THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF ECONOMICS

The Impact of Industrial Collapse on Communities: A Case Study of the American Automotive Industry

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SPRING 2024

A thesis
submitted in partial fulfillment
of the requirements
for a baccalaureate degrees
in Economics and Finance
with honors in Economics

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ABSTRACT

The goal of this thesis is to gain a quantitative understanding of the causal economic impacts of automotive plant closures in the United States on communities. It builds upon existing literature evaluating deindustrialization, creative destruction, and the microeconomic impacts of shocks by evaluating automotive assembly plant closures. To achieve this aim, a Difference-In-Difference analysis is conducted using an automotive assembly plant closure dataset spanning from 1999 to 2016 built by Venkataramani, Bair, O'Brien, and Tsai (2020) and economic data from the Federal Reserve. This analysis finds that there is a statistically significant relationship between plant closures and the socio-economic variables of resident population, median household income, per capita personal income, unemployment rate, percent of people in poverty, and the number of SNAP benefits recipients. Specifically, the model suggests that, in the wake of an automotive assembly plant closure, resident populations remain stagnant for up to six years, median household incomes remain stagnant for three years before returning to a consistent growth rate, per capita personal incomes retain a consistent rate of growth, unemployment rates peak of 2.59 percentage points higher after three years, percents of people in poverty increase by a total of 3.99 percentage points after six years, and the number of Supplemental Nutrition Assistance Program benefits recipients increase by 43,887.31 persons after six years.

TABLE OF CONTENTS

LIST OF FIGURES iv

LIST OF TABLES v

ACKNOWLEDGEMENTS vi

Chapter 1 Introduction 1

Background 1
Impact Goals 1
Thesis Overview 2

Chapter 2 Literature Review 4

History of Deindustrialization 4
The Australian Automotive Industry 5
___Spillover Effects 6
Creative Destruction 6
Worker and Community Impacts 7
___Long-Run Employment 7
___Long-Run Income 9
___Additional Impacts: Health & Mental Health 9

Chapter 3 Methodology 11

Data Description 11
___Resident Population 11
___Estimate of Median Household Income 12
___Per Capita Personal Income 12
___Unemployment Rate 13
___Estimated Percent of People of All Ages in Poverty 13
___SNAP Benefits Recipients 14
___Data Acknowledgement 14
___Plant Closure Dataset 14
Experimental Approach 17

Chapter 4 Results and Discussion 19

Resident Populations 19

Median Household Incomes 22
Per Capita Personal Incomes 24
Unemployment Rates... 27
Percent of People in Poverty... 29
SNAP Benefits Recipients.. 31

Chapter 5 Conclusion and Areas for Future Research.. 34

Appendix A Tables and Figures 37

BIBLIOGRAPHY... 48

LIST OF FIGURES

Figure 1. Map of All Counties in Study 15

Figure 2. Map of Counties in Study with Closed Plants 16

Figure 3. Impact of Plant Closures on Resident Populations 20

Figure 4. Impact of Plant Closures on Median Household Incomes 23

Figure 5. Impact of Plant Closures on Per Capita Personal Incomes 25

Figure 6. Impact of Plant Closures on Unemployment Rates 28

Figure 7. Impact of Plant Closures on Percents of People in Poverty 30

Figure 8. Impact of Plant Closures on SNAP Benefits Recipients 32

Figure 9. Trends in Resident Populations 42

Figure 10. Trends in Median Household Incomes 43

Figure 11. Trends in Per Capita Personal Incomes 44

Figure 12. Trends in Unemployment Rates 45

Figure 13. Trends in Percents of People in Poverty 46

Figure 14. Trends in SNAP Benefits Recipients 47

LIST OF TABLES

Table 1. Summary Statistics for the Economic Variables of Interest: 1999-2016....... 37

Table 2. Summary Statistics for the Economic Variables of Interest: 1999 38

Table 3. Summary Statistics for the Economic Variables of Interest: 2016 38

Table 4. Automotive Assembly Plants in Operation as of 1999 39

Table 5. Collected Table of Regression Outputs 41

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my family and friends for being the greatest support system throughout my college experience. It has not been a linear or traditional path by far, but I am so proud of everything I have accomplished and done. I truly could not have done any of it without you all supporting me along the way. Thank you for being my cheerleaders, lending an ear when I needed to vent, and for being a never-ending fountain of wisdom. Additionally, I would like to thank my professors, advisors, and all the Penn State staff who have helped me get here. I would especially like to thank Dr. Agnosteva and Dr. Roberts for their expertise, advice, and patience throughout this journey.

Chapter 1

Introduction

Background

The American automotive industry has become the archetype of industrial decline in the United States over the past decades (Venkataramani et al., 2020). As such, it has become increasingly politicized. The automotive industry became a focus of former president Donald Trump's election campaign in 2016. Then a presidential candidate, Trump vowed to renegotiate the North American Free Trade Agreement (NAFTA) and bring back outsourced automotive jobs to the United States. Some cite this focus as a driver of his success with union households in the Rust Belt, one of the key demographics that won him the election (Lansbury et al., 2017). Under the Trump administration, NAFTA was renegotiated into the United States-Mexico-Canada Agreement (USMCA) trade deal, with many stipulations surrounding and targeting the automotive industry specifically (Condon, 2019). With such a heightened focus on this industry, it is important to understand how industrial decline and plant closures in the automotive sector are impacting the communities facing these challenges.

Impact Goals

Many factors influence manufacturers' decisions to relocate production to other cities or countries or to simply close a plant. For example, under NAFTA, the Mexican automotive industry saw an intense period of growth due to its nearshoring status for the American market coupled with cheaper labor. However, this came at the cost of plant closures in the United States (Covarrubias V., 2020). The motivations for these decisions and the theory of creative destruction will be evaluated further in the literature review.

These plant closures severely impact the socio-economic health of the communities in which they were once located. These factors are reflected in indicators such as wage levels, social security, and poverty. Understanding the scope and depth of these effects could help inform future policy decisions. From a more micro focus, understanding the economic value added from a plant, especially through spillover effects, could help counties or states better target policies (Barnes et al., 2016). For example, one type of spillover effect is increased wage levels in an economy from a rise in overall output. Understanding the magnitude of this rise, and the ensuing rise in tax revenues, could aid in the crafting of policies to attract manufacturers. Various incentives such as tax breaks or other initiatives could be used to attract new plant openings or to retain currently operational plants (Baldwin, 2005; Jofre-Monseny et al., 2018). Other impact factors from plant closures to consider may be the consequences to mental health (Root, 1984), drug use and its effects (Venkataramani et al., 2020), the effects on the children of impacted workers (Mörk et al., 2020), and the role of unions (Lansbury et al., 2017).

Thesis Overview

The following chapters will explore plant closures as they relate to the socioeconomic well-being of the workers and communities they impact. Chapter 2 of this paper explores the existing literature relating to this paper's subject. More specifically, the topics of deindustrialization, creative destruction, and worker and community repercussions from plant closures are reviewed.

Following that, Chapter 3 discusses data sources and the methodology used in the analysis. Chapter 4 summarizes the results of the analysis and discusses their meaning in the context of this research. Finally, Chapter 5 concludes and explores areas for future research.

Chapter 2

Literature Review

History of Deindustrialization

Deindustrialization is a widespread, systemic divestment in creative capacity that results in a decline in manufacturing output, employment, and investment. In the context of the American automotive industry, namely the Big Three Detroit car manufacturers – General Motors, Ford, and Chrysler, this process is believed to have begun in the 1970's. However, based on corporate records and archival data, Battista (2022) theorizes that the deindustrialization of the American automotive industry began as early as the 1940's.

For this paper's context, deindustrialization will be evaluated through the impact of plant closures. This deindustrialization has significant economic and financial effects. Healey (1982) studies the effects of deindustrialization in the United Kingdom (UK) between 1967 and 1972 and finds that plant closures' impacts were felt at a national level. Their analysis finds that the decline in the British textile and clothing industry specifically caused a strain on the national budget, in the form of reduced tax revenue and higher welfare payments, in the UK in 1975. These were estimated to cost, at the time, £2 million per plant closure in which jobs were not replaced. The country's balance of payments was also significantly affected due to lost productivity and output.

The Australian Automotive Industry

Australia serves as a good case study for the impacts of automotive industry deindustrialization, as the remaining manufacturers in the country, General Motors, Ford, and Toyota, completely withdrew from the country in 2017.

Policy analysis by Lansbury et al. (2017), found that, regarding union organization, whether the union had a ‘cooperative’ or ‘adversarial’ relationship with the firms played no significant role in firms’ decisions to withdraw operations from the country. Additionally, from their assessments, they concluded that multinational automotive manufacturers are impacted little by governmental interference and assistance, especially in times of economic downturn, such as the Great Recession, in which financial strategy dominates decisions (Lansbury et al., 2017). In this vein, they conclude that, while withdrawal from Australia was driven by numerous factors, it was primarily prompted by an exchange rate that made the cost of production relatively higher in Australia, the Great Recession’s effect on the global automotive industry writ large, and the macroeconomic factors of globalization.

In their evaluation of the effect of globalization on the demise of the automotive industry in Australia, Lansbury et al. (2017) found insights they believed could apply to other nations. The global automotive industry has reached a level of overcapacity, largely driven by “the increasingly elaborate structure of global supply chains," and "the inevitable shift of auto plants from the West to the East [namely] China and India”. Cost evaluations are driving the shifts in the locations of these plants, with many production facilities being relocated to lower-cost economies, as well as the proximity to emerging markets.

Spillover Effects

Amid the industrial decline of the Australian automotive industry in 2014, the Australian government’s Productivity Commission, a policy review board, published a report on the efficacy of intervention policies. They found that policies such as subsidies had a marginal effect on the industry but had ultimately only delayed the exodus. However, Barnes et al. (2016) are critical of this assessment, and state that the government failed to account for various spillover effects on communities impacted by the plant closures. In their analysis of the Commission’s reports, they find that there are long-term economic and social effects being felt by these communities that were not accounted for in the original Productivity Commission report. Additionally, they find that the report failed to evaluate the quality of future work available to workers displaced by firm withdrawal from the country. These researchers cite that the following decent work indicators should be evaluated in future research as a form of spillover measurement: wage levels, gender equality, social security, union density, and collective bargaining rights. Analyzing these spillover effects, they cite, could provide the possibility for better research into the impacts of deindustrialization and insights into optimal policy responses. These types of spillover effects will be analyzed in this paper.

Creative Destruction

Creative destruction is a concept that describes a process in which new innovations replace and make old innovations obsolete. The fundamental idea at the core of this concept is that productivity growth is fueled by experimentation, which is a costly endeavor. Firms, faced with scarce resources, i.e., labor and capital, are therefore forced to allocate resources to projects where they believe they will be most productive (Andrews & Saia, 2017). In terms of the American automotive industry, this concept pertains to a firm's decision of whether to keep a given assembly plant open or not. When a firm is underperforming and reallocates resources, it may see productivity gains over time (Vermeulen & Braakmann, 2023). In the context of employment, creative destruction is necessarily linked to the destruction of jobs from layoffs or firm closures. However, proponents of this theory argue that the net benefits of innovation and the increase in net welfare levels often outweigh the individual effects (Andrews & Saia, 2017). The question, then, is not whether creative destruction is good or bad, but what is the optimal level?

Worker and Community Impacts

Long-Run Employment

Studies evaluating the relationship between plant closures and employment levels are inconclusive, likely due to the high number of confounding variables. Some studies show a reduced impact due to employment opportunities with other local firms or through the creation of new firms (Jofre-Monseny et al., 2018), while others cite a deeper long-term effect (Vermeulen & Braakmann, 2023).

One proposed theory for the varying effects is from a paper that evaluated the consequences of manufacturing job loss in Germany between 2002 and 2007 based on a layoff vs. plant closure vs. firm bankruptcy & plant closure criteria. Focusing on plant closure specifically, as that is what is pertinent to my evaluation, they found that firms tend to reduce the number of workers over a long period, leading to an inadequate estimation of the true effect of the closure on the employment level. However, they also acknowledge that, simultaneously, “rather smooth employment reductions probably make it easier for affected employees to find new jobs and for local labour markets as well as employment agencies to adjust to these job reallocation processes” (Fackler et al., 2018).

Jofre-Monseny et al. (2018) analyzes the closure of large manufacturing plants in Spain between 2001 and 2006 using a Difference-In-Difference (DID) model to estimate the effects on job loss. They find that for each job lost in the plant closure, there were only between 0.6 and 0.7 jobs lost in aggregate in the local industry affected by the closures. This loss was mitigated by “employment expansions in local incumbent firms and, to a lesser extent, by the creation of new firms in the local industry.”

