009	39111	3.17	42.0	41.1	6.4	19.4	6.6	12.4	92.2	236735
Mahoning	2010	37847	3.01	43.1	41.7	5.3	20.5	7.1	15.4	94.1	238310
Mahoning	2011	39356	2.85	43.2	38.4	6.7	20.9	7.5	11.6	94.5	237270
Mahoning	2012	39642	3.39	43.6	38.8	6.8	21.3	7.6	9.8	95.3	235145
Mahoning	2013	40843	2.96	43.3	37.7	7.3	22.0	7.5	9.9	94.2	233869
Mahoning	2014	41134	3.23	43.6	38.0	7.0	23.3	8.5	8.1	94.1	233204
Mahoning	2015	42295	1.75	43.5	37.8	7.2	15.3	8.2	8.4	94.0	231900
Mahoning	2016	42295	3.06	43.5	37.4	6.7	17.1	8.0	8.4	95.4	230008
Marion*	2005	38129	0.96	38.1	48.8	6.4	8.7	3.2	***7.2***	93.8	61031
Marion	2006	39585	0.87	38.8	45.5	6.1	6.9	5.0	5.8	102.4	65583
Marion	2007	40841	1.45	38.2	42.7	8.1	11.8	4.4	5.9	109.6	65248
Marion	2008	34449	0.96	38.2	48.1	6.1	10.4	4.6	7.3	105.9	65768
Marion	2009	39621	1.33	39.2	45.1	6.7	13.2	5.9	11.9	110.7	65655
Marion*	2010	38824	***3.08***	40.8	42.5	7.5	11.2	4.5	10.0	113.2	66482
Marion	2011	41133	0.48	40.2	42.7	8.9	11.8	5.3	13.6	113.1	66212
Marion	2012	43004	1.15	40.9	44.7	7.9	10.1	4.1	6.7	119.8	66238
Marion	2013	41849	1.45	40.1	42.9	8.9	12.7	4.9	9.5	116.4	65905
Marion*	2014	39233	***3.13***	41.5	40.4	9.2	15.5	5.3	8.8	114.7	65720
Marion	2015	42826	1.89	40.0	43.6	7.3	6.3	4.8	6.1	109.0	65355
Marion	2016	42826	1.00	41.8	45.8	7.3	7.9	3.8	6.1	111.8	65096
Medina	2005	62022	3.12	37.2	37.6	8.6	20.1	9.1	5.3	97.3	165491
Medina	2006	64579	3.28	38.1	34.5	7.4	19.0	7.7	4.9	99.7	169353
Medina	2007	61411	2.43	38.1	34.6	6.8	27.7	9.2	5.5	96.7	169832
Medina	2008	65381	4.09	38.7	32.0	8.1	31.3	9.7	4.9	96.5	171210
Medina	2009	66297	3.30	40.3	31.9	7.7	31.3	10.6	7.6	97.3	174035
Medina	2010	63543	2.81	40.8	33.1	8.3	29.2	9.3	7.8	95.9	172592
Medina	2011	59572	2.98	40.3	32.7	8.1	29.2	9.8	7.4	97.6	173262
Medina	2012	65078	2.92	41.8	31.6	10.9	29.8	10.5	5.2	97.4	173684
Medina	2013	66477	2.46	41.6	32.1	9.6	29.0	9.2	4.2	96.4	174915
Medina	2014	67969	2.78	41.3	33.7	9.2	31.2	10.4	4.7	96.5	176029
Medina	2015	72618	2.76	42.2	32.1	8.6	23.6	9.9	3.2	99.8	176395
Medina	2016	72618	2.96	42.3	31.0	8.9	22.6	10.5	3.2	97.8	177221
Miami	2005	46136	1.37	38.4	41.9	6.8	11.8	7.7	6.1	94.3	100220

Miami	2006	49086	1.03	39.5	41.4	6.6	14.9	5.7	4.2	98.4	101914
Miami	2007	50173	1.46	39.6	38.2	7.3	21.1	6.7	5.6	95.5	101038
Miami	2008	53091	1.62	39.0	38.4	7.4	21.4	7.5	5.2	96.2	101085
Miami	2009	49455	2.18	40.7	36.6	8.5	18.8	6.6	6.8	98.0	101256
Miami	2010	49222	2.02	41.2	41.3	8.7	19.8	8.7	9.9	97.4	102461
Miami	2011	46759	1.48	40.9	41.0	8.9	18.2	7.2	9.1	96.5	102857
Miami	2012	53101	1.30	40.6	33.8	11.4	22.6	7.3	9.8	97.7	103060
Miami	2013	51581	1.88	40.9	38.3	8.8	18.1	5.3	7.3	94.5	103439
