ABSTRACT

LAUTZENHEISER, JENNIFER NOELLE FEARNOW. Revisiting Employment Growth, Worker Mobility, and Economic Development. (Under the direction of Dr. Mitchell Renkow).

A county-level labor market model is estimated for North Carolina. The model spatially partitions labor market adjustments from employment growth into four labor supply responses: changes to in-commuting, out-commuting, unemployment, and labor force size. Results from analysis of 2010-2015 data suggest the single largest share of adjustments come from decreases in unemployment. Although spatial spillovers of employment growth—seen via changes to in-commuting—still exist, results from this time period indicate job "leakages" are smaller than previous estimates. The substantial leakages highlight the continued existence of potential mutual gains to regional cooperation. At the same time, the current analysis also suggests the financial incentives as a job creation strategy will be more "efficient," i.e., there will be fewer "leakages," in times of economic recovery as opposed to an economic boom.

Revisiting Employment Growth, Worker Mobility, and Economic Development

by
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DEDICATION

To Daniel, for your love and support.

BIOGRAPHY

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CHAPTER 1: INTRODUCTION

Economic theory tells us that an individual maximizes utility from income, leisure, and location subject to constraints on income, time, and space (Kasper, 1983). When labor markets experience employment shocks, individuals adjust their labor supply responses accordingly. For a positive employment shock to a given location, one will find in-migrants moving to areas with new job opportunities, retired/discouraged workers re-entering the workforce, unemployed individuals intensifying their job search, and area residents relocating or changing their commuting patterns.

This paper tries to measure the relative importance of these components of labor supply responses in North Carolina counties over the period 2010 to 2015. The motivation stems from the ongoing focus of policymakers and economic development professionals to focus on job creation. It relies on an approach developed by Renkow (2003) to analyze labor market adjustments in the 1980s—a time of economic growth. That paper, along with others from the same period of time, found that the benefits of employment growth are not confined to the county in which the new jobs are created. Those "leakages" were found to be substantial, suggesting the net benefits of local job creation investments might not generate a reasonable rate of return to the locality that made the investment.

Revisiting that study in a different macroeconomic environment, this thesis looks at North Carolina counties in a time of economic recession and recovery. [1] Analysis of the more recent data still show "leakages" to be substantial, albeit smaller than in the 1980s. They also show unemployment adjustments are large for this time period, suggesting that the benefits of

[1] Part of this work was funded by the Institute for Emerging Issues (IEI), a non-partisan public policy organization that exists to enhance North Carolina's long-term prosperity. IEI was interested in updating Renkow (2003) for the 2010-2015 time period. These years were also chosen because they represented a time period for which data was conveniently available.

financial incentives for job creation will be more efficient in times of recession and recovery than in boom periods.

The structure of the paper is as follows: Chapter Two motivates the study and reviews the literature on labor supply adjustments to employment growth and variables influencing those adjustments. Chapter Three provides the analytical framework. Chapter Four lays out the econometric model and estimation strategy and describes the data. Chapter Five presents the results, and Chapter Six concludes.

CHAPTER 2: BACKGROUND

2.1: Economic Development and Employment Growth

Policymakers and applied economists often focus on tangible indicators to measure economic development: higher property values, higher per capita income, an improved distribution of income, lower poverty rates, and, most importantly, increased employment, among others. The number of jobs created is the typical indicator for the success of economic development projects, particularly among elected officials. In fact, one of the stated goals of U.S. federal economic development programs—as outlined in the Public Works and Economic Development Act of 1965—is employment growth, specifically "job creation." [2]

At the local level, the assumption behind this focus on employment growth is that the benefits from new jobs go primarily, or even completely, to local residents; however, if this is not the case and jobs do not primarily go to local residents, the actual local benefits will be substantially less than envisioned. This is important because local governments often expend significant resources to promote economic development initiatives. [3]

A specific example can be seen in the 2013 announcement by the Economic Development Partnership of North Carolina (EDPNC) that MetLife, a global life insurance and benefits company, would create hubs for its U.S. retail business in Mecklenburg and Wake counties providing "2,600 jobs in Charlotte and Cary, North Carolina, by the end of 2015." [4]

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[2] Public Works and Economic Development Act of 1965, 42 U.S.C. 3121 (2018). Accessed February 22, 2020. https://legcounsel.house.gov/Comps/Public%20Works%20And%20Economic%20Development%20Act%20Of%20 1965.pdf

[3] One way local governments spur employment growth and entice businesses to relocate or expand operations in their jurisdiction is by investing in large infrastructure projects that improve road links, provide water and sewer systems, and the like. Another method is to use the tax system to offer financial incentives: employment tax subsidies, property tax abatement, and tax credits (Malpezzi, 2003). The North Carolina William S. Lee Act of 1996 expanded the use of financial incentives; and since its passage, North Carolina has been utilizing these incentives more readily (Morgan, 2009).

[4] "MetLife to Create Over 2,600 jobs in North Carolina." The Economic Development Partnership of North Carolina. March 07, 2013. Accessed February 22, 2020. https://edpnc.com/metlife-create-2600-jobs-north-carolina/

This project received over $87 million in state funding and up to $2 million from the One North Carolina Fund. As detailed in the press release, "[t]he One NC Fund provides financial assistance to local governments, to attract business projects that will stimulate economic activity and create new jobs. Companies receive no money upfront and must meet job-creation and investment performance targets to qualify for grant funds." [5]

The question is: who gets those jobs once they are created? Suppose all 2,600 of these MetLife jobs are, in fact, created in Mecklenburg County. What if only a portion of those jobs are actually taken by Mecklenburg county residents? And because the One NC Fund requires matching funds from participating county governments, the question then becomes whether the net benefits to the counties justify those expenditures, particularly if the counties see less residential property tax revenue and fewer consumption dollars in the final goods market than were anticipated.

This question of job allocation has important implications for the return on local economic development investments. For example, in his study of labor market adjustments in North Carolina over the period 1980 to 1990, Renkow (2003) found that roughly one-half of new jobs in metro counties were filled by in-commuters, i.e., non-residents commuting into that county, and that for non-metro counties, one-third of new jobs went to in-commuters.

That means that in the MetLife example, 1,300 of the 2,600 new jobs would potentially be taken by in-commuters to Mecklenburg county. If a hypothetical MetLife hub were placed in a nearby non-metro county, e.g., Anson county, 858 of those 2,600 new jobs would be taken by in-commuters. If these "leakages" are not accounted for, county governments will substantially overestimate the effectiveness of a local economic development program, residential demand for

[5] Ibid.

public services, and projected revenue from taxes (both residential property taxes and taxes associated with consumption spending in the final goods market), all of which make county fiscal management difficult.

2.2: Labor Supply Responses to a Positive Labor Demand Shock

When labor markets experience employment shocks, individuals adjust their supply responses accordingly. This paper studies a positive employment shock and decomposes subsequent county-level adjustments into three areas: labor force increases, unemployment decreases, and changes to commuting. Labor force increases are seen when new workers enter the workforce via in-migration and/or when discouraged and retired workers re-enter the workforce. Unemployment decreases are seen when unemployed individuals obtain employment. Commuting changes are seen when county residents obtain work closer to home and choose to not out-commute and when non-resident workers obtain work in a given area and in-commute. In the following sections, I briefly review the literature related to these components of overall labor supply response. [6]

2.2.1: Labor Force Increases

One possible supply response to a positive employment shock is an increase in the size of the labor force. When a county experiences job growth, the size of the county's labor force can change by either new residents migrating to that county or current residents re-entering the workforce. The size of the labor force response, therefore, depends on both the scale of migration and level of labor force participation.

[6] Notably absent is "teleworking." Remote workers and tele-commuters make up a larger percentage of the workforce as high-speed internet access and innovations like driver-less cars become more commonplace. Despite the growing trend to "work remotely," the model and data used in this paper neither address nor measure this form of employment.

The classical concept of migration is that workers move due to spatial differences in wage and/or employment (Sjaastad, 1962). Early studies on migration assumed workers were perfectly mobile (Henderson, 1974; Alonso, 1964) or had homogenous preferences (Roback, 1982). The conceptual story in these studies is that a positive local demand shock initially drives up both real wages and the employment rate; over time however, new workers (in-migrants) enter the local labor market, thereby pushing real wages down again.

The seminal work on regional migration as an adjustment to labor market shocks is Blanchard and Katz (1992). These authors study U.S. state labor markets from 1948 to 1990. Their primary findings are that migration is the primary adjustment mechanism to employment shocks, and that changes to employment are negligible in the long-run. In fact, they find that unemployment and participation rates return to previous levels after five to seven years largely because workers leave the state. Yeo and Holland (2004), looking at Washington State in the 1990s, also find that most new jobs go to in-migrants in the long-run, as opposed to county residents, but disagree with Blanchard and Katz on the five to seven year adjustment period finding the adjustment period is longer.

However, later studies suggest that migration plays a smaller role as an adjustment mechanism than was found by Blanchard and Katz. In re-estimating the Blanchard and Katz data with a different model which allows for longer lag lengths, Bartik (1993) finds migration plays a smaller role in labor market equilibration. Rowthorn and Glyn (2006) also extend the Blanchard and Katz analysis over a longer period of time (1948 to 2000) and over several different datasets (BEA, BLS, and Census). They conclude that the negligible long-run employment effects cited by Blanchard and Katz are due to measurement error and bias in their dataset; instead, they find employment rates permanently change in response to demand shocks and ultimately conclude migration plays a smaller role as an adjustment mechanism. Partridge et al. (2015) update Bartik (1993)'s survey with more recent studies and note the general consensus in the literature is that estimates are more similar to those reported by Bartik (1991, 1993) than by Blanchard and Katz (1992). [7] The literature suggests that this study will find a small migration response as part of the labor force increase. [8]

In addition to the migration response, the labor force participation might increase in response to employment shocks. Individuals who had previously left the workforce (retired or discouraged workers) might choose to re-enter alongside new workers. The literature suggests that short-run participation responses can be substantial. In studying 89 Metropolitan Statistical Areas (MSAs) from 1972 to 1986, Bartik (1991) finds that 16 out of 100 hypothetical new jobs would, in the long-run, go to local residents who otherwise would be out of the labor force. Furthermore, he finds local growth effects on labor force participation are extremely persistent. In studying 305 MSAs over the years 1975-1986, Eberts and Stone (1992) also find large responses to increased labor demand from labor force participation—larger than unemployment and migration. They estimate that 59-75% of an adjustment is explained by new labor force entrants.

The important role that labor force participation plays in the adjustment process is evident across various places and times. Decressin and Fatás (1995) look at 51 regions scattered across Europe and covering the years 1975 to 1987 and find that the primary supply adjustment to labor demand shocks is from labor force participation, yet it is overtaken by a migration

[7] It should also be noted that U.S. migration rates have been decreasing since the 1990s (Dao, Furceri, and Loungani, 2017; Beyer and Smets, 2015; Molloy, Smith, and Wozniak, 2011). Knowing this supports the hypothesis that a smaller portion of an employment increase would be captured by labor force size via the migration channel.

[8] This paper does not measure migration explicitly, and therefore, has no way of knowing if this is really the case; however, as part of both the labor force response and the literature on regional adjustments, the subject is included here briefly.

response five years after the shock. Yeo et al. (2005) also find long-run effects of employment on participation rates using impulse response analysis. [9] In studying Washington State over a 25-year period (1969-1993), these authors find almost 30% of the initial shock effect on labor force participation remains in the long-run. Dao, Furceri, and Loungani (2014) examine and compare regional adjustments in the United States (U.S.) and the European Union (E.U.). These authors study U.S. states over two 18-year subsamples (1976-1993 and 1994-2011) and 21 countries in the E.U. over a decade (1999 to 2009) to find that, over time in the U.S., the role of participation as an adjustment mechanism to regional shocks has increased whereas the role of migration has decreased. The opposite seems to be the case for the European countries in their study.