Contrary to the findings of the above papers, Vermeulen and Braakmann (2023) evaluate mass layoffs in Europe and find evidence of a long-term negative impact on the employment level. Defining mass layoffs as those of at least 250 jobs or at least 0.5% of the regional labor force, the researchers find a persistent reduction in regional employment by between 1% to 1.8%. This magnitude depended on the layoff's size and other conditions, such as whether the region was a more rural community with a shallower labor market.

Baldwin (2005) studies Canadian manufacturing plants between 1961 and 1999 and finds that the ability to relocate for a new position significantly impacts workers’ employment status after a plant closure. In scenarios where an active firm closes a manufacturing plant, there may be potential for workers to remain employed at that firm if they are willing and able to relocate. In this scenario and others, relocation costs are often a barrier to moving for a new position. Andrews and Saia (2017) cite that one policy area that can help ameliorate this issue is through local housing policies. Specifically cited examples of these types of policies are “high transaction taxes on buying and selling of dwellings, stringent land-use regulations, rent controls and other regulations that are overly generous to incumbent tenants.”

Long-Run Income

Economic shocks such as plant closures drastically reshape and reduce the market for labor within a community. Based on basic theories of supply and demand, it is intuitive that when the demand for labor falls, the new equilibrium wage level will be lower. This has been observed by many economists, who find that, in the wake of plant closures, when those affected find new jobs, they are often paid lower wages (Barnes et al., 2016; Healey, 1982; Baldwin, 2005).

Additional Impacts: Health & Mental Health

While plant closures are an economic phenomenon, they also have non-economic consequences. Many of these effects are harder to quantify, but still important to consider due to their significance on individual and community impact (Hamilton et al., 1990; Scheiring & King, 2023).

A grave example of the potential effects of plant closures comes from the journal article by Venkataramani et al. (2020) which analyzes the impact of automotive assembly plant closures in the United States between 1999 and 2016 on opioid mortality rates. The paper cites that “the erosion of long-standing economic opportunities has played a leading role in precipitating deaths from drug overdose, suicide, and other ‘deaths of despair’”. By utilizing a DID research methodology, these researchers found that there is a statistically significant relationship between plant closures and higher opioid overdose deaths, with young non-Hispanic white men being impacted at a disproportionately higher rate of 20.1 more deaths per 100,000 as opposed to the baseline increase of 8.6 per 100,000.

Another study from Root (1984) used survey and longitudinal data to evaluate individual mental health and the consequences of job loss due to manufacturing and industrial plant closures on family stability. Similar to the study above, they found that for those who lost their jobs and were suffering unemployment, there was a mental health toll. There is a general sense of aimlessness that the author likens to what many felt during the Great Depression. They also found that those affected became more reliant on both formal government welfare support and informal support systems, such as family assistance, through the duration of their unemployment. When forced into safety net reliance, many, especially the children of those unemployed, often felt overwhelming stigma. Those who could rely on informal family assistance did so, however, without the certainty of their family's capability of providing long-term support. Ultimately, of all families that were a part of this study, 20% sent out another member to either join or rejoin the workforce. This is an important factor to consider when analyzing employment levels post-closure.

Chapter 3

Methodology

This chapter introduces the datasets used in this thesis to analyze the relationship between county-level socio-economic well-being and automotive assembly plant closures. The following sections will introduce the datasets and describe their collection methodology, variables, and their limitations.

Data Description

The following six datasets are published and made available on the St. Louis Federal Reserve's website for Federal Reserve Economic Data (FRED). They publish these series of datasets on a schedule, annually or monthly, for each county in the United States. Their historic availability varies by county and year, but the data for all counties and years of interest for this paper are available from FRED. These socioeconomic datasets make up what is used in the analysis for the effects on each county that experienced an automotive assembly plant closure (Federal Reserve, 2024). Summary statistics for these data can be found in Table 1, Table 2, and Table 3.

Resident Population

These data originate from the U.S. Census Bureau's *'Annual Estimates of the Population for Counties'* report. This annual schedule measures the number of people residing within the defined county in thousands of persons and is not seasonally adjusted. Resident population estimates are made as of July 1 of each year, barring Census years, where the population survey data is used. The methodology for these estimates uses:

> … current data on births, deaths, and migration to calculate population change since the most recent decennial census. The annual time series of estimates begins with the most recent decennial census data and extends to the vintage year. Each vintage of estimates includes all years since the most recent decennial census (Federal Reserve, 2024).

Estimate of Median Household Income

These data originate from the U.S. Census Bureau's *'Small Area Income and Poverty Estimates'* report. This annual schedule estimates the total combined median annual income of the householder and all those 15 years of age or older per household within the defined area, is measured in dollars, and is not seasonally adjusted.

Per Capita Personal Income

These data originate from the U.S. Bureau of Economic Analysis, or the BEA's, *'Personal Income by County and Metropolitan Area'* report. This annual schedule measures the total "income by persons from all sources" in dollars and is not seasonally adjusted. According to the BEA,

> It is calculated as the sum of wages and salaries, supplements to wages and salaries, proprietors' income with inventory valuation and capital consumption adjustments, rental income of persons with capital consumption adjustment, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance. This measure of income is calculated as the personal income

of the residents of a defined area divided by the resident population of the area. In computing per capita personal income, BEA uses the Census Bureau's annual midyear population estimates (Federal Reserve, 2024).

Unemployment Rate

These data are gathered for the U.S. Bureau of Labor Statistics (BLS)' *'Unemployment in States and Local Areas (all other areas)'* report but originate from the Current Population Survey (CPS), also known as the household survey. This schedule is available with monthly and annual data and is not seasonally adjusted. It measures the level of unemployed persons as a percentage of the civilian labor force for the defined areas.

Estimated Percent of People of All Ages in Poverty

These data originate from the U.S. Census Bureau's *'Small Area Income and Poverty Estimates'* report. This annual schedule measures the level of local persons in poverty as a percentage of the defined area's population and is not seasonally adjusted. The Census Bureau calculates this by modeling "income and poverty estimates by combining survey data with population estimates and administrative records" (Federal Reserve, 2024).

SNAP Benefits Recipients

These data originate from the U.S. Census Bureau's *'Small Area Income and Poverty Estimates'* report. This annual schedule measures the number of persons enrolled in the Supplemental Nutrition Assistance Program, also known as SNAP, and is not seasonally adjusted.

Data Acknowledgement

While the Federal Reserve, BLS, and Census Bureau are reliable data sources, it is prudent to acknowledge that, as some of these measures rely on estimates, there is some margin for error inherent in this data.

Plant Closure Dataset

The plant closure dataset used in this thesis was originally collected for and published with the paper "Association Between Automotive Assembly Plant Closures and Opioid Overdose Mortality in the United States: A Difference-in-Differences Analysis" by Venkataramani et al. (2020). In this paper, the authors analyzed the effect of automotive assembly plant closures between 1999 and 2016 on opioid overdose mortality rates. Of the 58 plants open in 1999, 16 closed by 2016. These closures occurred between the years of 2002 and 2009. These plants span 14 states and 39 counties and belonged to 17 different manufacturers. Full details from this dataset can be found in Table 4. Maps showing the total 39 counties that make up the plant dataset and the 12 counties that experienced plant closure are available in Figure 1 and Figure 2, respectively. These authors found that these plant closures had a statistically significant impact on the mortality rates, especially amongst young white non-Hispanic men, whose opioid mortality rate increased by 20.1 deaths per 100,000.

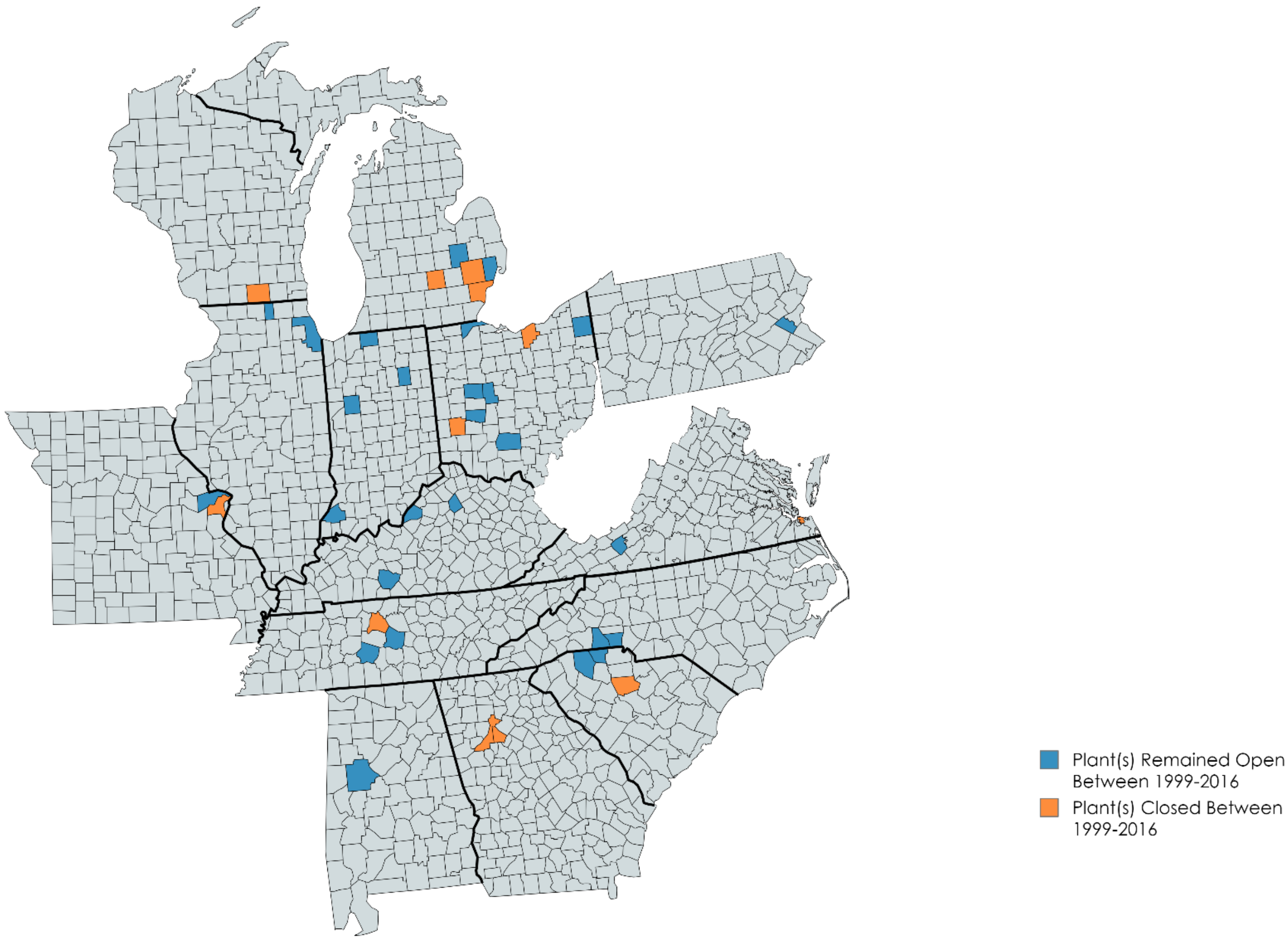

Figure 1. Map of All Counties in Study

This figure was generated using MapChart.net to show graphically the geographic spread of the 39 counties of interest in this paper. The 27 counties highlighted in blue had an automotive assembly plant(s) in operation in 1999 that did not experience closure by 2016. The 12 counties highlighted in orange had an automotive assembly plant(s) in operation in 1999 that did experience closure by 2016.