Miami	2014	51087	1.75	41.5	36.6	9.5	19.9	7.5	3.8	98.0	103900
Miami	2015	60170	0.91	42.2	35.6	8.4	14.1	8.1	4.3	95.8	104224
Miami	2016	60170	1.79	41.7	36.6	10.2	12.3	9.4	4.3	97.4	104679
Montgomery	2005	41004	2.82	38.6	31.1	8.0	14.7	8.9	8.2	92.5	531864
Montgomery	2006	41161	2.91	38.2	31.7	8.4	14.8	8.4	7.3	92.8	542237
Montgomery	2007	43939	3.19	38.8	31.4	7.8	25.4	9.4	8.0	92.6	538104
Montgomery	2008	45047	3.43	38.9	30.1	8.3	24.0	9.0	8.3	93.6	534626
Montgomery	2009	41426	3.12	38.5	27.9	8.3	24.7	10.4	13.3	92.2	532562
Montgomery	2010	40618	3.63	39.3	30.8	9.3	23.1	9.1	12.4	92.5	535059
Montgomery	2011	40602	3.87	39.8	29.1	8.9	24.3	9.7	10.8	91.9	537602
Montgomery	2012	42524	3.84	39.6	29.2	8.7	25.0	9.9	10.7	92.6	534325
Montgomery	2013	42776	3.81	39.0	29.0	10.1	25.0	10.1	10.2	92.5	535846
Montgomery	2014	42644	4.19	39.8	28.7	10.2	25.7	10.4	9.1	93.0	533116
Montgomery	2015	46936	4.69	39.3	28.3	9.9	16.1	11.5	7.0	93.2	532258
Montgomery	2016	46936	4.91	39.3	27.8	10.0	16.0	9.7	7.0	93.3	531239
Muskingum	2005	36870	0.21	37.9	47.0	8.7	6.6	4.2	10.3	92.8	83110
Muskingum*	2006	36047	***2.83***	37.5	46.1	6.2	8.5	5.7	8.1	92.2	86125
Muskingum*	2007	40702	***2.88***	38.3	45.8	6.1	13.4	6.1	13.6	90.9	85333
Muskingum	2008	41569	1.02	39.1	45.0	6.5	14.6	7.1	9.8	91.6	85087
Muskingum	2009	36989	1.28	40.0	44.6	7.3	13.6	4.6	10.4	91.6	84884
Muskingum	2010	40894	0.75	39.8	48.5	7.6	12.6	5.4	12.6	94.5	86142
Muskingum*	2011	38259	***3.01***	39.8	44.8	7.9	13.9	5.7	11.0	92.6	86237
Muskingum	2012	39266	0.83	39.5	42.2	9.4	13.7	3.6	8.8	95.7	85950
Muskingum*	2013	39212	***3.20***	40.9	41.0	8.3	15.8	5.9	9.0	95.8	85231
Muskingum	2014	41230	1.56	40.6	43.4	7.8	17.3	7.0	8.2	95.2	85818
Muskingum	2015	43422	0.73	39.8	40.3	9.4	10.6	4.9	6.8	94.9	86290
Muskingum	2016	43422	1.36	40.1	41.8	10.0	8.0	4.7	6.8	94.7	86068
Portage	2005	46842	2.28	37.3	42.1	6.4	15.8	8.1	8.4	96.7	147502
Portage	2006	43840	2.88	35.7	40.5	5.2	15.5	8.0	6.6	93.0	155012
Portage	2007	49983	2.36	35.9	41.0	6.8	24.3	9.6	6.2	95.5	155869
Portage	2008	52364	3.34	35.8	38.7	5.1	24.6	8.4	7.7	93.7	155991
Portage	2009	48897	2.12	37.6	39.3	5.6	24.3	9.1	13.7	94.2	157530

Portage	2010	49244	2.20	37.7	39.8	7.2	23.8	8.2	13.0	97.5	161386
Portage	2011	49554	3.19	36.8	37.9	7.4	24.0	9.6	10.2	96.7	161624
Portage	2012	52364	3.32	37.5	37.6	5.9	25.5	8.9	9.5	94.7	161451
Portage	2013	52337	4.12	37.0	39.9	5.5	24.4	8.8	9.6	95.1	163862
Portage	2014	51275	3.20	38.0	35.8	6.4	28.3	12.2	8.5	96.7	161882
Portage	2015	49695	5.03	37.7	37.8	6.7	17.4	9.2	6.2	94.2	162275