The vast literature studying local employment shocks specifically tries to measure increased labor force participation and unemployment. Bartik (1993) provides a survey and notes the majority view that, in the short term, 50-70% of adjustment to a local labor shock are reflected in either participation or unemployment. He then re-estimates data used by Blanchard and Katz (1992) to validate this finding. He finds that even seventeen years after an employment shock, 23% of the adjustment is reflected in increased participation rates.

2.2.2: Unemployment Decreases

A second possible labor supply response to a positive employment shock is decreased unemployment. With more jobs available, individuals who were previously unemployed are more likely to find employment. The literature suggests that positive employment shocks can produce significant decreases in local unemployment; however, it also suggests the size of the response will be heavily dependent on variable local market conditions—mitigated by the local speed of the adjustment process and augmented by local commuting patterns.

[9] Impulse response analysis of vector autoregressive systems is used to examine relationships of variables in dynamic models (Lütkepohl and Reimers 1992).

Looking at state-level data, Houseman and Abraham (1990) find a 1% increase in jobs decreases the unemployment rate by approximately 0.10 to 0.43 percent (e.g., from 5.0 percent to 4.9 percent or 4.57 percent). Gordon (1988) studies London and other areas of the United Kingdom from 1956 to 1986. He finds that the unemployment response to employment growth greatly depends on the size and type of area. Over 40% of Scotland's unemployment response to a demand shock remained after a year while London's unemployment response dissipated within a year. Bartik (1991) finds that for an increase of 100 jobs to a given area, 6 or 7 previously unemployed individuals residents would take those jobs. When studying the continental U.S. from 1970 to 1998, Partridge and Rickman (2006) estimate 20% of an adjustment is accounted for by decreased unemployment. Looking at Canadian provinces from 1976 to 2003, Partridge, Ali, and Olfert (2010) estimate 33% of an adjustment goes to decreased unemployment. Jimeno and Bentolila (1998) look at regions in Spain over the years 1976 to 1994 and find that changes to unemployment account for approximately one third of the adjustment to a labor demand shock. Dao, Furceri, and Loungani (2014) find regional labor shocks have, over time, triggered larger unemployment effects than migration effects.

Local growth effects on unemployment are also persistent (Bartik, 1991). Autor, Dorn, and Hanson (2013, 2015) find that local labor markets exposed to decreased labor demand experience increased unemployment. Over the past several decades, the United States has witnessed a regional divergence in long-term unemployment (Austin et al., 2018) and one source is the persistence of local labor demand shocks. Amior and Manning (2018) look at 722 commuting zones (CZs) across the continental U.S. over the period 1950 to 2010 and find that the speed of adjustment is slow: over a decade, local employment rates correct for only 40% of an initial shock. Yagan (2017, 2019) uses a cross-area research design and leverages spatial variation in Great Recession severity across states to find that "2015 employment rates remained low in the U.S. states that experienced relatively severe Great Recession shocks [of which North Carolina was one]—even though between-state differences in unemployment rates had returned to normal." [10] Yagan also looks at 722 CZs from 1999 to 2015 and finds large and significant effects of the severity of a shock on the likelihood of employment in 2015.

Employment effects of local demand shocks will be affected by job accessibility via commuting. Monte, Redding, & Rossi-Hansberg (2018) develop a quantitative general equilibrium model incorporating spatial linkages in goods and factor markets. They exploit quasi-experimental variation from a competition for million-dollar plants with data spanning 39 states and covering the period 1972-2003. They find that counties with more open commuting markets—i.e., counties with a lower ratio of home workers to residents—experience larger increases in employment in response to labor demand shocks. This suggests that non-metro counties would see larger employment increases as compared to metro counties since a larger number of non-metro county residents cross county lines for work.

2.2.3: Changes to Commuting

Commuting decisions are affected by obvious variables, commuting costs (Koslowsky, Kluger, and Reich, 1995; van Ommeren, Gutierrez-i-Puigarnau, 2011; Hartog and van Ophem, 1994) and commuting time (Clark, Huang, Withers, 2003); but they are also influenced by less obvious variables like life cycle stages (Graves and Linneman, 1979) and local housing markets (Greenlee and Wilson, 2016; van der Vlist, Gorter, Nijkamp, and Rietveld, 2002). Commuting links the workplace and residence locations, so much so that commuting accessibility is typically considered part of the housing bundle in many locations (Weinberg, 1979).

[10] Yagan, Danny. "Employment Hysteresis from the Great Recession," 2.

Commuting decisions may be interdependent with migration decisions, and these relationships can be substitutionary or complementary (Evers, 1989). A substitutionary relationship exists when out-commuting and in-migration are negatively related. An example is where an individual lives in one area, works in another, and then decides to move to be closer to her job. A complementary relationship exists when out-commuting and in-migration are positively related. Examples include: (1) where an individual lives and works in one area, migrates to a new area, and commutes back to her former residence area or (2) where an individual has different work and residence locations, gets a new job in a third location and decides to move not near her workplace but in a nearby area. If commuting and migration have more of a complementary relationship, commuting can decouple a county's population growth from employment growth. Complementarity of commuting and migration—whereby substantial population growth in non-metro counties coexisted with large increases in out-commuting—was seen in the 1980s in North Carolina (Renkow and Hoover, 2000) and 1990s in Canada (Partridge, Ali, and Olfert, 2010). Evidence of this complementarity suggests regional job growth might be more important than individual county job growth.

In studying commuting habits of North Carolina workers in the 1980s, Renkow (2003) finds that commuting is the largest labor supply response to employment growth. [11] Partridge, Rickman, and Li (2009) use a similar model framework to study all U.S. counties over a 15-year period from 1990-2005. They reach a similar conclusion to Renkow (2003)—that commuting is the largest labor supply response to employment shocks. Partridge, Rickman and Li also find that the commuting response is twice as large in metro counties than it is in non-metro counties.

[11] Specifically, he finds that 32.4% (51.5%) of labor supply adjustments to changes in employment growth were accounted for by increased in-commuting into non-metro (metro) counties; and 28.4% (37.3%) of adjustments in non-metro (metro) counties were attributable to decreased out-commuting.

[12] Détang-Dessendre et al. (2016) study "commune" level data for France over four 5- to 8-year subsets spanning 1982 to 2011 to look at the net commuting response to increases in employment. These authors define net-commuting as the employment in commune i divided by number of employed residents (i.e., the working population) in commune i, which produces a measure of how much of the workforce on net in-commutes into the local labor market. They estimate that in urban areas, the approximate share of labor market adjustments accounted for by net-commuting is between 12.7% and 15.2%; in rural areas, the adjustment share accounted for by net-commuting ranges from 23.9% to 36.6%.

2.3: Regional Considerations: Labor Supply Response in Metro and Non-metro Regions

A large body of evidence suggests that substantial metro and non-metro differences exist in how labor markets adjust to shocks. A common conception among regional economists is that agglomeration forces help explain these different adjustment responses across regions. Agglomeration forces are built on two market effects: (1) a home market effect and (2) a cost-of-living effect. The home market effect implies bigger regions host a disproportionate share of firms, thus pushing up nominal wages. More firms in that region imply greater local supply and hence lower prices, i.e., the cost-of-living effect. This pushes up real wages which, in turn, attracts more workers. This process continues giving rise to what Proost and Thisse (2019) call "cumulative causality," [13] where these effects snowball and create "core" metro regions and non-metro regions at the "periphery" (Krugman, 1991). These agglomeration economies explain the growth of cities and metro regions (Duranton and Puga, 2014; Glaeser and Gottlieb, 2009; Rosenthal and Strange, 2004) and, some believe, the growth of non-metro development (Hansen,

[12] They also find that labor force participation plays an increasingly larger role in the adjustment process the further one travels from metro areas.
[13] Proost, Stef and Jacques-François Thisse. "What Can Be Learned from Spatial Economics?" 590.

2016; Castle, Wu, and Weber, 2011; Olfert and Partridge, 2010; Irwin et al., 2010; Partridge et al., 2008). To control for any potential agglomeration effects, the model in this study includes regional employment and labor force variables.

The integration of labor markets across county lines, and of metro and non-metro regions, contributes to the speed and efficiency with which individuals respond to labor market shocks (Portnov and Wellar, 2004). Smaller communities might function as residence locations for workers traveling to larger communities within the commuting region (Fuguitt, 1991); in this sense, commuting operates as a substitute for migration. For example, Eliasson, Lindgren, and Westerlund (2003) study 290,000 individuals in Sweden from 1994 to 1995 and find that increased employment in areas neighboring one's residence decreases interregional migration and increases commuting. For this reason, non-metro counties often have larger ratio of out-commuters to home-workers, [14] than metro regions.

Clusters of counties with strong commuting ties are grouped into what the U.S. Department of Agriculture (USDA) calls commuting zones (CZs). CZs were first developed in 1980 by the USDA as a better way to delineate local economies and labor markets (Tolbert and Sizer, 1996). Until then, geographic specification was limited to states, counties, MSAs or Standard Metropolitan Statistical Areas (SMSAs) all of which produced distortionary measurements for labor studies—by restricting labor markets to state lines, using arbitrarily defined geographic areas, or relying on metro areas for measurement. The USDA chose to use a smaller unit of analysis (county and county equivalents) to create CZs. [15] These groups of counties, i.e., CZs, were specifically designed to promote analysis of non-metro labor market

[14] Throughout this paper, I use the term "home-worker" to denote those individuals who live and work within the same county.
[15] They did this by clustering counties into groups based on an algorithm created to minimize commuting flows between places.

performance and employment issues. The initial number of CZs began at 768 in 1980 and has been decreasing with time with (741 CZs in 1990 to 709 CZs in 2000) [16] as commuting has increased and labor markets have expanded. [17]

2.4: Temporal Considerations: Labor Supply Response after the Great Recession

The Great Recession of 2008 and the ensuing recovery overshadowed the labor and housing markets in unique ways. Thus, recognizing the time period of this study is important for identifying labor market adjustments that are potentially off trend to the literature.

The search literature helps inform our understanding of labor supply responses in times of recession when there is generally more uncertainty in market performance. Stigler (1961, 1962) first introduced the concept of "search" into labor economic models and most early search models were developed to explain the "unemployment search." The conceptual essence of search theory is that individuals search for goods on the basis of limited information. Thus, search theory helps us understand the dynamics of unemployment—searching for a job without full information of firms, their offers, etc. Additionally, it has implications for labor force attachment and participation in that a prolonged search might discourage workers enough to prompt them to leave the work force. Job searches (and any subsequent job changes) can be an important trigger in residential location choices, both for in-migrants and current area residents (Clark and Withers, 1999). This carries distinct implications for commuting behavior.

Most of the search theory related to labor force participation rates are focused on wages. In the neoclassical framework, labor supply will reach an equilibrium when relative wages across

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[16] This data product has been discontinued by the USDA, and although 2010 estimates are available at the Penn State website (https://sites.psu.edu/psucz/data/), they have not been officially adopted by the USDA. For this reason, I use the most recent official update available (2000).

[17] See the USDA Economic Research Service site on Commuting Zones and Labor Market Areas. Accessed March 25, 2020. https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/.

places equalize, net of the cost of mobility. If real wages fall below one's reservation wage—i.e., the wage equating marginal costs and expected marginal benefits of continued searching—workers might leave the labor force. Because this study looks at a time period during and immediately following the Great Recession, one might intuit that a larger portion of an employment increase would be captured by labor force participation seen by discouraged workers leaving and subsequently returning to the labor force.