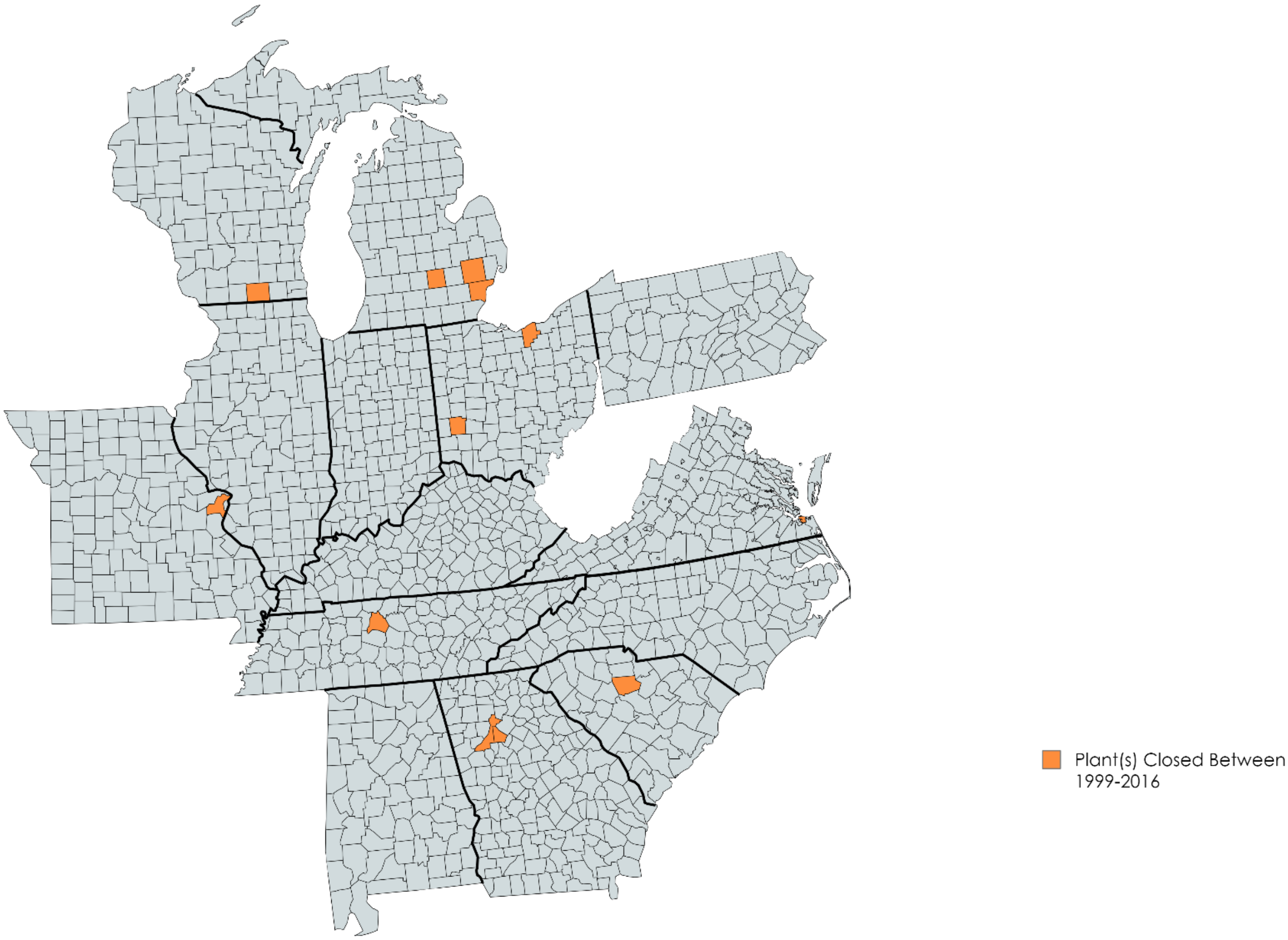

Figure 2. Map of Counties in Study with Closed Plants

This figure was generated using MapChart.net to show graphically the geographic spread of the counties of interest in this paper. As compared to the figure above, this map highlights only the 12 counties that experienced automotive assembly plant closure(s).

Venkataramani et al. collected this dataset of automotive assembly plants by using methods from academic literature and federal government reports and "triangulating data from industry trade publications, automotive company websites, and newspaper articles". They first established the baseline of what plants were open in the year 1999 and then used this information to establish which of those plants closed and which remained open. They took note of the company the plant assembled vehicles for, the plant's location, and, if applicable, the date of closure.

Experimental Approach

The above datasets are the basis for the analysis in this paper. Specifically, though, the Venkataramani et al. (2020) dataset enables the DID analysis of the socioeconomic impacts of plant closures. Based on this dataset, I was able to gather the socioeconomic panel data for the pertinent counties. Additionally, this dataset establishes the Treatment Group — those plants and counties who experienced closures, the Control Group — those who did not, and it enables pre- and post-treatment analysis.

The DID method of analysis seeks to isolate the pure treatment effect of an event or action as a quasi-experimental form of research. These analyses will seek to determine the true causal effect of plant closures on the above range of socioeconomic metrics, isolated from any pre-existing differences between the groups and the changes they experienced during the period analyzed between 1999 and 2006. Isolating the magnitudes of these causal effects on variables such as population, income, and poverty will provide insights into the scope and depth of these impacts and could help inform future policy decisions.

General Equation:

$$Y_{it} = \beta_0 + \beta_1 post_t + \beta_2 closure_i + \beta_3 post_t \times closure_i + e_{it}$$

In this model, Y represents the outcome variable. For this thesis, it will take the value of each of the variables of interest: resident population, median household income, per capita personal income, unemployment rate, percent of people in poverty, and SNAP benefits recipients. The variable *closure* represents a dummy variable for the treatment - (1) if a given county i is treated and experienced a closure and (0) for control counties that did not experience a closure. The variable *post* represents a dummy variable for time - (1) if after treatment or in the year t the plant closure occurs and (0) if before treatment, or before the year of the plant closure. In this model, β_3 represents the DID estimator or the coefficient of interest. The magnitude of this coefficient, along with the significance level, measures the strength of the causal effect of an automotive assembly plant closure on the variable of interest in each exposed county.

Chapter 4

Results and Discussion

Using the above model, the regression results provide insights into the causal effects of plant closures on each of the socio-economic variables of interest. This model enables measurement of the differences in both the before and after-effects of the plant closure, as well as the magnitude of difference between the counties that experienced the closures, exposed counties, and those that did not, unexposed counties. The following analyses reference figures or graphs and regression outputs. Each point on the graphs represents the difference in the variable of interest between exposed counties and unexposed counties relative to the year before the closure, denoted on the graph as year -1. Therefore, these outputs represent the causal impact of the event, the plant closure, on the exposed counties. This chapter compiles these results and discusses their implications.

Resident Populations

At the beginning of the period of study in this paper, 1999, the average resident population across the 39 counties of interest was 471,114 people. By 2016, the average county resident population rose to 488,980 people, an average growth of 17,866 persons or a 3.79% increase. Figure 9 in Appendix A displays trends in resident populations across counties with and without closures between the years 1999 and 2016.

The following analysis references Figure 3 and the regression output below. Resident populations remained stagnant in the five years following plant closures in exposed counties relative to unexposed counties. Five years after closure, resident populations in exposed counties increased by 344 people as compared to the year before the closure (95% CI, -17.72204 - 18.41092; P = 0.969). However, the high p-value for this coefficient indicates an inability to reject the null hypothesis that this coefficient is equal to zero. As can be observed in Figure 3 below, all the points representing the coefficients on the graph lie close to the zero-bound, confirming the lack of a statistically significant effect.

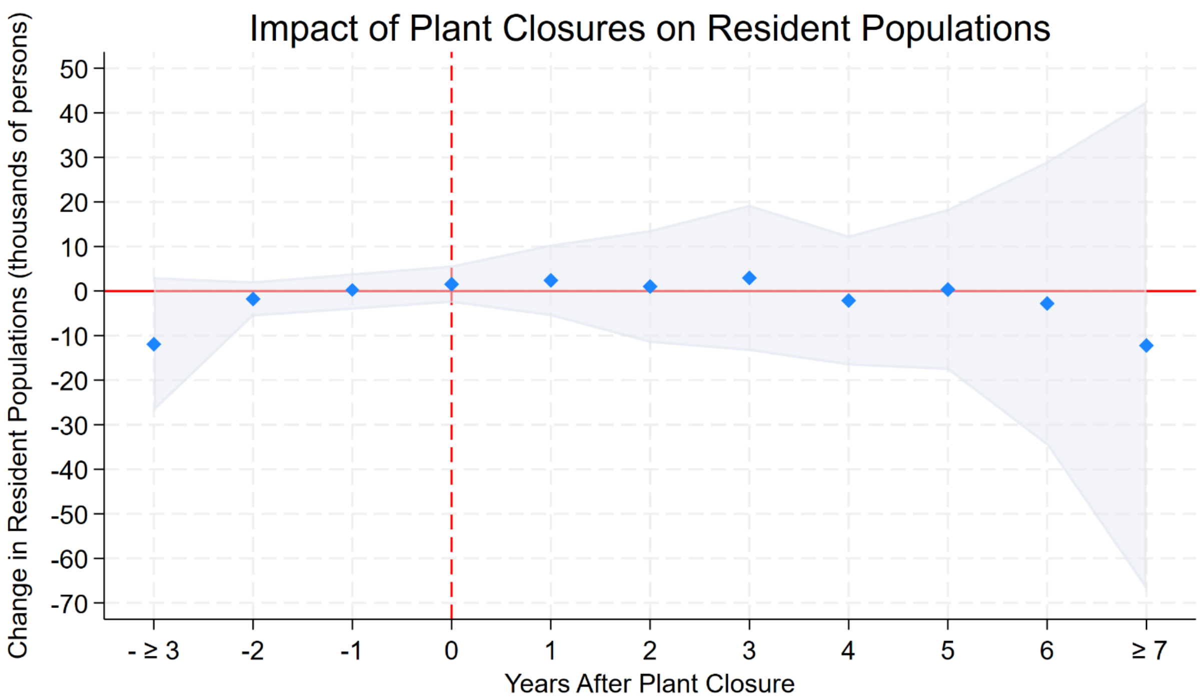

Figure 3. Impact of Plant Closures on Resident Populations

This figure was generated using Stata based on the dynamic DID model I created in the program. The grey-shaded region around the scatter plot represents the 95% confidence interval for the regression model.

The below regression output displays the regression results of the DID model for explaining changes in resident populations. This regression for the outcomes of resident populations yields a p-value of .0466 for the model, a value less than $\alpha = .05$, or a significance level of 5%. Therefore, the null hypothesis that R-squared is equal to zero can be rejected. This indicates a statistically significant relationship between the dependent variable, county-wide resident populations, and the independent variable, time after plant closure for exposed counties, at the 5% significance level (Sirkin, 2006). Additionally, the high adjusted R-squared value of .9989 indicates that the DID model is a strong fit for the data and that the plant closure model explains 99.89% of the variability in resident populations. However, such a high R-squared value is suspicious in DID models, and results from models yielding so are more subject to scrutiny and are to be interpreted with caution.

Statistics robust to heteroskedasticity Prob > F = 0.0466
R-squared = 0.9990
Adj R-squared = 0.9989
Within R-sq. = 0.0199

Res_Pop	Coefficient	Robust std. err.	t	P>|t|	[95% conf. interval]	
- ≥ 3	-11.93446	7.452887	-1.60	0.117	-26.975	3.106075
-2	-1.773998	1.961379	-0.90	0.371	-5.732221	2.184226
0	1.542504	2.080855	0.74	0.463	-2.656831	5.741839
1	2.396631	3.983808	0.60	0.551	-5.643018	10.43628
2	1.018692	6.275987	0.16	0.872	-11.64676	13.68415
3	2.948685	8.126565	0.36	0.719	-13.45139	19.34876
4	-2.127372	7.222237	-0.29	0.770	-16.70244	12.44769
5	.3444393	8.952305	0.04	0.969	-17.72204	18.41092
6	-2.78368	15.81605	-0.18	0.861	-34.70175	29.13439
≥ 7	-12.21337	27.15586	-0.45	0.655	-67.01612	42.58938
_cons	527.1812	19.82542	26.59	0.000	487.1719	567.1905

There is dissonance between the p-value for the model fit and the p-value for the individual coefficients. The high coefficient p-values indicate an inability to reject the null that the coefficients are zero. However, the model p-value and adjusted R-squared indicate that there is a statistically significant relationship between the dependent variable, county-wide resident populations, and the independent variable, time after plant closure for exposed counties at a significance level of 5%, and that the plant closure model explains 99.89% of the variability in resident populations. The high p-values are understandable given the marginal impacts of the closure on median household incomes. Given this, the model p-value and adjusted R-squared indicate that what marginal changes in resident populations occurred in exposed counties versus unexposed counties is explained by the closure model.

Median Household Incomes

At the beginning of the period of study in this paper, 1999, the average median household income across the 39 counties of interest was $41,103.36. By 2016, the average median household income rose to $53,227.92 for an average increase of $12,124.56, or 29.50% growth. Figure 10 in Appendix A displays trends in median household incomes across counties with and without closures between the years 1999 and 2016.

The following analysis references Figure 4 and the regression output below. Relative to the year before a closure, median household incomes were steadily rising in the years prior to plant closures, remained stagnant in the three years following plant closures, and then started to return to a steady rate of growth. In the three years after closure, median household incomes in exposed counties fluctuated between $94.9375 (95% CI, -1855.377 - 2045.252; P = 0.922) and $339.9375 (95% CI, -1905.618 - 2585.493; P = 0.761) greater than the year before the closure. This is very stagnant as compared to the annual rates of growth prior to this period and afterward, which have low p-values.