Portage	2016	49695	4.67	37.4	36.2	8.1	17.5	12.1	6.2	95.2	161921
Richland	2005	39220	1.40	39.4	46.2	7.4	8.9	4.3	6.1	93.1	121365
Richland	2006	38393	1.48	38.8	39.7	5.8	10.2	4.4	8.1	100.7	127010
Richland	2007	43445	1.72	40.1	43.0	7.8	15.5	5.2	7.6	102.8	125679
Richland	2008	42578	2.40	39.2	40.7	7.2	15.3	4.0	7.3	104.2	124999
Richland	2009	39350	1.54	40.6	43.9	8.2	12.9	5.9	9.4	101.2	124490
Richland	2010	41572	1.49	41.0	40.8	10.1	14.6	5.2	12.4	100.7	124177
Richland	2011	40117	1.15	41.7	40.1	7.6	15.5	5.3	9.5	101.8	123510
Richland	2012	41680	1.22	41.1	41.6	7.8	15.4	5.3	10.0	100.9	122673
Richland	2013	39455	1.84	41.0	41.3	8.6	15.3	4.1	9.8	101.8	121773
Richland	2014	41548	1.02	41.7	41.1	8.4	17.1	6.6	8.4	104.8	121942
Richland	2015	44073	1.33	40.7	40.7	9.1	9.6	4.8	7.3	100.6	121707
Richland	2016	44073	1.67	41.3	39.9	7.8	11.7	5.9	7.3	104.1	121107
Ross	2005	36638	0.83	37.4	47.8	5.7	8.3	4.7	9.3	96.3	69435
Ross	2006	37054	1.15	37.3	46.6	6.9	6.7	4.3	10.0	109.0	75556
Ross*	2007	42466	***2.88***	38.2	47.3	6.2	12.5	4.8	12.1	109.1	75398
Ross	2008	43966	0.60	38.2	39.4	6.4	14.9	5.4	11.2	110.9	76073
Ross	2009	41187	0.64	38.7	47.0	7.3	11.1	4.9	12.0	109.5	75972
Ross	2010	40811	0.86	40.0	42.7	7.0	15.5	5.8	18.6	112.3	78090
Ross	2011	43464	0.71	41.1	38.1	9.8	15.0	5.6	15.2	111.4	78249
Ross	2012	42951	0.60	39.8	42.9	8.2	14.0	5.8	13.1	109.8	77429
Ross*	2013	40493	***3.20***	39.6	46.0	9.0	13.4	5.0	11.1	108.3	77910
Ross	2014	40764	1.06	40.4	44.2	9.8	18.1	6.3	12.8	111.5	77159
Ross	2015	46422	0.68	41.0	41.4	8.4	10.4	3.9	6.7	111.3	77170
Ross	2016	46422	0.63	40.9	43.9	7.5	10.8	5.3	6.7	110.2	77000
Scioto*	2005	28348	***2.60***	37.7	40.0	8.2	7.7	4.4	12.3	92.7	73403
Scioto*	2006	29821	***2.83***	38.2	41.6	6.3	6.6	4.7	13.9	92.9	76441
Scioto*	2007	31446	***2.88***	37.6	41.7	7.5	10.8	5.2	10.5	94.2	75958
Scioto	2008	38097	1.25	37.0	39.5	8.1	13.6	5.2	6.7	96.6	76587
Scioto*	2009	29665	***2.85***	38.2	39.0	8.0	15.1	5.6	11.5	95.2	76334
Scioto	2010	36859	1.03	38.2	38.6	7.6	13.1	4.8	14.4	100.6	79506
Scioto*	2011	29657	***3.01***	38.6	40.2	8.0	11.8	4.8	11.3	96.5	79277
Scioto*	2012	36874	***2.92***	40.2	37.4	7.5	14.3	4.2	10.6	99.0	78477
Scioto	2013	37351	1.59	39.5	40.0	10.0	15.1	6.2	7.1	100.0	78153

Scioto	2014	38233	1.82	39.7	42.6	9.6	16.1	6.6	8.3	97.7	77258
Scioto	2015	39210	1.10	40.1	41.5	6.4	6.4	7.4	6.8	96.8	76825
Scioto	2016	39210	0.56	39.7	42.3	8.6	8.1	5.7	6.8	94.4	76088
Stark	2005	42303	2.00	39.5	42.7	6.3	13.0	6.5	7.2	93.9	371677
Stark	2006	42332	2.29	40.2	42.2	6.1	12.6	6.1	7.4	92.5	380575
Stark	2007	44891	1.98	40.2	41.0	7.2	22.1	7.5	7.1	93.0	378664