Search theory also helps elucidate movement in to and out of unemployment. Devine and Kiefer (1993) provide a summary of empirical studies which use the search framework. In addition to identifying the various factors affecting a worker's search, the authors note that the variation in job offer arrivals is more important in explaining variation in unemployment duration than variation in reservation wage. The duration of unemployment might be longer for workers during a recession because of the infrequency of job offer arrivals. If this is the case, in the wake of a recession when job offer arrivals increase, a large response would come from those individuals finding work again, i.e., a large adjustment of decreased unemployment.

Search theory could have implications for commuting as well. A household might be at an equilibrium with regards to its consumption of housing, commuting, and job choice; alternatively, a commuter might not be considered at an equilibrium because of search costs in finding a more amenable location. Van Ommerman (2000) uses a search model to look at job and residential mobility as it relates to commuting and suggests that "expectations of costly future job or residential moves prevents workers from reducing current commuting distance." [18] During the Great Recession and the slow recovery that followed it, when consumption spending was more limited, one might imagine that workers were more cognizant of the costs of job and

[18] van Ommeren, Jos. *Commuting and Relocation of Jobs and Residences,* 9.

residential moves and thus more willing to commute farther distances; alternatively, overall conditions might have improved enough over the 2010 to 2015 time period to encourage workers to make residential moves and decrease their commuting.

The Great Recession was intimately tied to the housing market—affecting and being affected by home values around the country. Many have wondered if the persistently high unemployment rate was caused by frictions in the housing market, i.e., the housing bust prevented geographic mobility by keeping workers "locked-in" to low-productivity regions (Karahan and Rhee, 2019). Some believe low and negative housing equity substantially reduces mobility (Karahan and Rhee, 2019; van Veldhuizen, Vogt, and Voogt, 2018; Bloze and Skak, 2016; Riley, Ngyuen, and Manturuk, 2015; Andersson and Mayock, 2014; Donovan and Schnure, 2011). On the other hand, there is limited evidence of low or negative equity effects on mobility (Steegmans and Hassink, 2018; Demyanyk et al., 2017; Valletta, 2013).

These latter studies note that the housing bust caused large percentage drops in mobility rates, but the levels of these declines were small (Modestino and Dennet, 2013) and the effects on unemployment negligible (Kothari, Saporta-Eksten, and Yu, 2013). Regardless of the direct effects of housing equity, it seems evident there is a relationship between housing and mobility because housing is arguably the largest investment a household makes and it is a durable good (Glaeser and Gyourko, 2005). The model in this paper includes housing costs, under the assumption it is an influential variable in making labor supply decisions.

CHAPTER 3: ANALYTICAL FRAMEWORK

In order to gauge the relative importance of different labor supply responses to employment growth, I use an analytical framework developed by Renkow (2003) with foundations in the fiscal and economic impact models of Swenson and Otto (1998) and Johnson and Scott (1997). Total employment in a given county i at time t (Emp_{it}) is comprised of "home-workers," i.e., those who live and work within the county (L_{it}) and "in-commuters," i.e., those who live in a different county but commute into the county for work ($Incom_{it}$):

$$Emp_{it} = L_{it} + Incom_{it} \tag{1}$$

The labor force of a given county i at time t (LF_{it}) is comprised of "home-workers," "out-commuters," i.e., those who live in the county and work in a different county ($Outcom_{it}$), and unemployed individuals ($Unemp_{it}$):

$$LF_{it} = L_{it} + Outcom_{it} + Unemp_{it} \tag{2}$$

Taken together, equations (1) and (2) reveal an identity partitioning of county i's labor force:

$$LF_{it} = Emp_{it} - Incom_{it} + Outcom_{it} + Unemp_{it} \tag{3}$$

Rearranging the equation, one can decompose an employment shock into its labor supply components:

$$Emp_{it} = Incom_{it} - Outcom_{it} - Unemp_{it} + LF_{it} \tag{4}$$

Taking first differences of equation (4) yields a decomposition of how employment changes in a county are accommodated:

$$\Delta Emp = \Delta Incom - \Delta Outcom - \Delta Unemp + \Delta LF \tag{5}$$

Commuters may change their behavior: non-resident workers may choose to commute into that county because there are now jobs they can access there; resident workers may choose not to out-commute to another county because there are now jobs they can obtain closer to home.

Unemployed individuals may take new jobs. And finally, county residents may join the labor force, non-resident workers may migrate to the county, or both—increasing the size of the labor force. Equation (5) represents a decomposition relationship. It is not causal; however, it shows the fraction of different types of workers responding to an employment shock, allowing us to answer the question of "who gets those new jobs?" Using equation (5) to estimate response shares of shocks requires one assumption: that short-run fluctuations in employment are demand-driven, not supply-driven. This seems reasonable for the particular time period under consideration, given it spans a time of economic recession and recovery.

CHAPTER 4: EMPIRICAL WORK

4.1: Empirical Model

I employ an empirical model put forward by Renkow (2003) to describe the changes to in-commuting, out-commuting, unemployment, and labor force:

$$\Delta Incom_i = f(\Delta Emp_i, \Delta LF_i, \Delta CZLF_i, \Delta RWage_i, \Delta RHouse_i,\ Metro_i) \tag{6}$$

$$\Delta Outcom_i = f(\Delta Emp_i,\ \Delta LF_i, \Delta CZEmp_i, \Delta RWage_i, \Delta RHouse_i, Metro_i) \tag{7}$$

$$\Delta Unemp_i = f(\Delta Emp_i, \Delta CZEmp_i, \Delta RWage_i,\ Metro_i) \tag{8}$$

$$\Delta LF_i = f(\Delta Emp_i, \Delta CZEmp_i, \Delta RWage_i, \Delta RHouse_i, Metro_i) \tag{9}$$

Where:

$CZLF_i$ $= labor\ force\ in\ other\ counties\ within\ county\ i\text{'s}\ commuting\ zone\ (CZ)$

$CZEmp_i$ $= total\ employment\ in\ other\ counties\ within\ county\ i\text{'s}\ CZ$

$RWage_i$ $= county\ i\ wage\ relative\ to\ other\ counties\ within\ county\ i's\ CZ$

$RHouse_i$ $= county\ i\ house\ prices\ relative\ to\ other\ counties\ within\ county\ i's\ CZ$

$Metro_i$ $= metro\ classification\ of\ county\ i$

The variables Emp_i and $CZEmp_i$ act as proxies for labor demand. In looking at equation (6), one can expect that a positive shock to employment in county i (ΔEmp_i) will have a positive effect on in-commuting to county *i*; an increase in the relative wage of county *i* will also be expected to positively affect in-commuting to county *i*; and, an increase in the relative price of housing in county i will positively affect in-commuting since greater housing costs would increase the likelihood that workers would choose to live elsewhere. The change in county i labor force includes changes to participation rates and migration. Because the two supply responses of migration and commuting can act as both substitutes and complements in different situations (within or between labor market areas), one cannot determine a priori the sign of an increase in labor force on in-commuting; however, one can assume that CZ labor force will positively affect in-commuting to county *i* as more individuals from other counties will be looking for jobs within their CZ.

In reviewing equation (7), a positive shock to employment in county *i* would be expected to lessen out-commuting *ceteris paribus*, since more jobs available in county *i* would enable current out-commuters to find jobs closer to their home. An increase in the relative wage and housing price should also have a negative effect on out-commuting for similar reasons—county *i* residents decrease their out-commuting because they are enticed to find jobs in their county of residence. A positive increase in CZ employment suggests a positive effect on out-commuting, i.e., more jobs are available to county *i* residents in other nearby counties. Just like with in-commuting, one cannot determine a priori the sign of an increase in labor force on out-commuting.

In looking at equation (8), we anticipate that an increase in both employment and CZ employment will decrease the number of those unemployed. The sign of the unemployment response of an increase in county *i*'s relative wage depends on the size of the labor force response. If the positive increase to the labor force entices more workers than available new jobs, unemployment might increase; if the positive increase to the labor force is less than the increase to the number of new jobs, unemployment might decrease.

Looking at equation (9), we anticipate an increase in employment to increase the labor force—either by enticing county *i* residents into the labor force or by attracting new residents to county *i* via migration. The same positive effect would be expected with an increase to CZ employment. An increase in the relative wage is expected to positively affect the labor force via the same channels. An increase in the relative housing price would negatively affect the labor force response increasing the likelihood county i residents would relocate.

Lastly, being a metro county is expected to positively affect all labor supply responses via agglomeration and/or scale effects. [19]

4.2: Estimation

Equations (6) through (9) are estimated with three-stage least squares (3SLS). The four dependent variables in the system ($\Delta Incom$, $\Delta Outcom$, $\Delta Unemp$, ΔLF) are regressed on employment growth (ΔEmp) and the other identified factors affecting adjustment responses. Vital to the analysis, the system is constrained to satisfy the identity partitioning in equation (5). Totally differentiating equation (4) with respect to Emp yields:

$$\frac{dIncom}{dEmp} - \frac{dOutcom}{dEmp} - \frac{dUnemp}{dEmp} + \frac{dLF}{dEmp} = 1 \tag{10}$$

This suggests a cross-equation restriction on the employment growth coefficients to be estimated in the in-commuting, out-commuting, unemployment, and labor force equations:

$$\beta_{InCom} - \beta_{OutCom} - \beta_{Unemp} + \beta_{LF} = 1 \tag{11}$$

Using first differences eliminates time-invariant characteristics (county-specific unobservable impacts) and thus the need to include county fixed-effects. Endogenous variables in the system include the first differences of the four dependent variables and the employment growth variable. The endogeneity of ΔEmp violates the non-randomness assumption in the multiple linear regression model. In this case, OLS for each equation may be inconsistent and biased. I use instrumental variable (IV) techniques to account for endogeneity and apply it to the system of equations. Estimators from a system using IVs and two-stage least squares (2SLS) is

[19] It should also be noted that there is an assumption underlying the model that the economy moves from one equilibrium to another.

consistent but inefficient because 2SLS does not make use of cross-sectional correlations of disturbances. Using three-stage least squares (3SLS) makes use of the correlations; and more importantly, it allows me to impose the cross-equation coefficient restriction (equation 11).

I first run the model as a seemingly unrelated regression (SUR) to obtain results as if there was no endogeneity, and then I run the system using 3SLS estimation.

4.3: Data and Variable Construction

I use a two-period panel covering 2010 and 2015 data for North Carolina's 100 counties, as well as 32 non-North Carolina counties within the same CZ as a North Carolina county—counties located in Georgia (3), South Carolina (3), Tennessee (1), and Virginia (25). See Appendix A for detailed information on variable construction and Appendix B for a list of North Carolina counties grouped by CZ.

The key data come from two data sources: the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program and the Bureau of Labor Statistic's Local Area Unemployment Statistics (LAUS). LEHD collects Origin-Destination Employment Statistics (LODES) data indicating the county of residence and county of work for all labor force participants. From these data, I establish the number of in-commuters and out-commuters for a given county. I use Local Area Unemployment Statistics (LAUS) county tables to obtain the annual average employment number and unemployment rate which are used in conjunction with the commuting estimates to calculate the number of home workers, the number of workers in the labor force, and the number of unemployed individuals (see Appendix A for details).

From the U.S. Department of Agriculture (USDA), I obtain CZ groupings for each county. CZ employment numbers for each county were calculated as the sum of total employment within the county's CZ less that particular county's employment. CZ labor force was constructed in a similar fashion. The USDA also provides Rural Urban Continuum Codes (RUCCs). RUCCs are ordered one through nine where codes 1-3 are metro counties classified by size and codes 4-9 are non-metro counties classified by degree of urbanization and adjacency to metro areas. I use the RUCCs to distinguish between metro and non-metro counties and create a metro dummy variable to account for potential scale effects. See Figure 4.1 for a map of North Carolina counties identified by metro designation and Figure 4.2 for a map of North Carolina counties grouped into commuting zones.