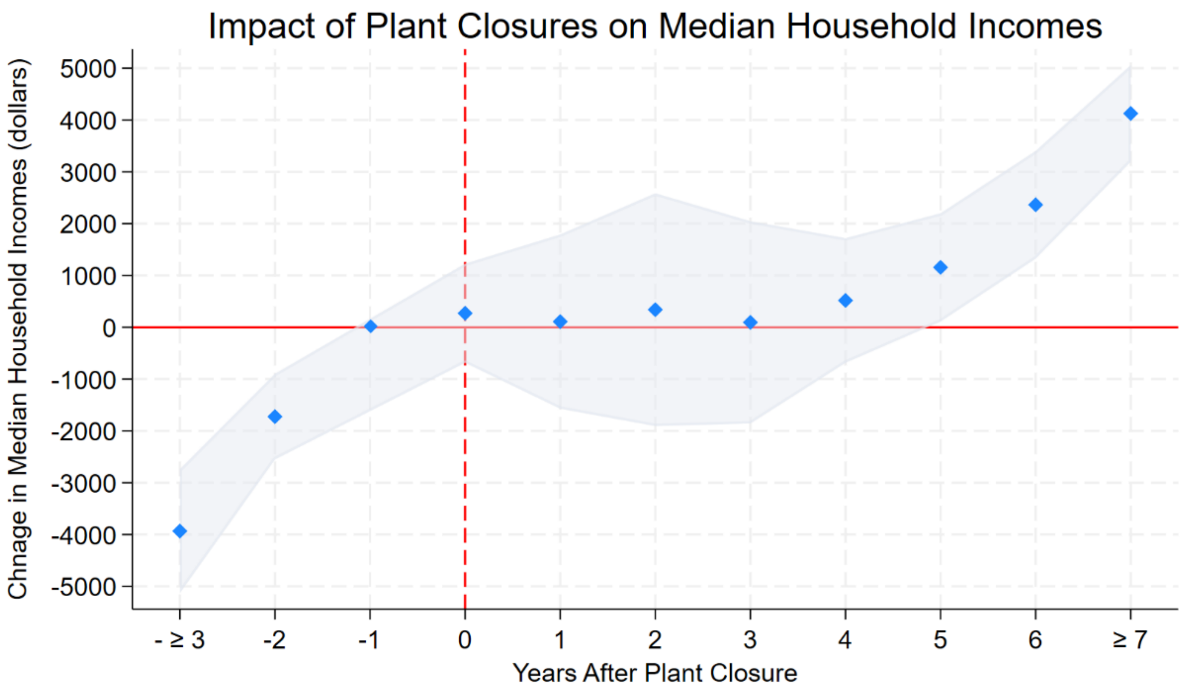

Figure 4. Impact of Plant Closures on Median Household Incomes

This figure was generated using Stata based on the dynamic DID model I created in the program. The grey-shaded region around the scatter plot represents the 95% confidence interval for the regression model.

However, the high p-value for the coefficients in this period, the year of the closure and the four years thereafter, indicate an inability to reject the null hypothesis that these coefficients are equal to zero. Given the trend of stagnation in median household income growth, the high p-values are understandable. They further support the finding that plant closures hindered median household income growth in exposed counties.

The below regression output for the outcomes of resident populations yields a p-value of 0.00, a value less than $\alpha = .01$, or a significance level of 1%. The null hypothesis that R-squared is equal to zero can be rejected, indicating a statistically significant relationship between the dependent variable, county-wide median household incomes, and the independent variables, time after plant closure, at the significance level of 1%. Additionally, the high adjusted R-squared value of .8455 indicates that the DID model is a strong fit for the data and that the plant closure model explains 84.55% of the variability in resident populations.

Statistics robust to heteroskedasticity   Prob > F = 0.0000
R-squared = 0.8559
Adj R-squared = 0.8455
Within R-sq. = 0.1988

Med_House	Robust Coefficient	std. err.	t	P>|t|	[95% conf. interval]	
- ≥ 3	-3932.301	592.1148	-6.64	0.000	-5127.237	-2737.365
-2	-1723.938	409.1728	-4.21	0.000	-2549.682	-898.1934
0	271.0625	473.4542	0.57	0.570	-684.4068	1226.532
1	109.9375	832.7256	0.13	0.896	-1570.571	1790.446
2	339.9375	1112.718	0.31	0.761	-1905.618	2585.493
3	94.9375	966.42	0.10	0.922	-1855.377	2045.252
4	517.4375	595.2822	0.87	0.390	-683.8906	1718.766
5	1156.187	516.9312	2.24	0.031	112.9781	2199.397
6	2364.125	514.4617	4.60	0.000	1325.899	3402.351
≥ 7	4126.36	460.9586	8.95	0.000	3196.108	5056.612
_cons	44608.78	356.9065	124.99	0.000	43888.51	45329.04

Per Capita Personal Incomes

At the beginning of the period of study in this paper, 1999, the average per capita personal income across the 39 counties of interest was $27,042.15. By 2016, average per capita personal income rose to $43,028.62, a growth of $15,986.47 or 59.12%. Figure 11 in Appendix A displays trends in per capita personal incomes across counties with and without closures between the years 1999 and 2016.

The following analysis references Figure 5 and the regression output below. Per capita personal incomes in affected counties continued to increase even after plants closed. Six years after closure, per capita personal incomes had increased by $6,285.25 as compared to the year before the closure (95% CI, 4658.661 - 7911.839; P = 0.000). The low p-values for the coefficients for this range indicate the null hypothesis that these coefficients are equal to zero can be rejected, indicating that plant closures had a statistically significant impact on per capita personal incomes in this range of time. This would indicate that those who remained employed were able to not only retain their level of earnings, but that their earnings also continued rising at a consistent rate.

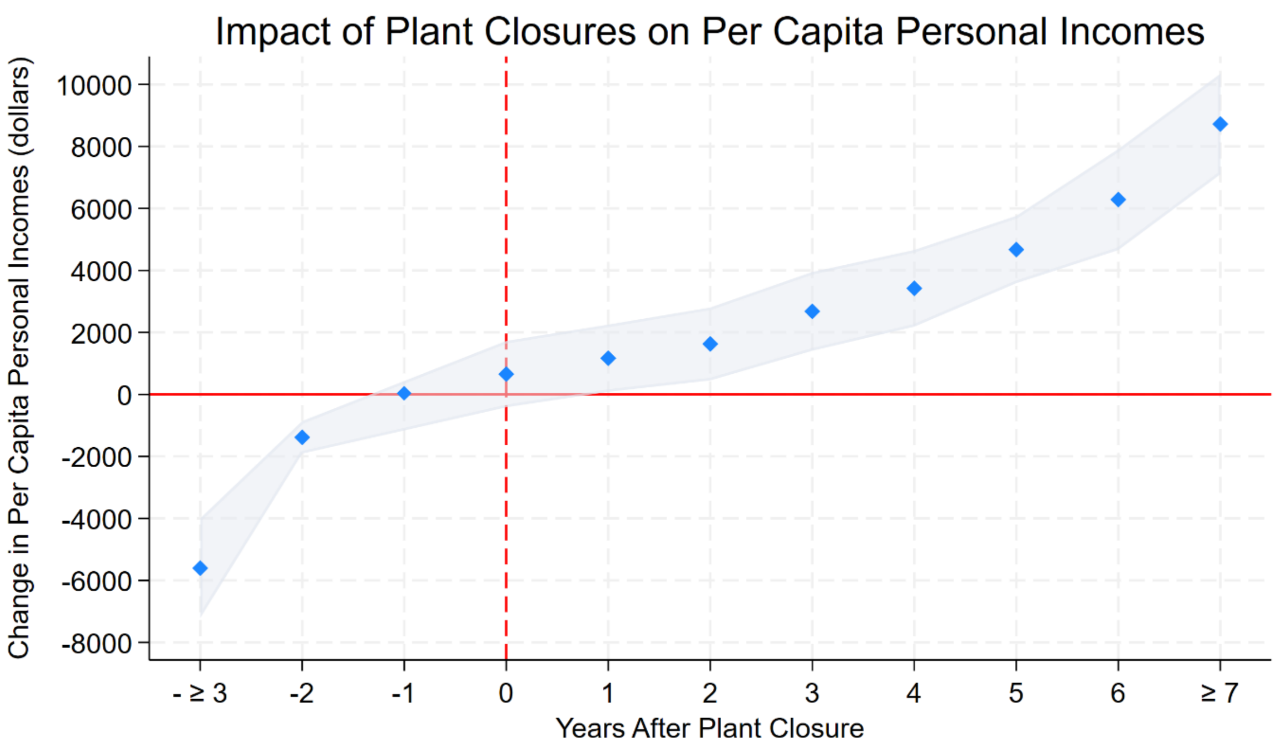

Figure 5. Impact of Plant Closures on Per Capita Personal Incomes

This figure was generated using Stata based on the dynamic DID model I created in the program. The grey-shaded region around the scatter plot represents the 95% confidence interval for the regression model.

The below regression output for the outcomes of resident populations yields a p-value of 0.00, a value less than $\alpha = .01$, or a significance level of 1%. The null hypothesis that R-squared is equal to zero can be rejected, indicating a statistically significant relationship between the dependent variable, county-wide per capita personal incomes, and the independent variables, time after plant closure, at the 1% significance level. Additionally, the high adjusted R-squared value of .8159 indicates that the DID model is a strong fit for the data and that the plant closure model explains 81.59% of the variability in resident populations.

Statistics robust to heteroskedasticity Prob > F = 0.0000
R-squared = 0.8283
Adj R-squared = 0.8159
Within R-sq. = 0.3759

PCPI	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
- ≥ 3	-5603.871	794.55	-7.05	0.000	-7207.338	-4000.404
-2	-1383.625	258.4892	-5.35	0.000	-1905.277	-861.9728
0	655	528.6222	1.24	0.222	-411.8027	1721.803
1	1167.312	536.1896	2.18	0.035	85.23804	2249.387
2	1628.75	581.18	2.80	0.008	455.8812	2801.619
3	2678.75	628.7266	4.26	0.000	1409.928	3947.572
4	3421.75	611.3736	5.60	0.000	2187.948	4655.552
5	4673.312	536.7626	8.71	0.000	3590.082	5756.543
6	6285.25	806.0075	7.80	0.000	4658.661	7911.839
≥ 7	8721.425	801.5417	10.88	0.000	7103.849	10339
_cons	30061.4	599.0887	50.18	0.000	28852.39	31270.41

Unemployment Rates

At the beginning of the period of study in this paper, 1999, the average unemployment rate across the 39 counties of interest was 3.89%. By 2016, average unemployment rates rose by 1.06 percentage points to 4.95%. Figure 12 in Appendix A displays trends in unemployment rates across counties with and without closures between the years 1999 and 2016.

The following analysis references Figure 6 and the regression output below. Compared to the year before a plant closure, unemployment rates rose in the year of the plant closure, as well as the three following years. Three years after closure, unemployment rates had increased by 2.5875 percentage points as compared to the year before the closure (95% CI, 1.619399 - 3.5556; P = 0.000). The low p-values for the coefficients for this range indicate the null hypothesis that these coefficients are equal to zero can be rejected, indicating that plant closures had a statistically significant impact on unemployment rates in this range of time.

This regression for the outcomes of resident populations yields a p-value of 0.00, a value less than $\alpha = .01$, or a significance level of 1%. The null hypothesis that R-squared is equal to zero can be rejected, indicating a statistically significant relationship between the dependent variable, county-wide unemployment rates, and the independent variables, time after plant closure, at the significance level of 1%. The low adjusted R-squared value of .3058 indicates that the DID model is not the strongest fit for the data as the plant closure model explains 30.58% of the variability in unemployment rates. However, DID models with low R-squared values are seen as less subject to scrutiny than DID models with extremely high R-squared values.

It is important to acknowledge that there is dissonance between the p-values for the model and the adjusted R-squared. The low coefficient p-values indicate an ability to reject the null that the coefficients are zero. Additionally, the low model p-value indicates the same. However, the low model adjusted R-squared indicates a low explanatory power of the independent variable, time after plant closure for exposed counties, on the dependent variable of county-wide unemployment rates.