Stark	2008	44447	1.76	40.4	41.3	6.2	19.6	6.5	7.3	92.5	379214
Stark	2009	44362	1.52	40.7	39.6	6.9	20.4	6.7	11.4	93.6	379466
Stark	2010	42664	1.97	41.6	39.5	8.4	20.5	7.1	12.3	94.8	375321
Stark	2011	41827	1.77	41.7	39.7	8.3	20.7	6.2	11.0	95.1	375087
Stark	2012	45617	2.01	41.6	38.0	8.5	21.3	7.0	9.9	93.9	374868
Stark	2013	44979	2.27	41.6	38.1	8.1	22.3	7.9	8.6	94.2	375432
Stark	2014	47713	1.71	41.9	37.9	8.7	22.1	7.7	6.5	93.7	375736
Stark	2015	50994	2.36	42.1	38.0	8.8	13.4	8.3	6.3	93.8	375165
Stark	2016	50994	2.17	41.6	38.5	7.8	14.8	9.4	6.3	94.1	373612
Summit	2005	43941	3.44	38.6	32.2	6.9	19.1	10.2	6.8	93.2	536957
Summit	2006	44747	3.90	38.7	32.8	7.2	18.9	9.5	6.2	92.9	545931
Summit	2007	47333	3.76	39.2	35.4	6.8	29.0	10.3	7.5	93.7	543487
Summit	2008	49411	4.12	39.7	31.4	8.7	30.5	10.7	7.3	93.5	542562
Summit	2009	46974	4.02	39.7	32.8	8.4	28.2	9.8	11.1	92.8	542405
Summit	2010	45593	4.31	40.2	31.9	8.0	29.8	10.0	11.6	93.7	541565
Summit	2011	46429	4.03	40.4	32.7	8.0	28.1	10.3	11.1	93.2	539832
Summit	2012	48798	4.62	40.9	33.4	7.9	29.2	10.5	9.7	93.7	540811
Summit	2013	49232	5.22	40.8	33.1	8.1	31.2	10.9	9.4	94.2	541824
Summit	2014	50365	4.36	40.8	32.1	9.0	30.3	10.4	6.7	93.5	541943
Summit	2015	52036	4.98	41.0	32.1	8.9	19.3	11.8	5.0	94.4	541968
Summit	2016	52036	5.27	41.1	31.5	9.4	20.1	11.2	5.0	94.3	540300
Trumbull	2005	40922	1.58	41.3	46.6	6.5	10.0	4.9	6.2	93.5	215254
Trumbull	2006	42344	1.46	41.1	45.8	5.6	10.0	4.8	7.8	94.1	217362
Trumbull	2007	41566	1.13	41.3	45.6	5.5	17.1	5.6	6.7	93.0	213475
Trumbull	2008	41037	1.41	41.7	47.7	5.2	16.4	4.6	7.6	93.8	211317
Trumbull	2009	40880	1.40	42.4	44.9	5.9	14.5	4.6	12.2	94.1	210157
Trumbull	2010	40153	1.72	42.7	44.3	7.1	17.8	5.6	10.8	93.5	209936
Trumbull	2011	40867	1.81	43.4	44.9	6.9	17.1	5.5	8.5	93.8	209264
Trumbull	2012	41049	1.15	43.3	46.8	7.4	15.3	4.0	9.4	94.8	207406
Trumbull	2013	41798	1.59	43.7	44.1	7.9	18.4	5.5	8.4	94.2	206442
Trumbull	2014	43039	1.35	43.9	45.4	6.5	16.7	5.6	5.9	94.5	205175
Trumbull	2015	45552	1.72	43.8	45.6	7.5	11.8	5.7	5.4	95.9	203751
Trumbull	2016	45552	1.24	44.2	44.6	7.0	13.8	5.8	5.4	93.4	201825
Tuscarawas	2005	39411	0.81	38.6	48.4	6.3	8.8	5.7	6.0	95.8	90781

Tuscarawas*	2006	37560	***2.83***	39.2	51.1	5.2	7.5	3.0	7.7	94.5	91766
Tuscarawas	2007	40699	0.94	39.5	46.8	8.1	15.4	5.5	4.7	93.5	91398
Tuscarawas	2008	42992	1.49	39.1	50.9	4.7	12.9	4.2	5.8	92.8	91348
Tuscarawas	2009	40801	1.08	41.2	48.9	6.6	13.5	5.4	11.5	96.1	91137
Tuscarawas	2010	38882	1.36	40.9	52.0	4.6	17.8	7.6	7.8	95.7	92542
Tuscarawas	2011	42082	1.02	40.9	46.2	6.7	15.2	4.9	10.1	94.5	92508