The Bureau of Labor Statistics (BLS) publishes quarterly data on employment and wage (QCEW). From this data, I obtain the total industry annual average pay in each county for the years 2010 and 2015. I also obtain median house values (in USD) from the 1-year American Community Survey (ACS). All prices were deflated using a GNP deflator of (218.1/237) to obtain the real, in 2010 dollars, prices in 2015.

My instrument set includes the change in employment, in-commuting, and out-commuting as calculated with the 5-year ACS. [20] It also includes other right-hand side variables in the system: the change to CZ labor force, CZ employment, relative house prices, and relative wages. Lagged measures of county area, population, and density, as in Renkow (2003), are obtained via the 2010 Decennial Census and included. Lastly, I include a metro dummy variable. As noted previously, please find more detail on data construction in Appendix A.

[20] The 5-year ACS provides worker origin-destination data similar to LODES. Graham, Kutzbach, and McKenzie provide a thorough design comparison of the two products. From these data, I calculate home workers, in-commuters, and out-commuters, and employment (using the unemployment rate). Because the 5-year ACS produces "period estimates"—2010 estimates represent commuting characteristics of the population from January 1, 2006 through December 31, 2010—they cannot be used to identify what is going on in any particular year in the period. I use these data as part of my instrument set, however, as they provide an alternative measure of labor supply adjustments occurring in the period prior to the years covered in my analysis.

4.4: Descriptive Statistics

Descriptive statistics for both metro and non-metro counties are provided in Table 4.1. Not surprisingly, metro counties have larger values for all variables. As indicated by Figure 4.3, the number of home-workers in metro counties grew by 16.1% and the number of home-workers in non-metro counties fell by 1.3%. Because home-workers represent the largest labor force component, it is no surprise that the same trends are reflected in the labor force numbers over the 2010-2015 period: growth in metro counties of 5.1% and a loss in non-metro counties of 1.5% (see Figure 4.4).

Employment increased in both metro and non-metro counties over the time period, and it grew more in metro counties (10.9%) than in non-metro counties (4.8%). In both metro and non-metro counties, 2015 unemployment rates dropped by nearly 50% from 12.0% to 6.5% in on-metro areas and from 10.3% to 5.4% in metro counties. This decrease in unemployment over time is noticeable for both areas (see Figure 4.5).

Now we look at commuting patterns. On average, more jobs in metro counties (approximately 3-5% more) are filled by in-commuters as compared to non-metro counties (see Figure 4.6). Out-commuters make up approximately 5% more of the resident population in non-metro counties than in metro counties (see Figure 4.7). Non-metro counties experience net out-commuting as opposed to metro counties (see Figure 4.8). Out-commuting increased in both types of counties with less of an increase in non-metro areas: by 19.5% in metro and by 10.3% in non-metro. In-commuting also increased in both types of counties with a smaller increase in non-metro areas: 18.6% in metro and 10.2% in non-metro.

Metro-to-metro commuting accounts for roughly one-half of all commutes: 52.4% in 2010 and 53.3% in 2015. The number of metro-to-metro commuters was at least twice as large as the next largest group of commuters, those originating in non-metro counties and traveling to metro counties (see Figure 4.9). The number of metro-to-metro commuters noticeably increased between the two periods (about 11.6%) whereas metro-to-non-metro, non-metro-to-metro, and non-metro-to-non-metro commuting numbers were relatively stable across the time periods.

In disaggregating the commuting patterns further by RUCCs, one can see that the bulk of the remaining commuting flows (approximately 80%) involves commuting either to or from non-metro counties adjacent to metro counties (see Figure 4.10). In both years, approximately 17% of metro commuters traveled to non-metro adjacent areas for work; approximately 72% of non-metro adjacent commuters traveled into a metro area for work; and approximately 21% of non-metro adjacent commuters traveled to other non-metro adjacent counties for work. There also seems to be high rates of commuting from non-metro non-adjacent areas to metro areas (approximately 50%).

In both years, approximately 40% of commutes were made within the residence CZ and approximately 60% of commutes were made outside the residence CZ (see Figures 4.11-4.13). Both kinds of commuting increased over time, with more of an increase in within-CZ commuting: by 16% for within-CZ commuting and 6% for between-CZ commuting.

Real wage was higher in metro counties (see Figure 4.14). Real wage increased for both metro and non-metro counties, but metro areas experienced a larger increase (1.7%) compared to non-metro counties (0.4%). Real house prices were larger in metro counties (see Figure 4.15). Both metro and non-metro counties experienced decreases in real house prices over the period considered, with the decrease in metro counties (5%) being slightly less in metro counties than in non-metro counties (5.5%).

CHAPTER 5: RESULTS

In this section, I report the econometric estimates for the empirical model presented in Section 4.1 (equations (6)-(9)). I estimated the model both as a system of seemingly unrelated regressions (SUR) as well as via three stage least squares (3SLS). I present the results in that order. Also note that for the preferred (3SLS) model, I estimated a "pooled" model for all counties and separate models for metro and non-metro counties. This was done to see if there were significant empirical differences in how labor market adjustments manifest themselves across the rural-urban continuum.

The right-hand side variable of interest in each estimation is county employment growth. Each of the four employment growth coefficients is the share of the labor market adjustment due to the corresponding dependent variable; therefore, they are constrained to sum to one (as described in equation (11)).

5.1: SUR Estimates for All Counties

To begin, I look at the SUR regressions for all NC counties (please refer to Appendix C for OLS results). These results are the estimates as if the disturbances and regressors are uncorrelated; in other words, assuming no endogeneity. Table 5.1 presents the SUR results for all counties. Signs are as expected for the employment growth coefficients: negative in the out-commuting and unemployment equations and positive in the in-commuting and labor force equations. These results suggest approximately one-half of a labor force adjustment (55%) is accounted for by changes to commuting: 44% by increased in-commuting and 12% by decreased out-commuting. They also suggest decreased unemployment accounts for the bulk (37%) of the remaining adjustments and labor force increases account for a relatively small percentage (7%).

The large footprint of reduced unemployment in overall adjustment seems reasonable given the more recent data are in the wake of the recession.

Changes in county labor force are highly significant determinants for in-commuting and out-commuting. Changes in real wages are a significant determinant of being in the labor force. In terms of regional variables, both being a metro county and changes to the CZ employment, are highly significant for out-commuting and labor force changes. This seems to make sense—as labor markets expand, county out-commuting and labor force growth become more dependent on nearby counties and their employment growth.

5.2: 3SLS Estimates for All Counties

The SUR results provide estimates under the assumption of zero correlation between the error terms and the regressors; however, we know there is endogeneity within the system because the four dependent variables are jointly determined with employment growth. To correct for this, I use IV techniques. The eleven instruments include lagged values of the 5-year period change in county employment, in-commuting, and out-commuting; 2010 county area, 2010 county population, and 2010 county density; as well as the other plausibly exogenous right-hand side variables in the system of equations (the change in CZ labor force, CZ employment, relative house prices, relative wages, and the metro dummy).

IV estimators may be biased when instruments are "weak" and when there are many overidentifying restrictions. IV models with F-statistics of an excluded variable less than ten are generally considered to possess "weak instruments," meaning the correlation with endogenous regressors is low. The F-statistics for the first stage regressions indicate that the choice of instruments is reasonable, i.e., not "weak." Additionally, the model is overidentified, but not grossly so. This gives us reasonable confidence in the unbiasedness of the IV estimates.

Table 5.2 presents the 3SLS results (first and second stage regressions may be found in Appendix D). The overall fit of the model is strong (system weighted $R^2 = 0.929$). Again, the coefficients of interest are the four employment growth coefficients. They all have the expected signs and are all significant at the 1% level. Compared with the SUR results, the 3SLS results indicate a somewhat more modest, but still substantial, in-commuting response (30% compared to 44%), and somewhat greater out-commuting response (17% as compared to 12%). Implied decreases in unemployment are similar (33% versus 37%) across the two estimators. Interestingly, decreased unemployment is the largest single labor supply response in the preferred (3SLS) specification. Finally, the largest difference between the two estimations was found for the labor force response. The 3SLS results suggest that 19.5% of overall labor market adjustment occurred via changes in labor force size, whereas the SUR results indicated only 7% of the adjustment is accounted for with changes to labor force size.

Table 5.3 compares the labor market responses estimated here to those found by Renkow (2003) for the 1980s. In-commuting, in particular, represents leakages associated with employment shocks. The 3SLS results estimate that 30% of new jobs will go to non-residents who commute into a county experiencing an employment shock. These estimates for in-commuters are lower than what Renkow (2003) found for either metro counties (52%) or non-metro counties (32%). The 3SLS results also suggest that changes in out-commuting composed a smaller share of overall labor market response than was found in the 1980s.

The response of labor force size to an increase in employment is similar to what Renkow found in metro regions with the 1980s data; but there is reason to believe that the underlying channels for the labor force increase are different across the two sets of results. Renkow (2003) attributes the labor force increase to migration, whereas it seems probable the newer data reflect more of a participation response, i.e., discouraged workers who left the labor force and previously retired individuals who suffered large losses during the depths of the recession re-entered the labor force to increase participation rates. In addition, one might expect that migration response in the current analysis would be less important quantitatively because of the shorter period of time considered (five years, as opposed to 10 years in the earlier analysis).

The largest difference between the two studies is seen in the unemployment response. In the 1980s, decreased unemployment as a labor supply response to an employment shock was found to represent only a very small fraction of overall adjustment (1.7%). In the more recent data, the percentage of the adjustment taken by decreased unemployment is 33.4%. I surmise that this finding for 2010-2015 reflects the large number of workers without jobs during the Great Recession who found new employment by the end of 2015. It seems plausible that in times of recession and recovery, the reservation wage for an unemployed individual would be lower than it would be if that worker was out-commuting; therefore, with an employment shock, those new jobs would likely go to unemployed persons first while commuters are more willing to maintain their commute and current jobs until the market improves.

I look once more at the 3SLS results for all counties to see if any other variables are significant. Because the data used were from a time of recession which was initiated by a housing crisis, one would imagine the relative cost of housing would be a significant determinant of a labor supply response. This simply does not seem to be the case. County labor force, CZ employment, and being a metro county are significant determinants for labor force increases and out-commuting while the relative wage is only found to be a significant determinant of labor force increases.

5.3: 3SLS Estimates for Metro and Non-Metro Counties

In order to account for differences between metro and non-metro areas, I run the same set of regressions disaggregating by county metro designation. I refer to Appendix D for first- and second-stage results. All F-statistics from the first stage are greater than ten except for in-commuting and labor force in the non-metro specification—obviously reflecting “weak” instruments for non-metro data.

The 3SLS results for county employment disaggregated by metro designation are presented in Table 5.4. The results for metro counties have employment growth coefficients that are quite similar to what was found in the pooled model; however, the model for the non-metro counties did not perform well. Out-commuting, in particular, is troubling because the employment growth coefficient is large and does not have the correct sign. This may be, in part, due to having applied an outdated RUCC designation to the data. It might also be due to the fact that out-commuting is restricted to “within-CZ” commuting which accounts for 40% of overall commutes. This would be an excellent area for future research.

CHAPTER 6: CONCLUSION

In this paper, I have estimated a county-level labor market model for North Carolina that partitions labor market adjustments from employment growth into four labor supply responses: changes to in-commuting, out-commuting, unemployment, and labor force size. Results from the preferred specification suggest the largest share of employment growth from 2010 to 2015 (approximately one-third) was accommodated by decreases in unemployment. Additionally, increases to the labor force accounted for roughly 20% of new jobs over that period and reductions in out-commuting accounted for an additional 17%. From a local public finance perspective, this means that in a time of economy recovery following a recession, the largest portion of direct income-generation benefits of financial incentives for job creation strategies will go to local county residents.