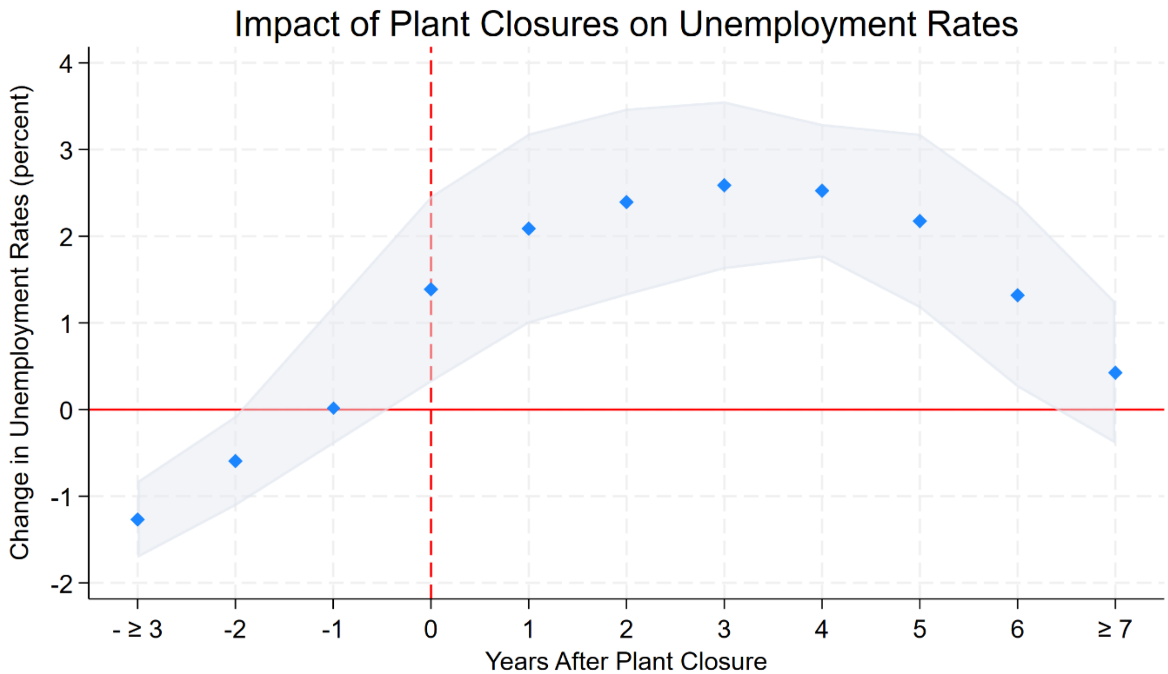

Figure 6. Impact of Plant Closures on Unemployment Rates

This figure was generated using Stata based on the dynamic DID model I created in the program. The grey-shaded region around the scatter plot represents the 95% confidence interval for the regression model.

One potential reason for this lack of explanatory power is that the people who work in these plants do not necessarily live in the same county as where the plant is located. To counter this in their research, Venkataramani et al. built a model that included data from all counties in a so-called 'commuting zone' (2020). These zones represent contiguous groups of counties that are used to define local labor markets. The model used in this paper, rather, captures the unemployment effects on those employees who did live in that county, as well as any potential spillover effects on businesses in the county. This applies to every regression in this paper but is more evident here.

Statistics robust to heteroskedasticity   Prob > F = 0.0000
R-squared = 0.3525
Adj R-squared = 0.3058
Within R-sq. = 0.1520

Unem_Rate	Robust Coefficient	std. err.	t	P>|t|	[95% conf.	interval]
- ≥ 3	-1.268589	.2196158	-5.78	0.000	-1.711792	-.8253863
-2	-.59375	.2581617	-2.30	0.026	-1.114741	-.0727586
0	1.3875	.5329278	2.60	0.013	.3120083	2.462992
1	2.0875	.5430944	3.84	0.000	.9914912	3.183509
2	2.39375	.5340361	4.48	0.000	1.316021	3.471479
3	2.5875	.4797132	5.39	0.000	1.619399	3.5556
4	2.525	.381545	6.62	0.000	1.755011	3.294989
5	2.175	.4986492	4.36	0.000	1.168685	3.181315
6	1.31875	.5271445	2.50	0.016	.2549294	2.382571
≥ 7	.425196	.4058763	1.05	0.301	-.3938955	1.244287
_cons	6.212474	.2848524	21.81	0.000	5.637618	6.787329

Percent of People in Poverty

At the beginning of the period of study in this paper, 1999, the average estimated percentage of people in poverty across the 39 counties of interest was 10.86%. By 2016, the average estimated percentage of people in poverty rose 4.12 percentage points to 14.98%. Figure 13 in Appendix A displays trends in percentages of people in poverty across counties with and without closures between the years 1999 and 2016.

The following analysis references Figure 7 above and the regression output below. Compared to the year before a plant closure, percents of people in poverty began rising in the year of the closure and kept rising for six years. Six years after closure, percents of people in poverty increased by 3.99375 percentage points compared to the year before the closure (95% CI, 2.776803 - 5.210697; P = 0.000). The low p-values for the coefficients for this range indicate the null hypothesis that these coefficients are equal to zero can be rejected, indicating that plant closures had a statistically significant impact on percents of people in poverty in this range of time.

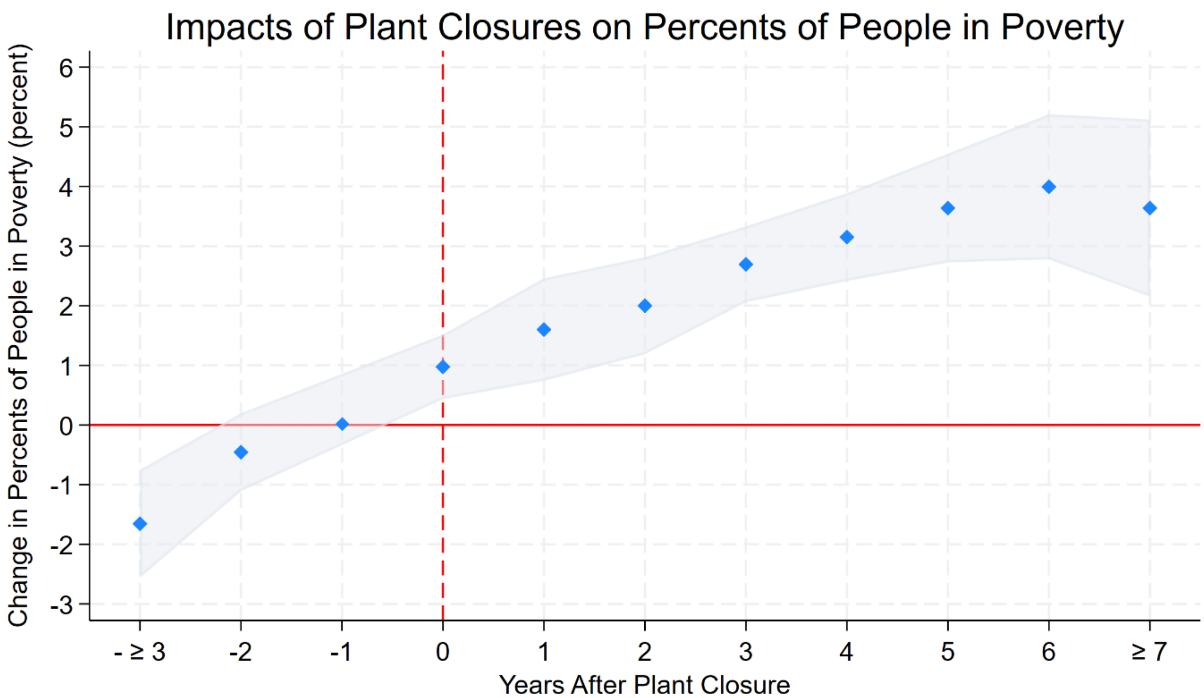

Figure 7. Impact of Plant Closures on Percents of People in Poverty

This figure was generated using Stata based on the dynamic DID model I created in the program. The grey-shaded region around the scatter plot represents the 95% confidence interval for the regression model.

The below regression for the outcomes of resident populations yields a p-value of 0.00, a value less than $\alpha = .01$, or a significance level of 1%. The null hypothesis that R-squared is equal to zero can be rejected, indicating a statistically significant relationship between the dependent variable, county-wide percents of people in poverty, and the independent variables, time after plant closure, at a significance level of 1%. Additionally, the high adjusted R-squared value of .7595 indicates that the DID model is a strong fit for the data and that the plant closure model explains 75.95% of the variability in county-wide percents of people in poverty. The low model p-value and the coefficient p-values in addition to the high adjusted R-squared indicate strong statistical evidence for the causal effects of automotive assembly plant closures on an increase in percents of people in poverty in exposed counties.

Statistics robust to heteroskedasticity Prob > F = 0.0000
R-squared = 0.7757
Adj R-squared = 0.7595
Within R-sq. = 0.2676

Est_Poverty	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
- ≥ 3	-1.655887	.448254	-3.69	0.001	-2.5605	-.7512735
-2	-.4562499	.3231865	-1.41	0.165	-1.108467	.195967
0	.9749999	.2678713	3.64	0.001	.4344137	1.515586
1	1.6	.4254746	3.76	0.001	.7413577	2.458643
2	2	.4021725	4.97	0.000	1.188383	2.811617
3	2.69375	.3146104	8.56	0.000	2.05884	3.32866
4	3.15	.3642138	8.65	0.000	2.414987	3.885013
5	3.6375	.4513401	8.06	0.000	2.726659	4.548341
6	3.99375	.6030215	6.62	0.000	2.776803	5.210697
≥ 7	3.637338	.7351725	4.95	0.000	2.1537	5.120976
_cons	11.075	.5459124	20.29	0.000	9.973309	12.1767

SNAP Benefits Recipients

At the beginning of the period of study in this paper, 1999, the average number of SNAP benefits recipients across the 39 counties of interest was 34,344.15 people. By 2016, the average number of SNAP benefits recipients rose by 41,819.39 people to 76,163.54 people, representing

121.77% growth in the average number of benefits recipients by county. Figure 14 in Appendix A displays trends in SNAP benefits recipients across counties with and without closures between the years 1999 and 2016.

The following analysis references Figure 8 and the regression output below. Compared to the year before a plant closure, the number of SNAP benefits recipients began rising in the year of the closure and kept rising for the following six years.

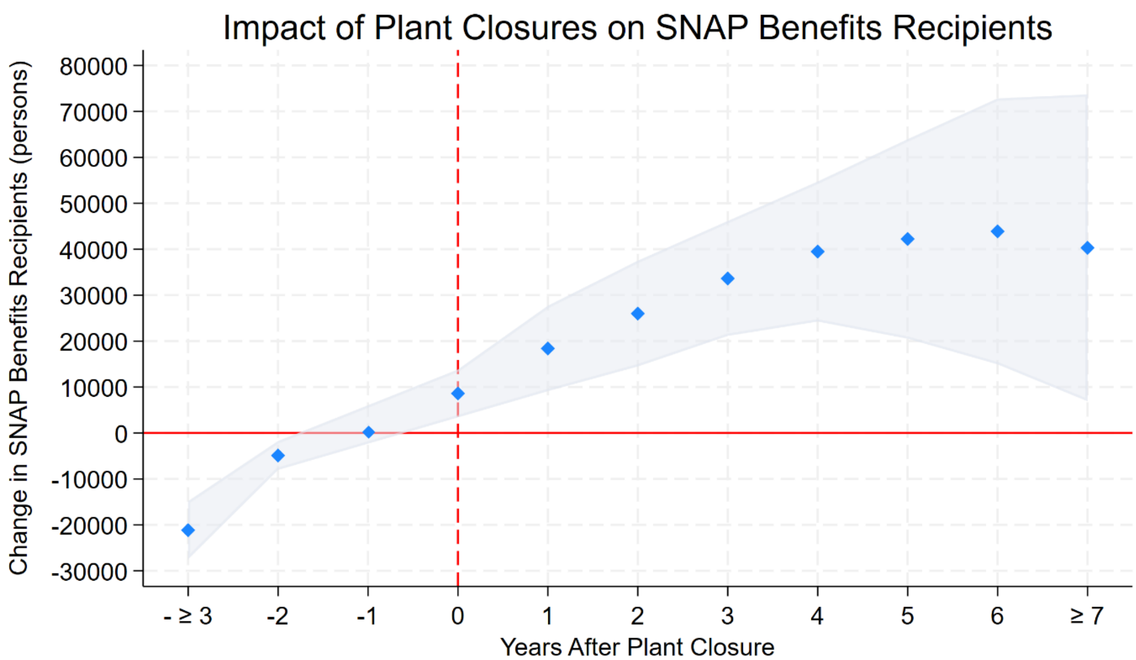

Figure 8. Impact of Plant Closures on SNAP Benefits Recipients

This figure was generated using Stata based on the dynamic DID model I created in the program. The grey-shaded region around the scatter plot represents the 95% confidence interval for the regression model.