Tuscarawas	2012	43702	1.30	40.8	48.6	7.1	13.3	4.2	8.4	97.8	92392
Tuscarawas	2013	44130	1.07	40.9	47.7	7.4	14.9	4.9	7.7	96.5	92672
Tuscarawas	2014	46253	2.04	41.1	47.5	7.5	12.4	3.1	4.7	97.2	92788
Tuscarawas	2015	50440	1.77	41.6	45.9	6.8	10.9	5.0	4.5	97.3	92916
Tuscarawas	2016	50440	2.50	39.3	43.5	6.3	11.9	6.7	4.5	95.9	92420
Warren	2005	63580	4.89	35.4	29.8	7.7	21.8	12.3	5.0	97.1	190403
Warren	2006	66834	5.00	35.5	30.5	7.4	21.7	12.0	6.1	101.0	201871
Warren	2007	71088	4.15	35.5	29.0	8.8	35.0	12.7	3.7	102.2	204390
Warren	2008	70504	4.21	35.8	27.8	7.7	35.8	14.2	6.3	100.5	207353
Warren	2009	68114	5.26	37.7	28.6	7.8	35.6	13.8	9.1	104.5	210712
Warren	2010	66499	4.70	37.1	28.4	7.7	36.1	11.7	8.5	101.7	213192
Warren	2011	69201	5.42	37.3	28.5	9.0	37.6	14.2	8.2	102.0	214910
Warren	2012	72898	6.57	39.0	28.4	7.8	37.9	14.7	5.7	99.0	217241
Warren	2013	73432	6.75	39.3	25.1	8.8	41.0	15.2	8.1	101.5	219169
Warren	2014	71731	5.65	39.3	27.9	8.6	40.5	14.8	5.0	100.8	221659
Warren	2015	80207	5.26	39.5	24.0	10.5	26.3	14.1	3.2	100.6	224469
Warren	2016	80207	6.25	39.0	25.8	8.2	27.8	15.1	3.2	101.5	227063
Wayne	2005	44118	1.19	37.3	43.4	5.5	10.1	6.6	6.3	100.1	110327
Wayne	2006	45271	1.79	37.2	45.6	6.3	10.3	6.2	5.9	98.4	113950
Wayne	2007	46678	1.47	37.1	39.9	6.1	22.0	8.0	6.8	100.1	113554
Wayne	2008	48360	0.84	37.2	44.9	6.0	16.1	4.6	4.3	98.5	113812
Wayne	2009	47562	1.98	38.6	44.8	6.0	19.2	6.1	8.2	96.3	114222
Wayne	2010	46288	1.70	38.3	43.0	5.4	19.8	6.2	9.0	96.5	114505
Wayne	2011	46827	1.48	38.8	42.9	6.8	19.8	7.2	7.6	97.2	114611
Wayne	2012	47946	2.41	39.7	40.1	6.6	23.8	9.3	5.0	99.3	114848
Wayne	2013	49849	1.80	39.1	43.7	6.3	18.4	6.8	3.6	97.4	115071
Wayne	2014	49988	2.13	38.5	39.9	7.3	20.1	7.2	4.6	98.0	115537
Wayne	2015	53434	2.06	38.6	38.1	7.3	14.0	8.4	3.9	98.6	116063
Wayne	2016	53434	1.97	38.7	40.0	8.5	12.7	7.8	3.9	100.0	116470
Wood	2005	46893	3.08	35.2	33.2	11.2	17.5	10.2	4.8	97.1	115904
Wood	2006	51442	2.78	33.6	34.5	9.4	16.9	12.7	6.7	95.0	124183
Wood	2007	50276	3.22	33.3	33.7	7.7	31.7	12.1	8.5	95.2	125399
Wood	2008	54681	1.89	34.0	34.1	9.3	28.5	9.1	8.6	93.7	125340
Wood	2009	49959	2.77	35.1	36.8	8.2	28.1	11.2	11.9	92.3	125380

Wood	2010	47485	2.91	35.7	30.2	11.1	28.4	11.2	13.7	96.0	125502
Wood	2011	49792	3.61	35.6	29.7	10.5	31.6	13.3	8.6	94.8	126355
Wood	2012	49575	3.77	34.8	31.5	10.3	28.3	11.5	8.4	95.5	128200
Wood	2013	51680	2.68	34.6	31.3	10.7	29.6	12.4	8.3	95.5	129264
Wood	2014	54402	3.43	34.3	31.5	10.2	33.9	14.5	6.1	96.1	129590
Wood	2015	60166	2.82	34.6	31.4	10.8	19.2	12.9	3.9	97.7	129730
Wood	2016	60166	2.80	34.8	28.3	10.3	19.2	15.2	3.9	100.5	130219