In-commuting represents "leakages" of job creation investments to other counties. The current analysis indicates the magnitude of the estimated in-commuting response is large (approximately 30%), though substantially smaller than was found by Renkow (2003) in the 1980s. Given there was such a large response from in-commuting in the 1980s and that county residents benefitted the most in the early 2010s, this suggests financial incentives as a job creation strategy will be more "efficient," i.e., there will be fewer leakages, in times of economic recovery as opposed to an economic boom.

The fact that some of the benefits of job creation subsidies are likely to flow to other counties validates the potential mutual net gains from regional cooperation. The findings presented here indicate that in-commuting and out-commuting accounted for roughly one-half of overall adjustment over the period of analysis. Although smaller than earlier findings, the size of these commuting responses seem to suggest that commuting will continue to play large role as an adjustment mechanism. This has led some analysts (e.g., Goetz et al. 2010) to claim commuting is the best argument for creating new forms of municipal governance. Workers seem to have little regard for administrative boundaries like counties; therefore, it would be more efficient and potentially more effective to match jobs with workers if economic development initiatives and local governments better reflected these realities of cross-county border flows of workers and economic activity. The evidence found here suggests that counties would do well to coordinate with other counties in attempting to promote employment growth.

And certainly, some of this coordination is already being done. In 2014, North Carolina legislation enabled the creation of "Prosperity Zones." The EDPNC helped launch and support these zones to "enhance collaboration and cooperation between state agencies, local governmental agencies and other regional entities and to facilitate administrative efficiencies within State government." [21] Representatives across different levels of state government form "regional teams acting as resource matchmakers" [22] of funding, supply chain connections, trainings, and environmental services, among others. This seems to be a promising start to regional cooperation and a way to ensure benefits to localities justify job creation expenditures.

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[21] "Prosperity Zone Presentation for the Joint Legislative Economic Development and Global Engagement Oversight Committee." North Carolina Department of Commerce. January 11, 2018. Accessed March 26, 2020. https://ncleg.gov/DocumentSites/Committees/JLEDGEOC/2017-2018/Meetings/2018-01-11%20Prosp%20Zones,%20Econ%20Well-Being,%20Utility%20Acct,%20SB%20660,%20ED%20Awards/002%20Commerce_Prosperity_Zone_Presentation_2018-01-11.pdf

[22] Ibid.

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TABLES

Table 4.1: Summary Statistics of Metro and Non-Metro North Carolina Counties

Variable	Mean	CV	Min	Max
			Metro Counties	
2010 Labor Force[a]	95,118	1.17	9,389	502,428
2015 Labor Force[a]	99,985	1.25	9,470	565,288
2010 Employment[a]	85,240	1.18	8,415	448,844
2015 Employment[a]	94,531	1.25	8,930	534,989
2010 In-commuters[b]	16,726	1.59	969	116,785
2015 In-commuters[b]	19,837	1.64	1,149	151,233
2010 Out-commuters[b]	14,971	0.99	2,073	72,065
2015 Out-commuters[b]	17,896	1.03	2,184	83,547
2010 Unemployment[a]	9,878	1.09	974	53,584
2015 Unemployment[a]	5,454	1.17	540	30,299
2010 Home-workers[b]	37,438	1.48	1,833	237,118
2015 Home-workers[b]	43,464	1.66	1,618	323,010
2010 CZ employment[a]	465,391	0.75	59,449	938,634
2015 CZ employment[a]	519,713	0.79	61,446	1,086,876
2010 Real wage[c]	35,736	0.21	26,822	63,521
2015 Real wage[c]	36,361	0.21	27,574	60,775
2010 Real house price[c]	150,603	0.28	82,600	258,800
2015 Real house price[c]	143,070	0.27	75,645	250,861
			Non-Metro Counties	
2010 Labor Force[a]	19,809	0.76	1,659	78,671
2015 Labor Force[a]	19,528	0.78	1,574	82,183
2010 Employment[a]	17,419	0.76	1,414	68,532
2015 Employment[a]	18,255	0.79	1,400	77,666
2010 In-commuters[b]	2,264	0.97	94	11,706
2015 In-commuters[b]	2,496	1.08	102	16,467
2010 Out-commuters[b]	3,259	1.07	84	16,451
2015 Out-commuters[b]	3,596	1.19	102	23,100
2010 Unemployment[a]	2,390	0.80	245	10,139
2015 Unemployment[a]	1,273	0.76	147	4,517
2010 Home-workers[b]	6,409	0.87	5	26,965
2015 Home-workers[b]	6,329	0.94	5	31,675
2010 CZ employment[a]	257,101	1.20	12,848	938,634
2015 CZ employment[a]	282,204	1.25	12,857	1,086,876
2010 Real wage[c]	30,746	0.10	25,952	40,060
2015 Real wage[c]	30,871	0.10	25,794	42,387
2010 Real house price[c]	125,015	0.37	69,200	342,100
2015 Real house price[c]	118,104	0.34	64,602	260,800

[a] indicates data is from LAUS, [b] indicates data is from LODES, and [c] indicates data is from ACS

Table 5.1: SUR Results for All North Carolina Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
County Employment	0.438***	-0.115***	-0.375***	0.072***
	(0.033)	(0.033)	(0.011)	(0.007)
County Labor Force	-0.156***	0.418***		
	(0.049)	(0.048)		
CZ Employment		0.015***	-0.001	0.028***
		(0.002)	(0.003)	(0.004)
CZ Labor Force	0.005**			
	(0.002)			
Relative Wage	-2,234.23	895.19	4,085.79	20,441.88***
	(2,287.22)	(2,718.39)	(2,892.74)	(4,517.53)
Relative Housing Price	424.73	-1,096.19		-4,651.19**
	(1,334.01)	(1,411.97)		(2,240.598)
Metro	-74.886	1,190.835***	-103.737	3,457.115***
	(239.477)	(285.734)	(300.121)	(459.209)
Intercept	-243.427*	184.697	-818.181***	-841.935***
	(139.861)	(171.183)	(179.255)	(282.882)
N	100	100	100	100

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.
System weighted $R^2 = 0.995$.

Table 5.2 3: SLS Results for All North Carolina Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
County Employment	0.298***	-0.172***	-0.334***	0.195***
	(0.044)	(0.044)	(0.012)	(0.011)
County Labor Force	0.158**	0.476***		
	(0.065)	(0.064)		
CZ Employment		0.016***	-0.001	0.025***
		(0.002)	(0.003)	(0.004)
CZ Labor Force	0.000			
	(0.002)			
Relative Wage	-4,251.53*	1,725.83	2,645.96	15,982.75***
	(2,407.43)	(2,727.11)	(2,897.38)	(4,531.68)
Relative Housing Price	534.14	-1,199.19		-3,601.58
	(1,442.18)	(1,448.38)		(2,245.46)
Metro	-358.62	1,340.18***	-419.93	2,528.241***
	(253.92)	(289.086)	(301.84)	(463.663)
Intercept	-8.124	213.047	-856.633***	-912.99***
	(150.869)	(176.373)	(179.681)	(281.84)
N	100	100	100	100

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.
System weighted $R^2 = 0.930$.

Table 5.3: Response to Employment Growth, 1980-1990 vs. 2010-2015

	1980-1990		2010-2015
Activity	Metro	Non-Metro	All Counties
Increased in-commuting	51.5%	32.4%	29.8%
Decreased out-commuting	28.4%	37.3%	17.2%
Decreased unemployment	1.7%	1.7%	33.4%
Increased labor force size	18.5%	28.7%	19.5%

Table 5.4: 3SLS Results for Metro and Non-metro North Carolina Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
		Metro		
County Employment	0.321***	-0.160**	-0.290***	0.229***
	(0.063)	(0.061)	(0.019)	(0.020)
County Labor Force	0.086	0.468***		
	(0.093)	(0.090)		
CZ Employment		0.027***	0.004	0.049***
		(0.005)	(0.006)	(0.01)
CZ Labor Force	0.009*			
	(0.005)			
Relative Wage	-13,950.20*	-5,353.74	6,086.68	40,481.64***
	(7,030.37)	(7,898.056)	(8,767.51)	(13,862.42)
Relative Housing Price	8,195.27	-7,324.46		-38,092.30***
	(6,047.54)	(5,832.81)		(10,468.74)
Intercept	-403.210	1,078.615**	-1,949.010***	184.571
	(357.956)	(441.309)	(462.657)	(734.699)
N	35	35	35	35
		Non-Metro		
County Employment	0.341***	0.409***	-0.761***	0.306***
	(0.061)	(0.078)	(0.085)	(0.094)
County Labor Force	0.172**	0.239***		
	(0.081)	(0.082)		
CZ Employment		0.003*	0.001	0.005
		(0.002)	(0.003)	(0.003)
CZ Labor Force	-0.001			
	(0.001)			
Relative Wage	-5.35	1,883.26	1,426.11	3,662.99
	(1,124.66)	(1,408.35)	(2,109.70)	(2,698.68)
Relative Housing Price	-837.49	94.33		967.29
	(581.06)	(730.41)		(790.09)
Intercept	-4.662	-5.392	-552.11***	-586.097***
	(85.813)	(100.285)	(125.58)	(159.676)
N	65	65	65	65

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.
System weighted R^2 = 0.922 (0.696) for the metro (non-metro) regression.