Six years after closure, the number of SNAP benefits recipients increased by 43,887.31 compared to the year before the closure (95% CI, 14961.13 - 72813.5; P = 0.004). The low p-values for the coefficients for this range indicate the null hypothesis that these coefficients are equal to zero can be rejected, indicating that plant closures had a statistically significant impact on the number of SNAP benefits in this range of time. This regression for the outcomes of resident populations yields a p-value of 0.00, a value less than $\alpha = .01$, or a significance level of 1%.

Statistics robust to heteroskedasticity Prob > F = 0.0000
R-squared = 0.9263
Adj R-squared = 0.9210
Within R-sq. = 0.1663

SNAP	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
- ≥ 3	-21151.21	3120.409	-6.78	0.000	-27448.45	-14853.97
-2	-4896.437	1552.092	-3.15	0.003	-8028.685	-1764.19
0	8614.625	2574.007	3.35	0.002	3420.069	13809.18
1	18394.25	4596.625	4.00	0.000	9117.885	27670.61
2	25991.31	5697.063	4.56	0.000	14494.17	37488.45
3	33637.5	6189.046	5.44	0.000	21147.5	46127.5
4	39495.31	7543.035	5.24	0.000	24272.85	54717.77
5	42234.06	10749.6	3.93	0.000	20540.5	63927.63
6	43887.31	14333.5	3.06	0.004	14961.13	72813.5
≥ 7	40312.91	16540.41	2.44	0.019	6933.01	73692.81
_cons	34783.11	12503.24	2.78	0.008	9550.555	60015.66

The null hypothesis that R-squared is equal to zero can be rejected, indicating a statistically significant relationship between the dependent variable, county-wide SNAP benefits recipients, and the independent variables, time after plant closure, at a significance level of 1%. Additionally, the high adjusted R-squared value of .9210 indicates that the DID model is a strong fit for the data and that the plant closure model explains 92.10% of the variability in resident populations. The low model p-value and the coefficient p-values in addition to the high adjusted R-squared indicate strong statistical evidence for the causal effects of automotive assembly plant closures on an increase in the number of SNAP benefits recipients in exposed counties.

Chapter 5

Conclusion and Areas for Future Research

This thesis seeks to assess the magnitude of socio-economic effects felt by communities that experience automotive assembly plant closures. The existing literature describes the types of effects felt, but fails to adopt a robust, quantitative approach to evaluate the impact of these events. The goal of this paper is to gain a better understanding of the magnitude and duration of these socio-economic shocks so they may be used to help better inform future policy decisions. Such potential policies range from optimal unemployment assistance to local housing policies. The analysis finds that plant closures did have a statistically significant impact on the variables of resident populations, median household incomes, per capita personal incomes, unemployment rates, percent of people in poverty, and the number of SNAP benefits recipients.

Resident populations remain stable in counties that experienced plant closures for the ensuing five years. This aligns with the literature, which indicates that barriers to relocation often impinge upon workers moving after large economic shocks such as plant closures (Baldwin, 2005).

Median household incomes remain stagnant in counties that experienced plant closures for the ensuing three years. This is converse to per capita personal incomes, which maintained gradual growth despite plant closures. However, unemployment rates were also shown to increase in the three years following a plant closure. This, coupled with stagnation effects on median household incomes while per capita personal incomes continued to grow would indicate that the effects on median household incomes are likely correlated with the effects on unemployment rates. Additionally, the finding that personal incomes maintained gradual growth is contrary to the existing literature, which indicates that shocks such as a plant closure typically reduce wage levels within the labor market (Barnes et al., 2016; Healey, 1982; Baldwin, 2005).

The most compelling findings come from the impacts on the percentage of people in poverty and the number of SNAP benefits recipients in exposed counties. These both have low model p-values, low coefficient p-values, as well as high adjusted R-squared values. These regressions find that, six years after an automotive assembly plant closure, the percent of people in poverty increased by 3.99 percentage points and that the number of SNAP benefits recipients increased by 43,887.31 compared to the year before the closure and relative to unexposed counties.

This analysis uses socio-economic data from various governmental sources, and the plant closure data set from the Venkataramani et al. (2020) paper. A dynamic DID regression model is used to conduct an event study of the impact of the plant closures on the socio-economic variables of interest. These variables were selected based on the literature review, especially from analysis of the withdrawal of the automotive industry writ large from Australia between 2014 and 2017 (Lansbury et al., 2017; Barnes et al., 2016), as well as their availability at the granular level of a county for the entire period of interest, 1999 through 2016.

Using counties was useful in the model as a proxy for establishing the affected populations for this thesis. This model is limited, however, as it captures the impact of plant closures on those employees who did live in that county and some spillover effects on businesses in the county. To counter the reality that not all employees live in the same county as where the assembly plant they work is located nor would all spillover effects be felt there, Venkataramani et al. (2020) built their model around ‘commuting zones’ rather than only the county of the plant location. These zones better define local labor markets and would likely yield more statistically significant results. Other avenues for better defining the populations affected by closures could involve gathering manufacturer employment data, perhaps from governmental tax departments such as the IRS or the Census Bureau, and creating broader geographic impact zones based on those data.

Additionally, more research should be done into the disparate impacts of the closures on unemployment rates and median household incomes, which were felt primarily for three years, versus impacts on the percentage of people in poverty and SNAP benefits recipients which were felt for twice as long, increasing for six years following a closure. This finding is intriguing and worthy of closer examination. The lingering effects on poverty and welfare dependence, even as unemployment rates begin to fall and household incomes begin to rise, is an area of research that could prove fruitful for better crafting policies to aid the communities that experience plant closures or other similar economic shocks.

Appendix A

Tables and Figures

Table 1. Summary Statistics for the Economic Variables of Interest: 1999-2016

Variable	Mean	Standard Deviation	Minimum	Maximum
Median Household Income (dollars)	$46,269.98	$8,616.53	$28,875.00	$80,696.00
Per Capita Personal Income (dollars)	$34,724	$8,657	$19,503	$77,349
Resident Population (thousands of persons)	480.62	872.63	22.65	5,376.75
Unemployment Rate (percent of the population)	6.7%	2.6%	1.9%	16.1%
Estimated Percent of People in Poverty (percent of the population)	14.0%	4.5%	4.1%	26.3%
SNAP Benefits Recipients (thousands of persons)	63.58	13.56	0.73	1,032.89

The above dataset contains summary statistics for the variables of interest in this study from each of the 39 counties between the years 1999 and 2016, for a total of 702 observations for each variable.

Table 2. Summary Statistics for the Economic Variables of Interest: 1999

Variable	Mean	Standard Deviation	Minimum	Maximum
Median Household Income (dollars)	$41,103.36	$6,919.09	$28,875.00	$62,344.00
Per Capita Personal Income (dollars)	$27,042.15	$5,382.80	$19,503.00	$44,725.00
Resident Population (thousands of persons)	471.11	901.05	23.17	5,365.34
Unemployment Rate (percent of the population)	3.9 %	1.3%	1.9%	8.8%
Estimated Percent of People in Poverty (percent of the population)	10.9%	3.2%	4.5%	18.4%
SNAP Benefits Recipients (thousands of persons)	34.34	83.48	0.73	475.78

The above dataset contains summary statistics for the variables of interest in this study from across the 39 counties in this study in the year 1999.

Table 3. Summary Statistics for the Economic Variables of Interest: 2016

Variable	Mean	Standard Deviation	Minimum	Maximum
Median Household Income (dollars)	$53,227.92	$9,902.62	$36,715.00	$80,696.00
Per Capita Personal Income (dollars)	$43,028.62	$9,572.42	$30,888.00	$77,349.00
Resident Population (thousands of persons)	488.98	869.53	22.65	5,223.39
Unemployment Rate (percent of the population)	4.9%	.97%	3.5%	7.1%
Estimated Percent of People in Poverty (percent of the population)	15.0%	4.4%	5.2%	22.9%
SNAP Benefits Recipients (thousands of persons)	76.16	159.79	2.69	930.02

The above dataset contains summary statistics for the variables of interest in this study from across the 39 counties in this study in the year 2016.

Table 4. Automotive Assembly Plants in Operation as of 1999

	Company	Location	State	County	Date Closed
1	DaimlerChrysler	Vance, AL	AL	Tuscaloosa	
2	General Motors	Doraville, GA	GA	DeKalb	9/1/2008
3	Ford	Hapeville, GA	GA	Fulton	10/1/2006
4	DaimlerChrysler	Belvidere, IL	IL	Boone	
5	Ford	Chicago, IL	IL	Cook	
6	Toyota	Princeton, IN	IN	Gibson	
7	General Motors	Roanoke, IN	IN	Huntington	
8	AM General	Mishawaka, IN	IN	St. Joseph	
9	Subaru	Lafayette, IN	IN	Tippecanoe	
10	Ford	Louisville, KY	KY	Jefferson	
11	Ford	Louisville, KY	KY	Jefferson	
12	Toyota	Georgetown, KY	KY	Scott	
13	General Motors	Bowling Green, KY	KY	Warren	
14	General Motors	Flint, MI	MI	Genesee	
15	General Motors	Lansing, MI	MI	Ingham	5/1/2005
16	General Motors	Lansing, MI	MI	Ingham	3/1/2006
17	General Motors	Lansing, MI	MI	Ingham	
18	General Motors	Lansing, MI	MI	Ingham	
19	DaimlerChrysler	Sterling Heights, MI	MI	Macomb	
20	DaimlerChrysler	Warren, MI	MI	Macomb	
21	Ford	Wixom, MI	MI	Oakland	5/1/2007
22	General Motors	Pontiac, MI	MI	Oakland	9/1/2009
23	General Motors	Lake Orion, MI	MI	Oakland	
24	Autoalliance	Flat Rock, MI	MI	Wayne	
25	DaimlerChrysler	Detroit, MI	MI	Wayne	
26	Ford	Dearborn, MI	MI	Wayne	
27	Ford	Detroit, MI	MI	Wayne	
28	Ford	Wayne, MI	MI	Wayne	
29	DaimlerChrysler	Detroit, MI	MI	Wayne	
30	Ford	Dearborn, MI	MI	Wayne	2/1/2004
31	Ford	Wayne, MI	MI	Wayne	
32	General Motors	Detroit, MI	MI	Wayne	
33	General Motors	Wentzville, MO	MO	St. Charles	
34	DaimlerChrysler	Fenton, MO	MO	St. Louis	7/1/2009
35	DaimlerChrysler	Fenton, MO	MO	St. Louis	10/1/2008
36	Ford	Hazelwood, MO	MO	St. Louis	3/1/2006
37	Freightliner/Sterling	Cleveland, NC	NC	Cleveland	

38	Freightliner	Mt. Holly, NC	NC	Gaston	
39	International	Springfield, OH	OH	Clark	
40	Honda	East Liberty, OH	OH	Logan	
41	Ford	Avon Lake, OH	OH	Lorain	
42	Ford	Lorain, OH	OH	Lorain	12/1/2005
43	DaimlerChrysler	Toledo, OH	OH	Lucas	
44	DaimlerChrysler	Toledo, OH	OH	Lucas	
45	General Motors	Moraine, OH	OH	Montgomery	12/1/2008
46	Kenworth	Chillicothe, OH	OH	Ross	
47	General Motors	Warren, OH	OH	Trumbull	
48	Honda	Marysville, OH	OH	Union	
49	Mack	Macungie, PA	PA	Lehigh	
50	DaimlerChrysler	Gaffney, SC	SC	Cherokee	
51	Mack	Winnsboro, SC	SC	Fairfield	11/1/2002
52	BMW	South Greer, SC	SC	Spartanburg	
53	Peterbilt	Madison, TN	TN	Davidson	12/1/2009
54	General Motors	Spring Hill, TN	TN	Maury	
55	Nissan	Smyrna, TN	TN	Rutherford	
56	Ford	Norfolk, VA	VA	Norfolk City	6/1/2007
57	Mack/Volvo	Dublin, VA	VA	Pulaski	
58	General Motors	Janesville, WI	WI	Rock	4/1/2009

The above dataset contains information from the automotive assembly plant closure dataset built by Venkataramani, Bair, O'Brien, and Tsai (2020). The plants in blue are the plants that experienced closure within the timeframe of study.

Table 5. Collected Table of Regression Outputs

VARIABLES	(1) Res_Pop	(2) Med_House	(3) PCPI	(4) Unem_Rate	(5) Est_Poverty	(6) SNAP
-3	-11.93	-3,932***	-5,604***	-1.269***	-1.656***	-21,151***
	(7.453)	(592.1)	(794.5)	(0.220)	(0.448)	(3,120)
-2	-1.774	-1,724***	-1,384***	-0.594**	-0.456	-4,896***
	(1.961)	(409.2)	(258.5)	(0.258)	(0.323)	(1,552)
0	1.543	271.1	655	1.388**	0.975***	8,615***
	(2.081)	(473.5)	(528.6)	(0.533)	(0.268)	(2,574)
1	2.397	109.9	1,167**	2.088***	1.600***	18,394***
	(3.984)	(832.7)	(536.2)	(0.543)	(0.425)	(4,597)
2	1.019	339.9	1,629***	2.394***	2.000***	25,991***
	(6.276)	(1,113)	(581.2)	(0.534)	(0.402)	(5,697)
3	2.949	94.94	2,679***	2.587***	2.694***	33,637***
	(8.127)	(966.4)	(628.7)	(0.480)	(0.315)	(6,189)
4	-2.127	517.4	3,422***	2.525***	3.150***	39,495***
	(7.222)	(595.3)	(611.4)	(0.382)	(0.364)	(7,543)
5	0.344	1,156**	4,673***	2.175***	3.637***	42,234***
	(8.952)	(516.9)	(536.8)	(0.499)	(0.451)	(10,750)
6	-2.784	2,364***	6,285***	1.319**	3.994***	43,887***
	(15.82)	(514.5)	(806.0)	(0.527)	(0.603)	(14,334)
7	-12.21	4,126***	8,721***	0.425	3.637***	40,313**
	(27.16)	(461.0)	(801.5)	(0.406)	(0.735)	(16,540)
Constant	527.2***	44,609***	30,061***	6.212***	11.08***	34,783***
	(19.83)	(356.9)	(599.1)	(0.285)	(0.546)	(12,503)
Observations	774	774	774	774	774	774
R-squared	0.999	0.856	0.828	0.353	0.776	0.926

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The above table contains summary outputs for the statistics for the 6 regressions from this study. It shows the effects of plant closures on resident populations, median household incomes, per capita personal incomes, unemployment rates, percents of people in poverty, and numbers of SNAP benefits recipients in the affected counties relative to the time, in years, before or after the closure. The number of observations is higher than in other tables, 774 vs. 702, representing the counties with multiple plant closures whose before and after status had to be accounted for multiple times.

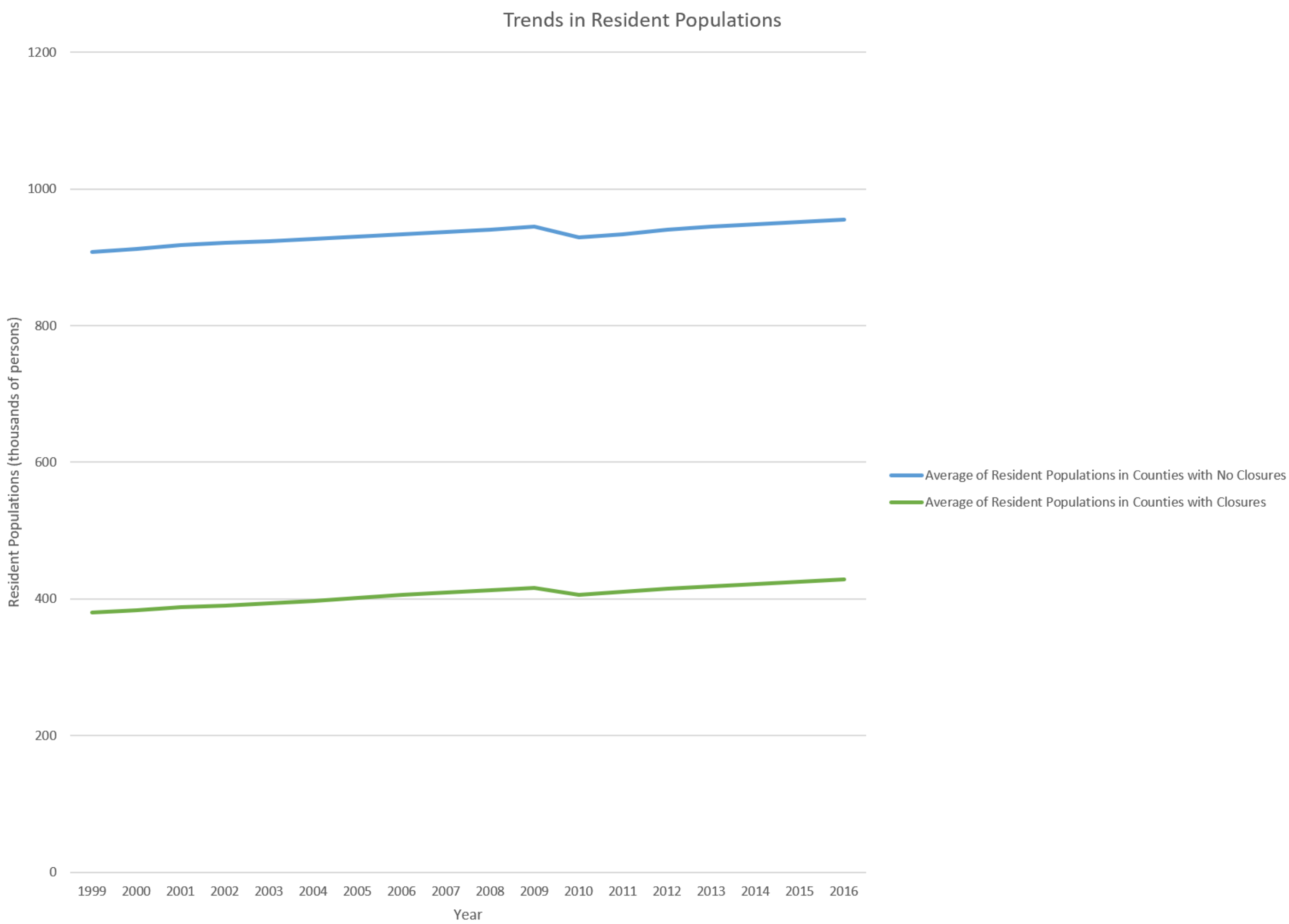

Figure 9. Trends in Resident Populations

The above graph displays the trends in the average resident population across counties with and without automotive assembly plant closures between the years 1999 and 2016.

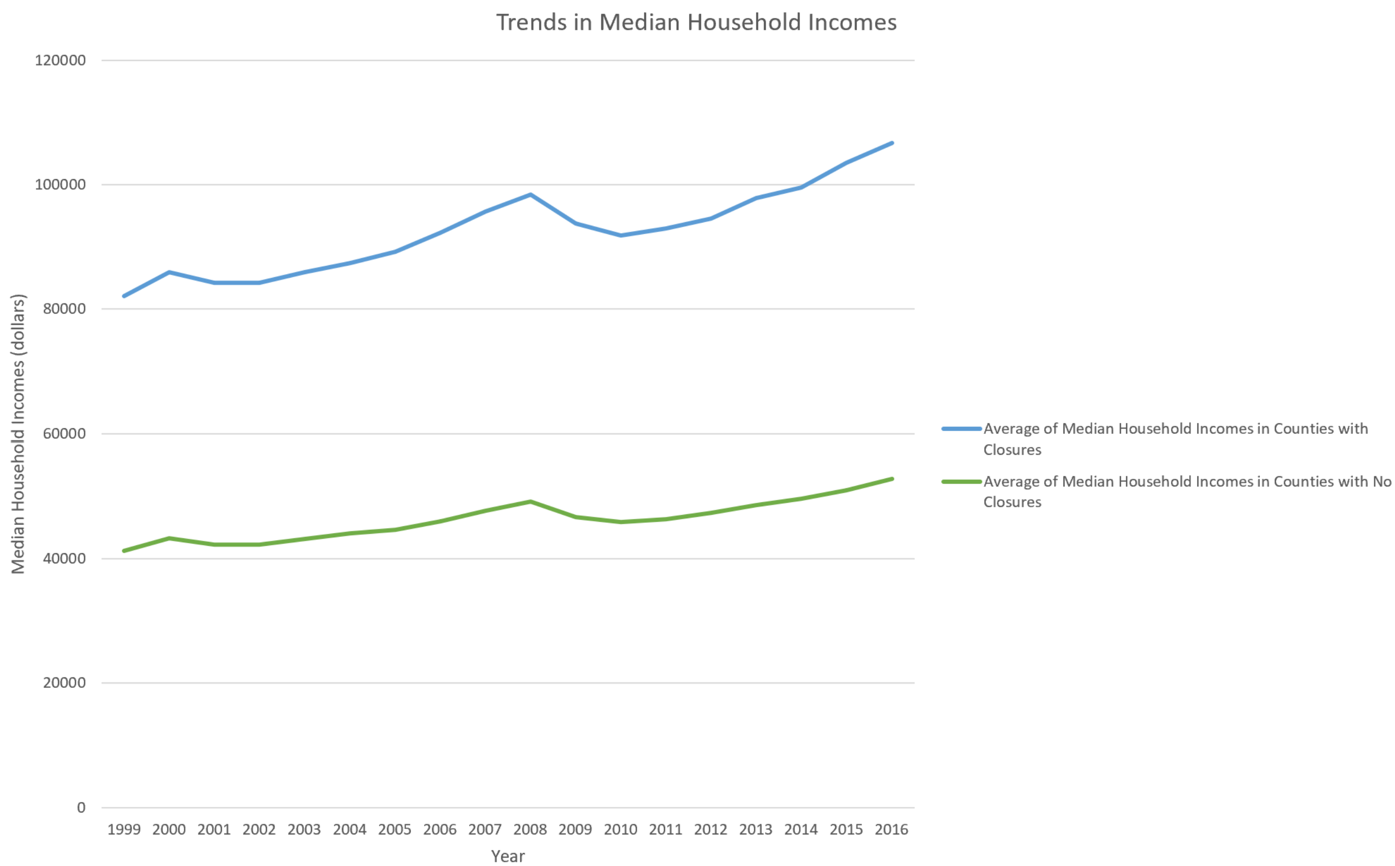

Figure 10. Trends in Median Household Incomes

The above graph displays the trends in average median household income across counties with and without automotive assembly plant closures between the years 1999 and 2016.

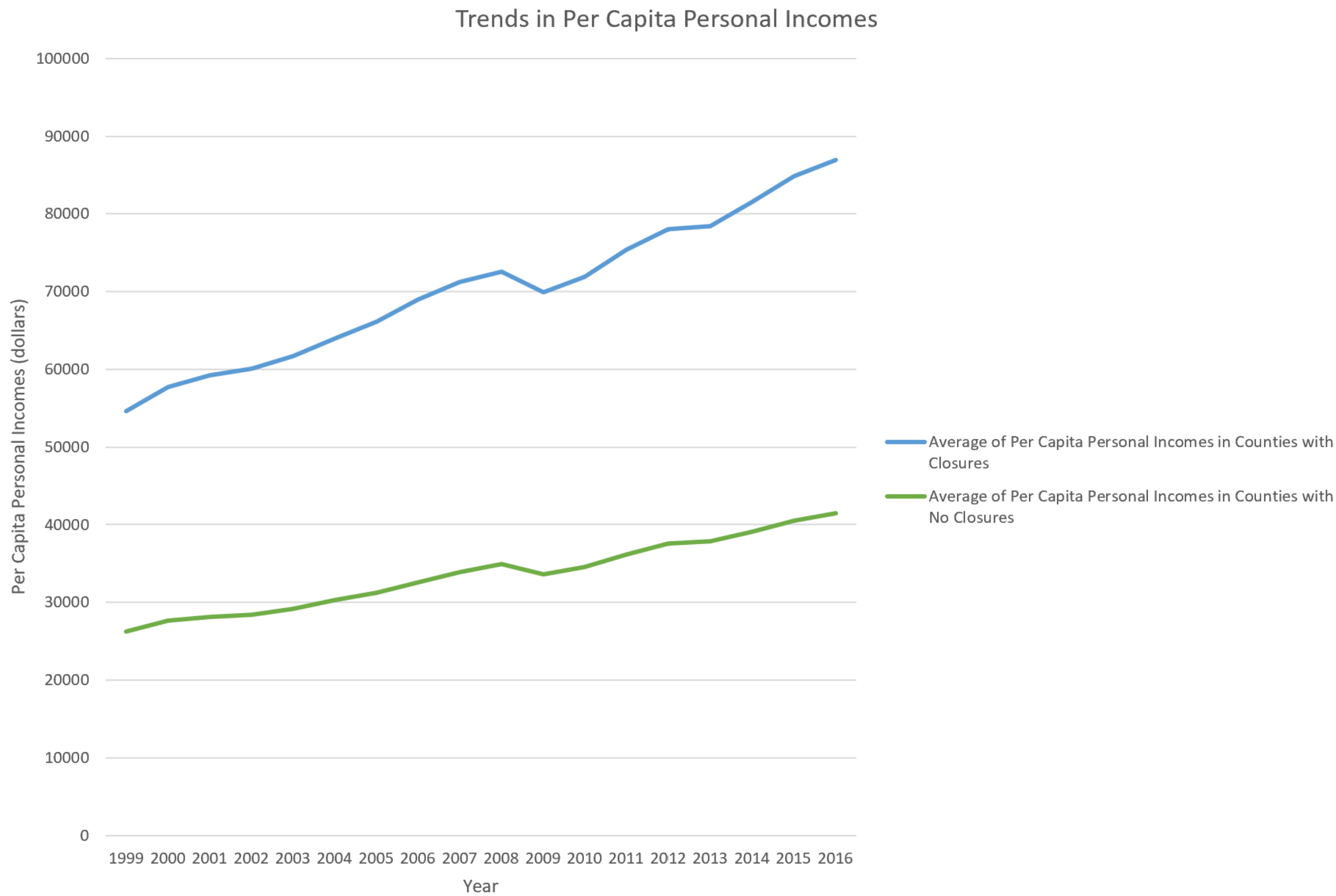

Figure 11. Trends in Per Capita Personal Incomes

The above graph displays the trends in average per capita personal income across counties with and without automotive assembly plant closures between the years 1999 and 2016.