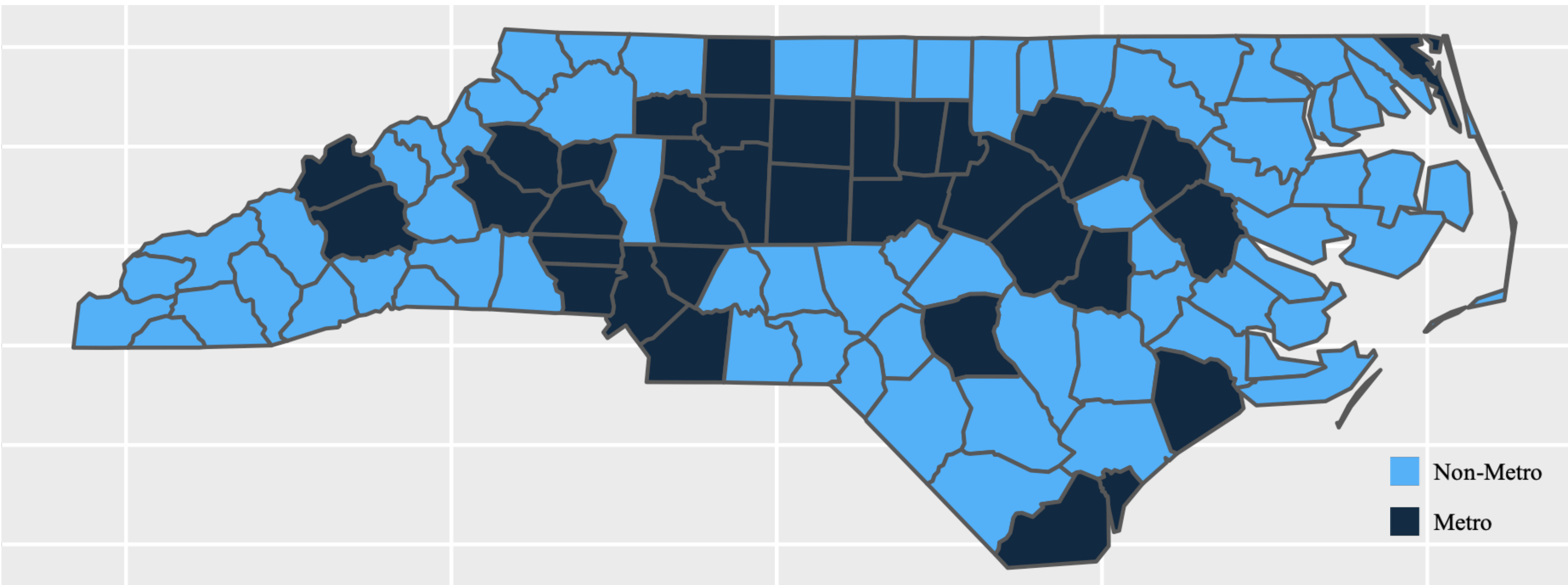

Figure 4.1: Map of North Carolina Metro and Non-Metro Counties

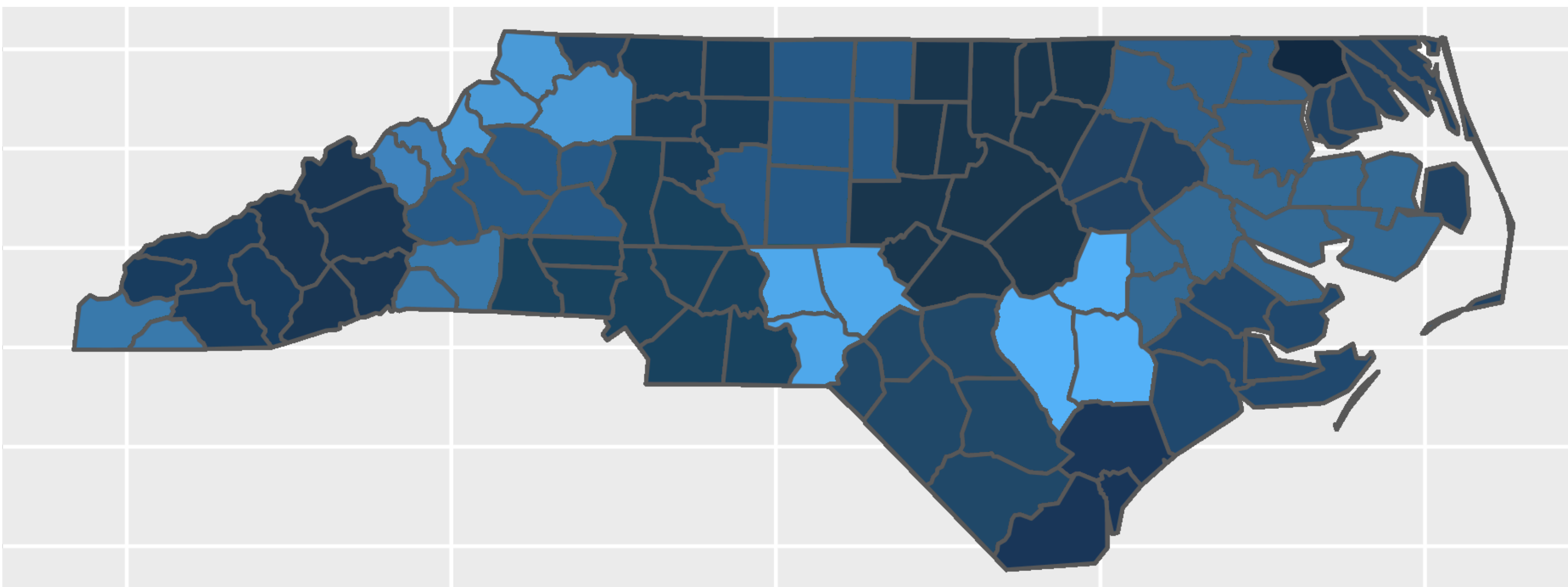

Figure 4.2: Map of North Carolina Commuting Zones

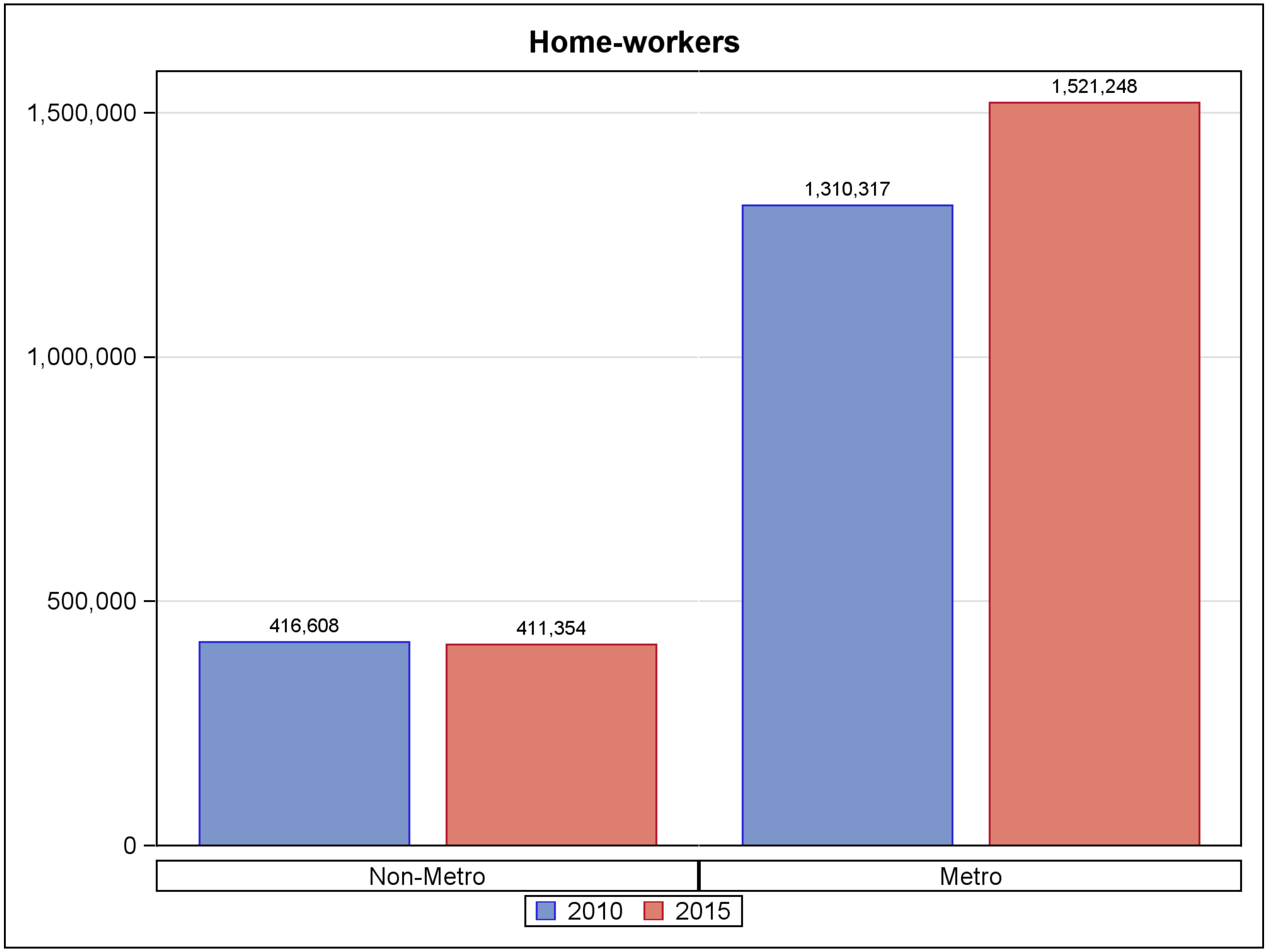

Figure 4.3: Total Home-workers by Metro Designation and Year

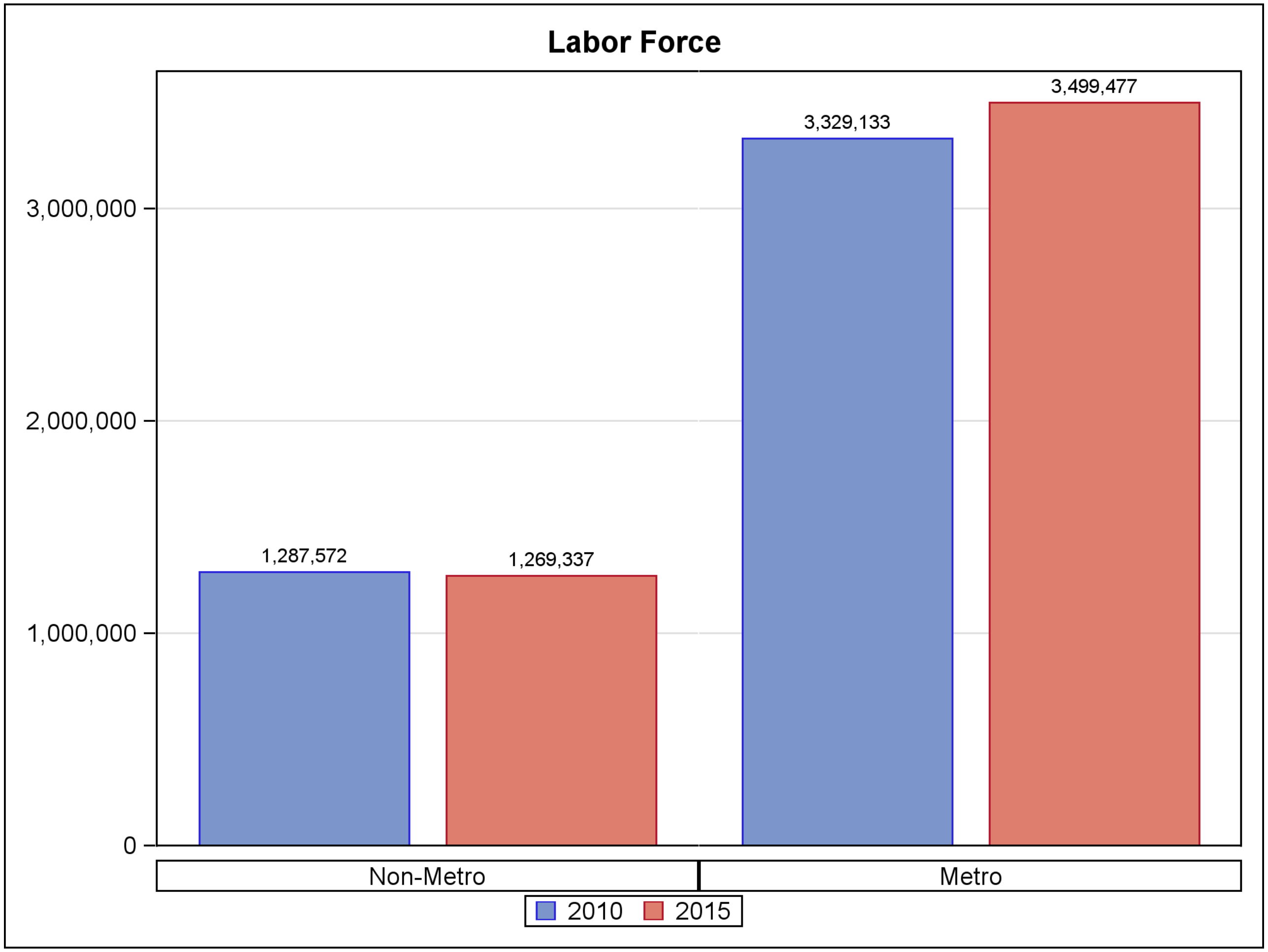

Figure 4.4: Total Labor Force by Metro Designation and Year

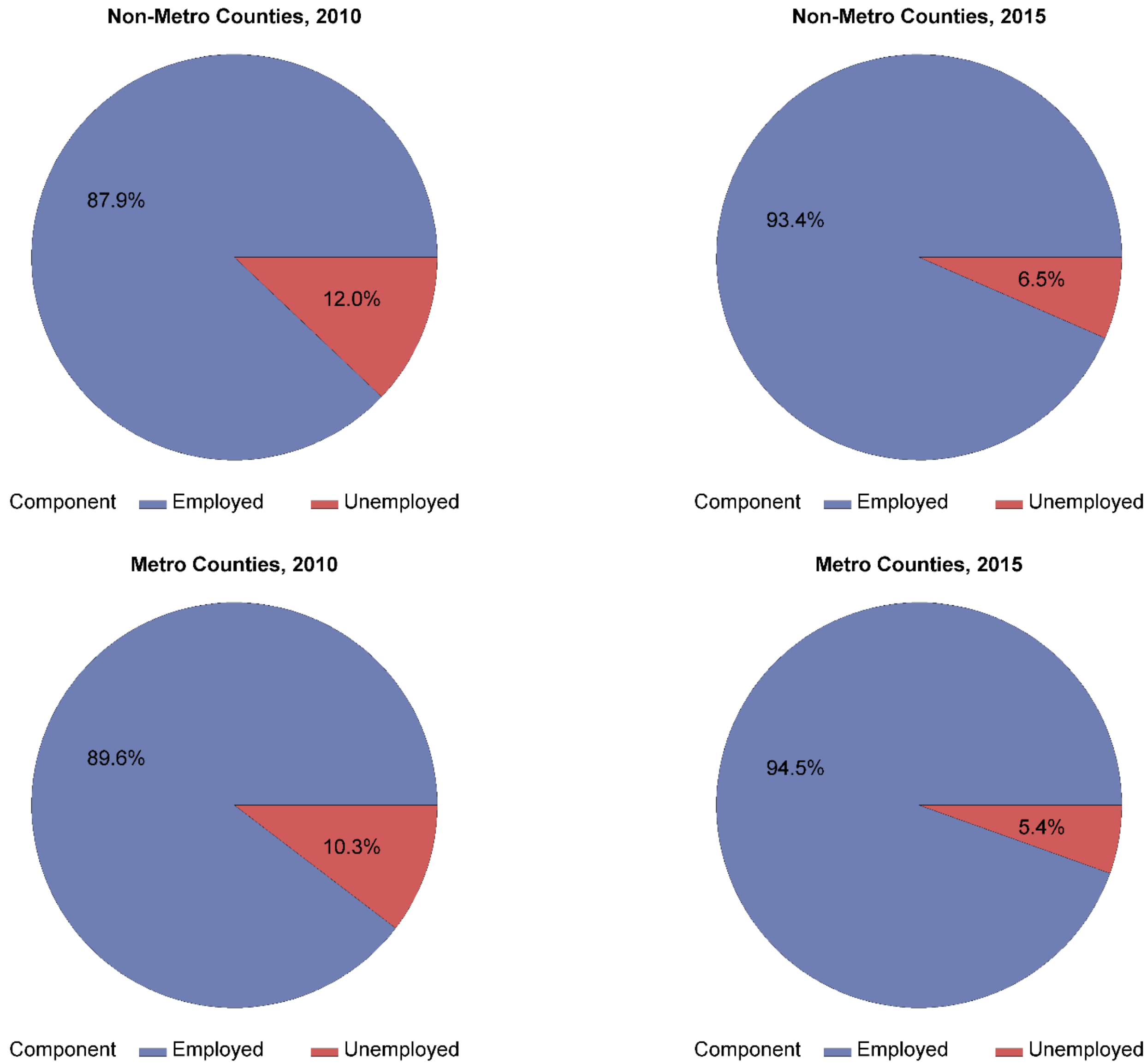

Figure 4.5: Unemployment by Metro Designation and Year

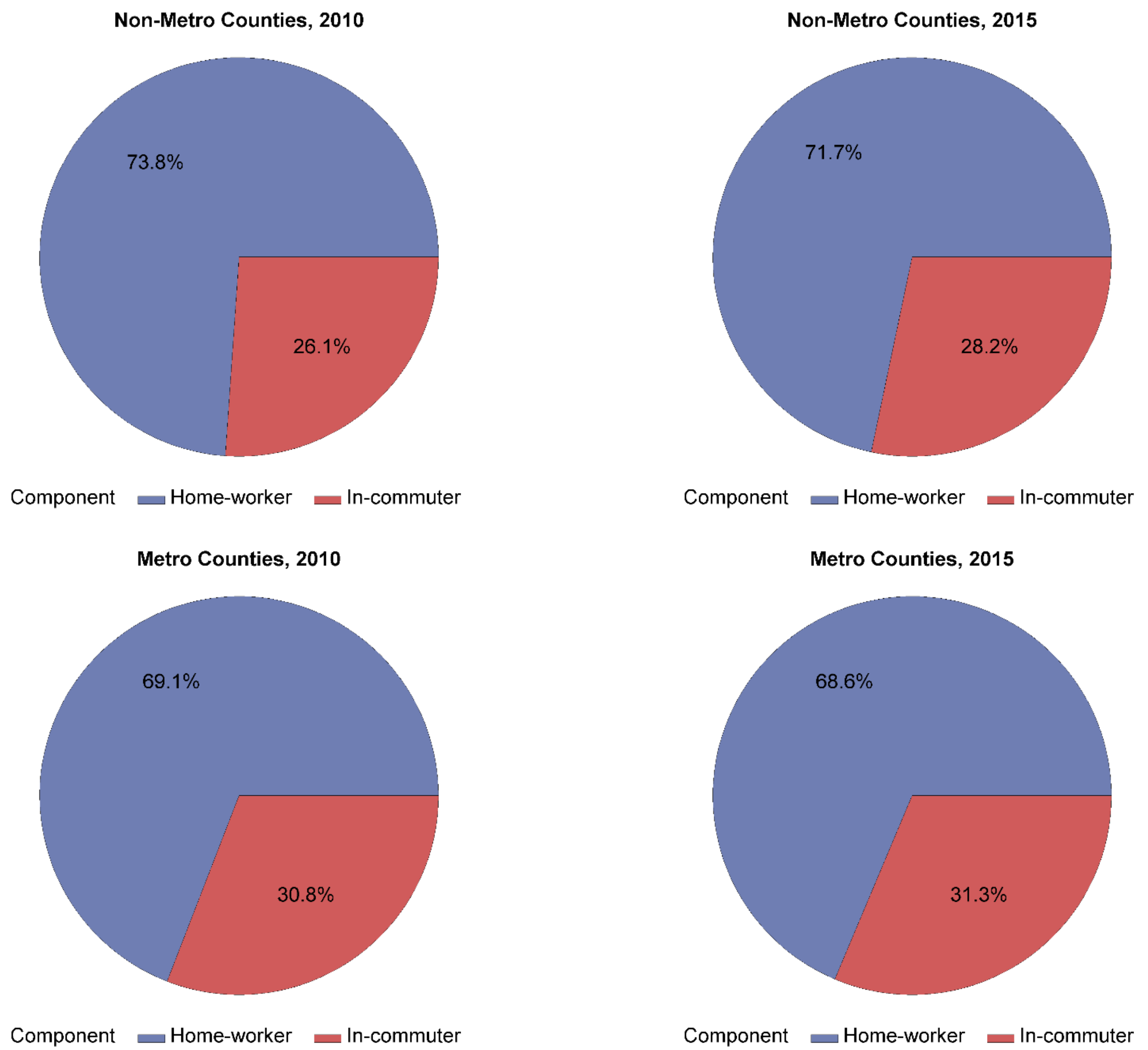

Figure 4.6: Employees by Metro Designation and Year

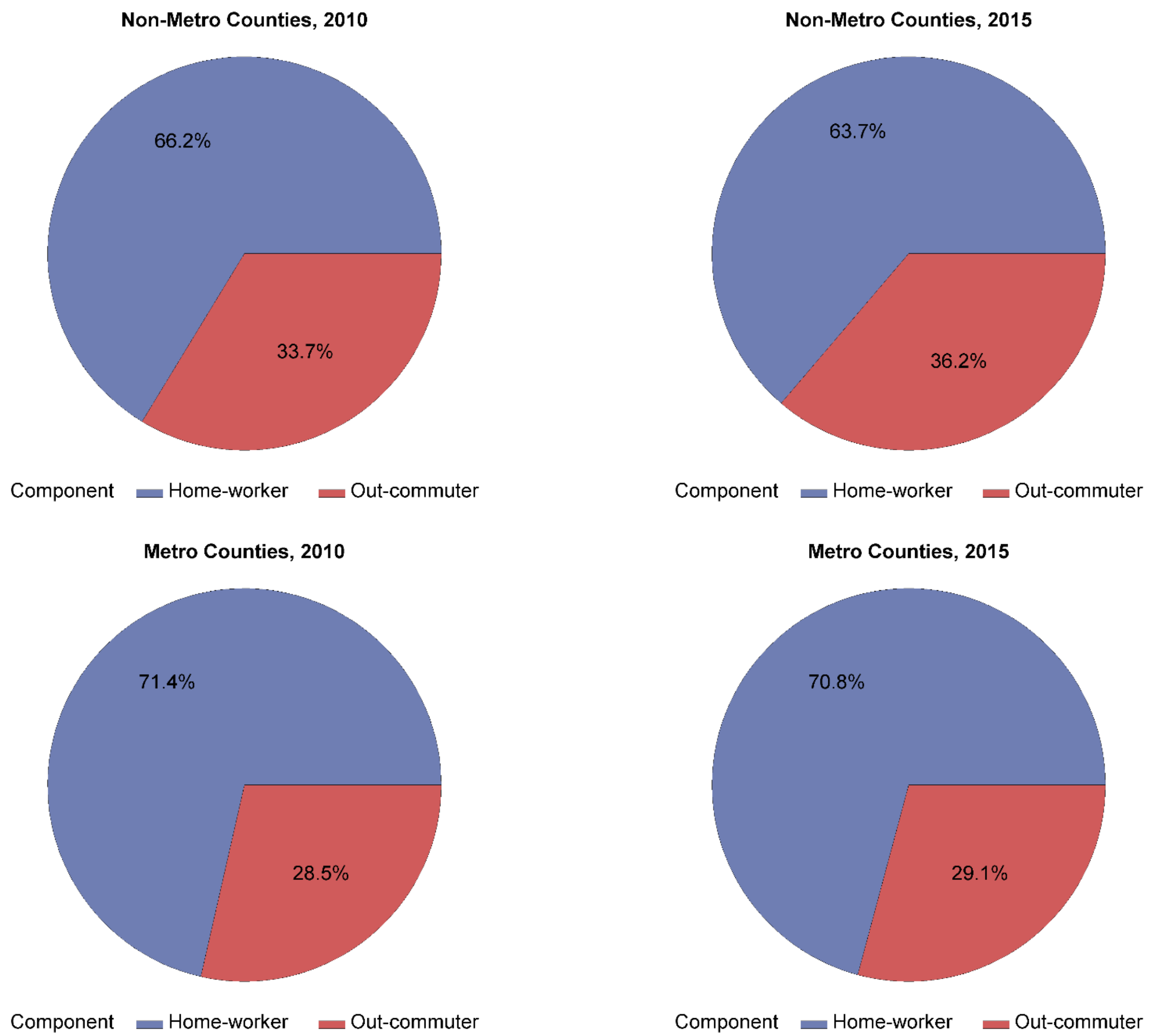