Figure 12. Trends in Unemployment Rates

The above graph displays the trends in average unemployment rates across counties with and without automotive assembly plant closures between the years 1999 and 2016.

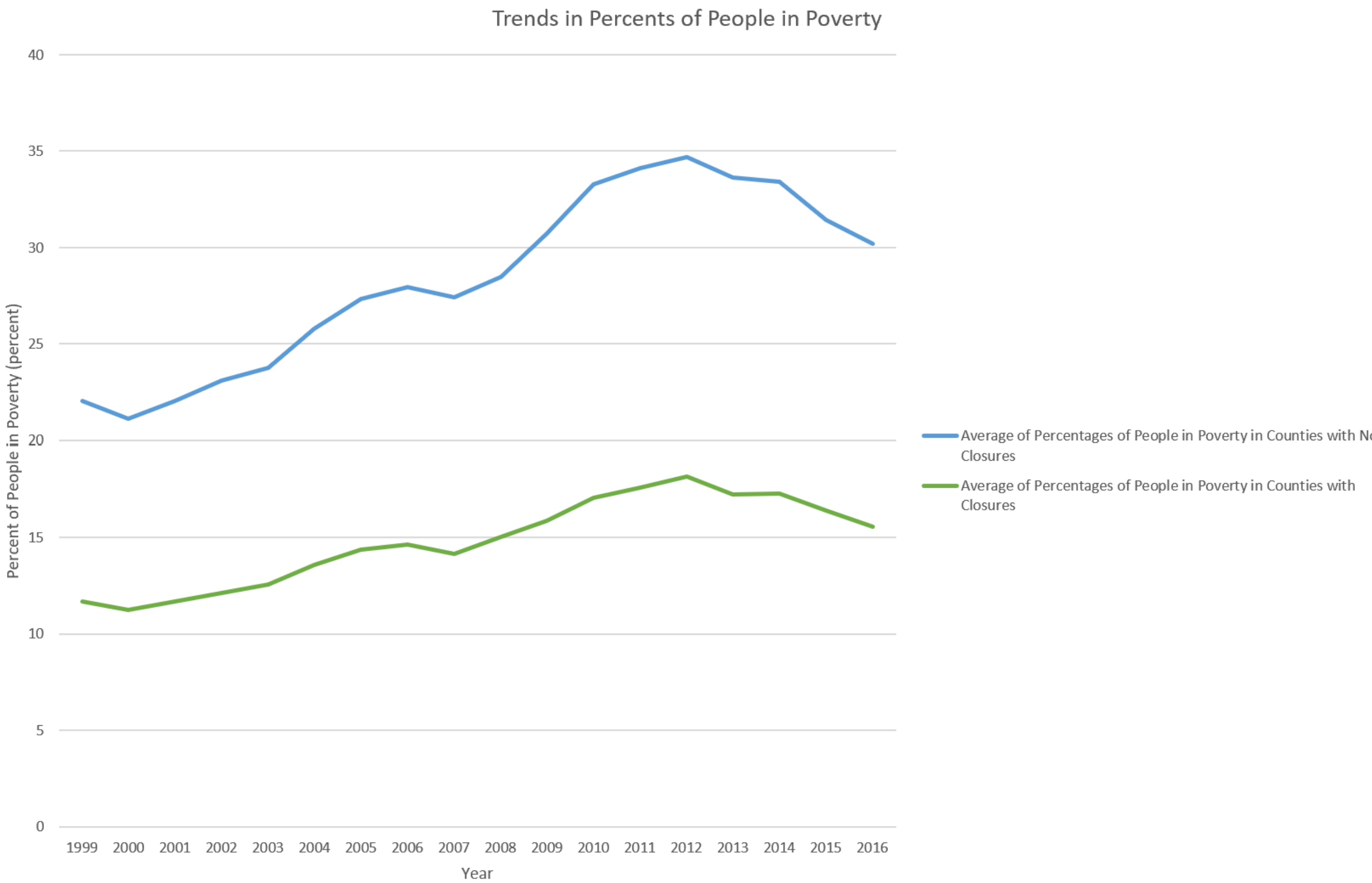

Figure 13. Trends in Percents of People in Poverty

The above graph displays the trends in the average percents of people in poverty across counties with and without automotive assembly plant closures between the years 1999 and 2016.

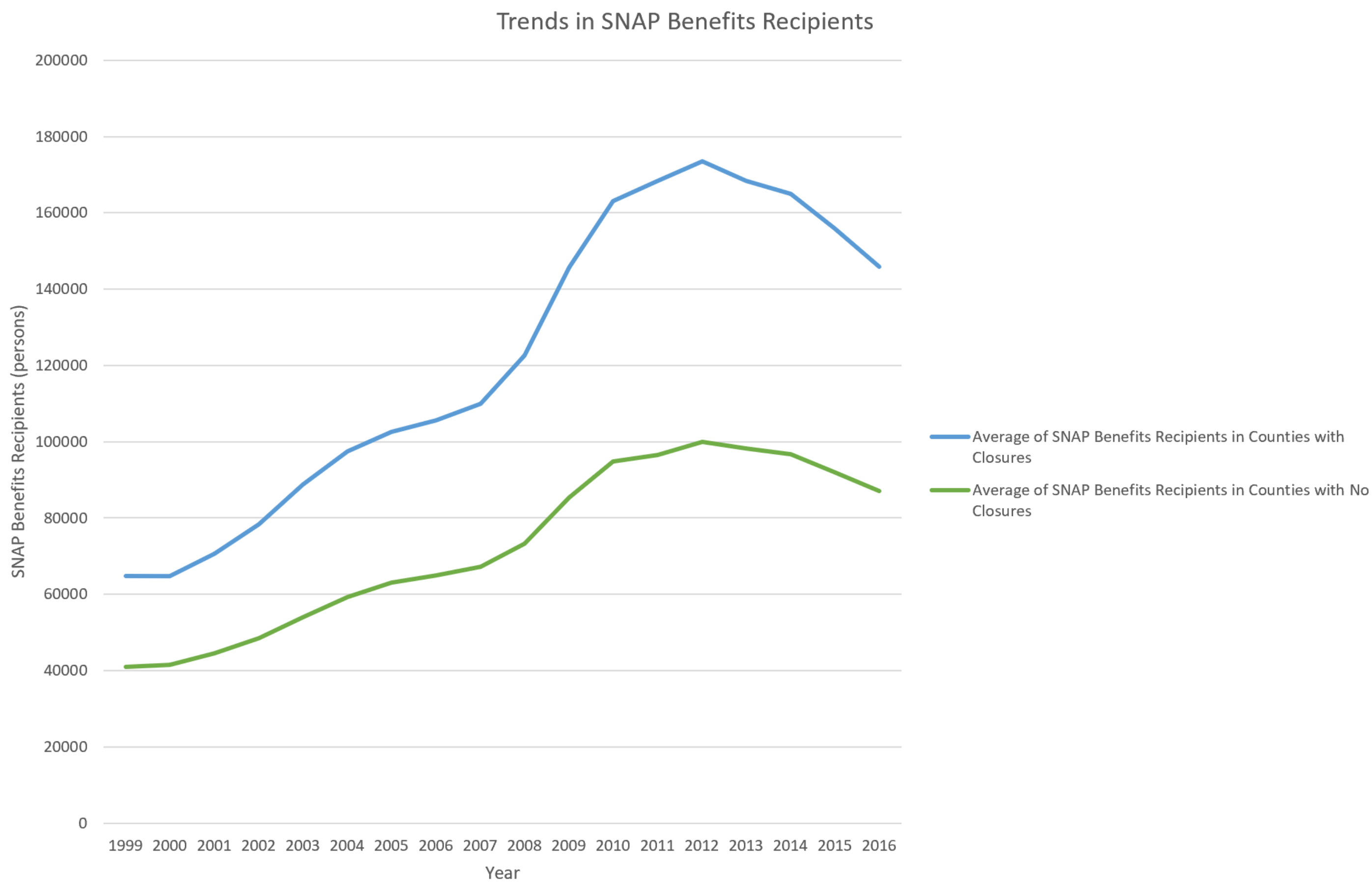

Figure 14. Trends in SNAP Benefits Recipients

The above graph displays the trends in the average number of SNAP benefits recipients across counties with and without automotive assembly plant closures between the years 1999 and 2016.

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Academic Vita - Isabella Pusateri

EDUCATION

The Pennsylvania State University University Park, PA
Smeal College of Business
College of the Liberal Arts May 2024
Schreyer Honors College
IES Abroad - Vienna (Study abroad program) August 2022 - December 2023
Bachelor of Science in Finance
Bachelor of Science in Economics

Work Experience

PPG Industries, Inc. ***Summer 2020 – Present***

Primer's Week Externship Program *July 2020*

Corporate Audit Services Internship *May 24 – July 30, 2021*

- Helped prepare for and assisted with Finance and IT audit walkthroughs
- Performed testing of Finance and IT SOX controls
- Led my team in the implementation of new technologies in the Global Resource Planning Project

Finance, Automotive OEM Internship *May 23 – July 29, 2022*

- Developed data visualization dashboards in Power BI to compare sales and other metrics cross-regionally
- Analyzed costing structures between countries using data from Oracle BI in Excel enabling over a million dollars in savings for the company annually

Customer Invoicing & Incentive Accounting Internship *May 29 – August 4th, 2023*

- Reviewed and processed funding of prebate payments to customer partners of the auto refinish business
- Collaborated with tax and customer service team members to ensure proper sales tax documentation
- Analyzed trends in invoice adjustments to make recommendations for future audit assurances

Campus Involvement

Student Programming Association *August 2020 – Present*

- Determined how to best utilize student activity fees to plan events that were engaging and relevant to students
- Active member of the Special Events, Concerts, and Lectures committees
- Voted by executive team as the October 2021 member of the month for the "…immense help during the transition to in-person events through staffing events and active participation in committee meetings"

Tarriff Center Scholars – Founding member *October 2020 – May 2021*

- Organization out of the Smeal College of Business to create a business journal centered around the principles of ethics and corporate social responsibility
- Leader of the Organizational Affairs Committee – creating the structure and a platform for the organization

Volunteer

THON *September 2019 - Present*

- Committees: Rules & Regulations (2019 – 2021), Special Events (2021 – 2022)
  - Managed the security at THON events, saving the organization hundreds of thousands of dollars
  - Developed and deployed safe and efficient security protocols for using metal detectors in my role as a metal detector specialist
  - Was a leader on my team and facilitated security education lessons as a Security Leader
  - Mentored new THON members and underclassmen during unprecedented lockdowns

ADDITIONAL EXPERIENCE/HONORS/SKILLS/INTERESTS

Paterno Fellows Program Fellow

Honors Program including advanced academic coursework, thesis, study abroad and/or internship, ethics study, and leadership/service commitment

Schreyer Honors College Scholar

Honors Program including advanced academic coursework and the writing of a senior thesis

Advanced level German language skills – B2/C1 level fluency

Proficient in Microsoft Programs including strong Excel and Power BI skills, Other: Stata, Adobe Creative Cloud