Figure 4.7: Residents by Metro Designation and Year

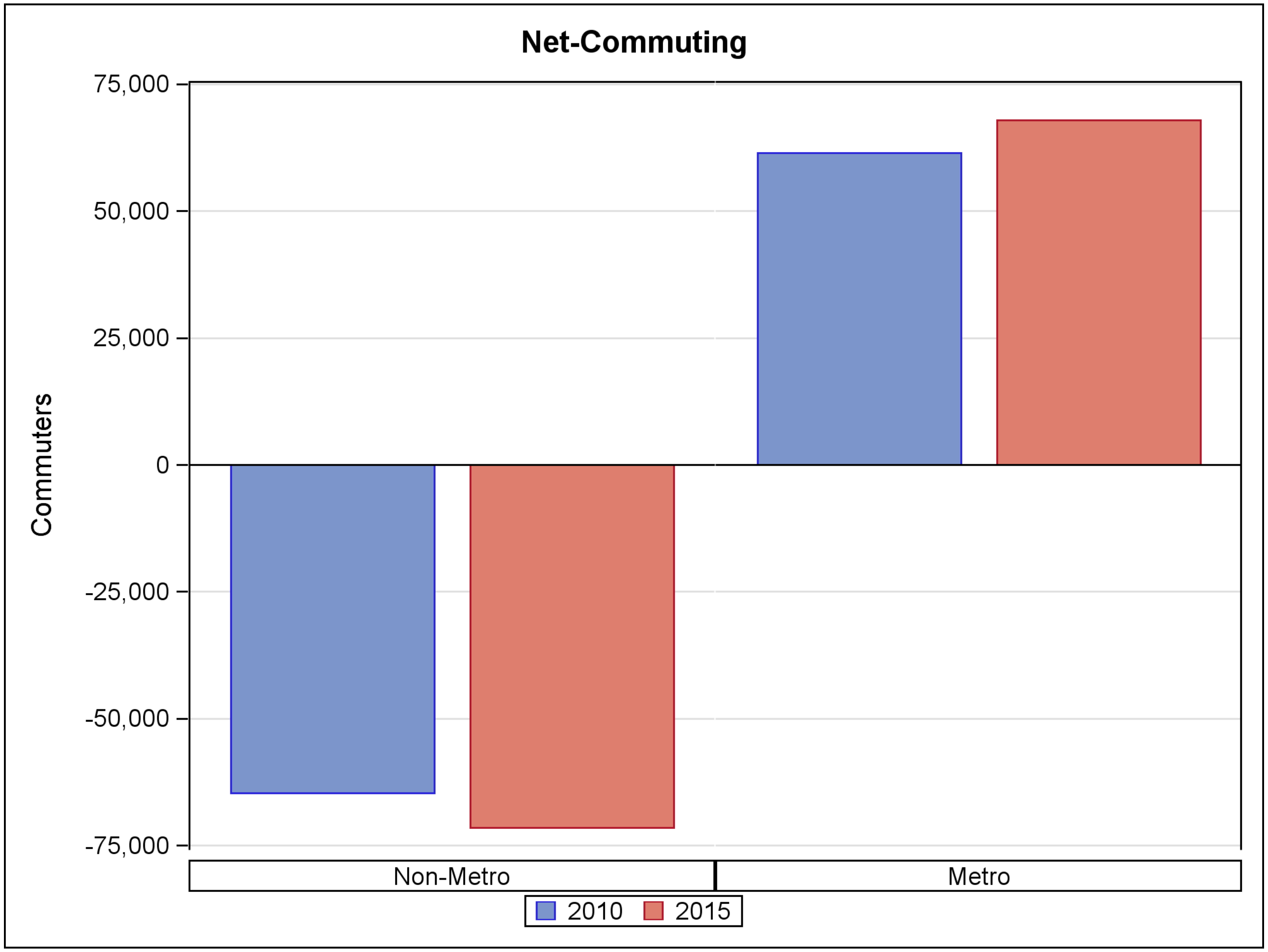

Figure 4.8: Net-Commuting by Metro Designation and Year

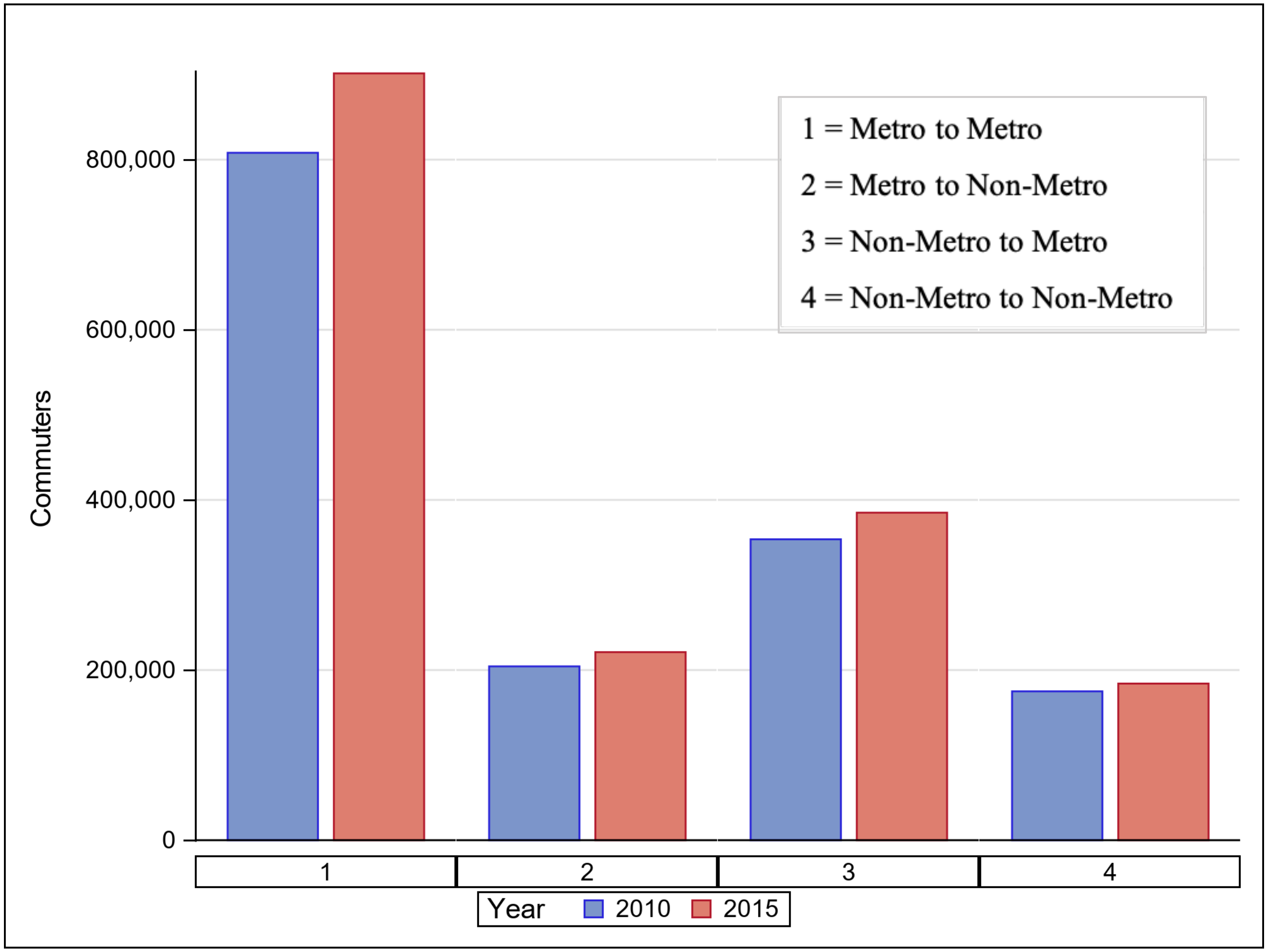

Figure 4.9: Commuting Between Metro and Non-Metro Counties

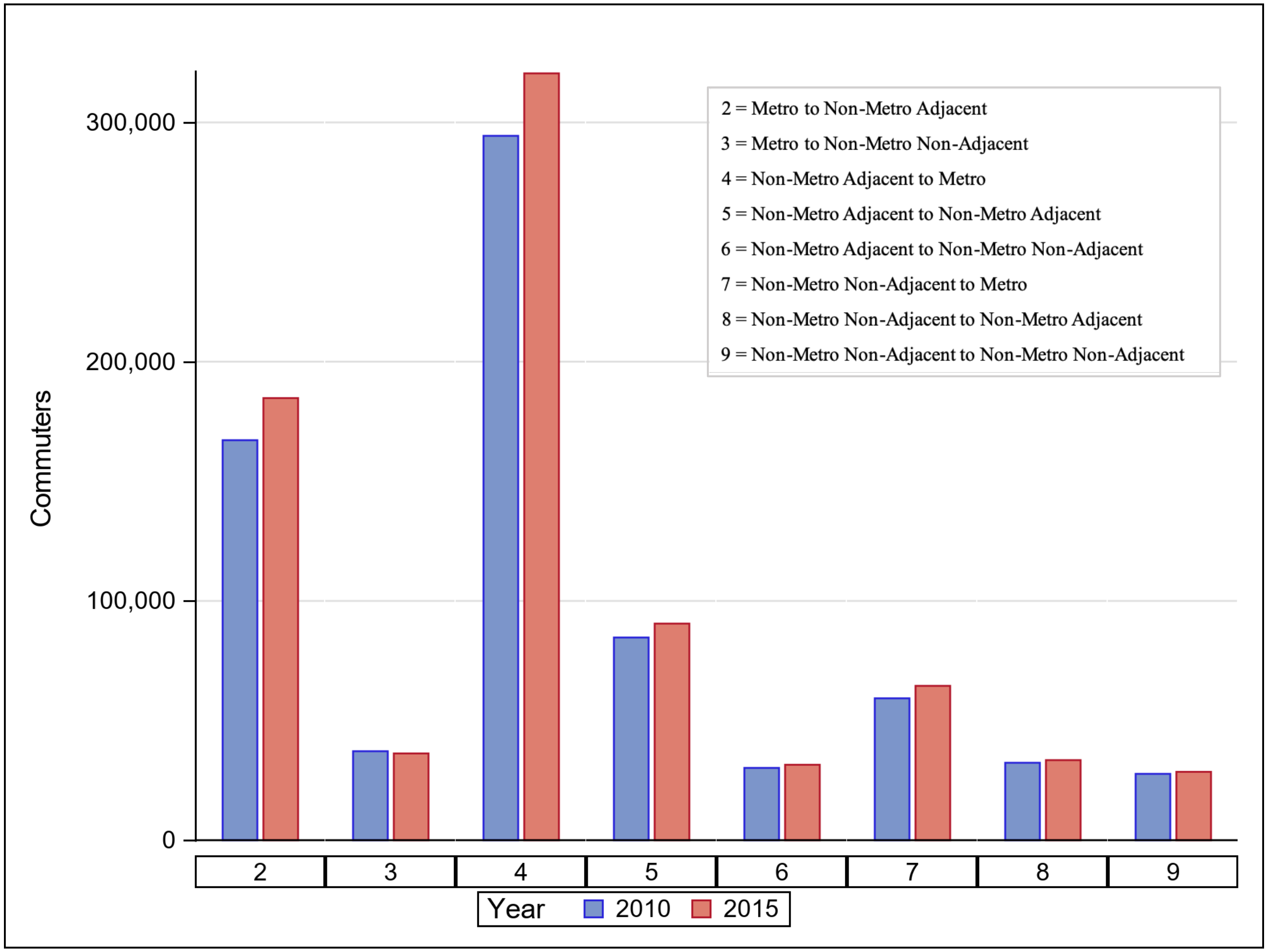

Figure 4.10: Commuting Along the Rural-Urban Continuum

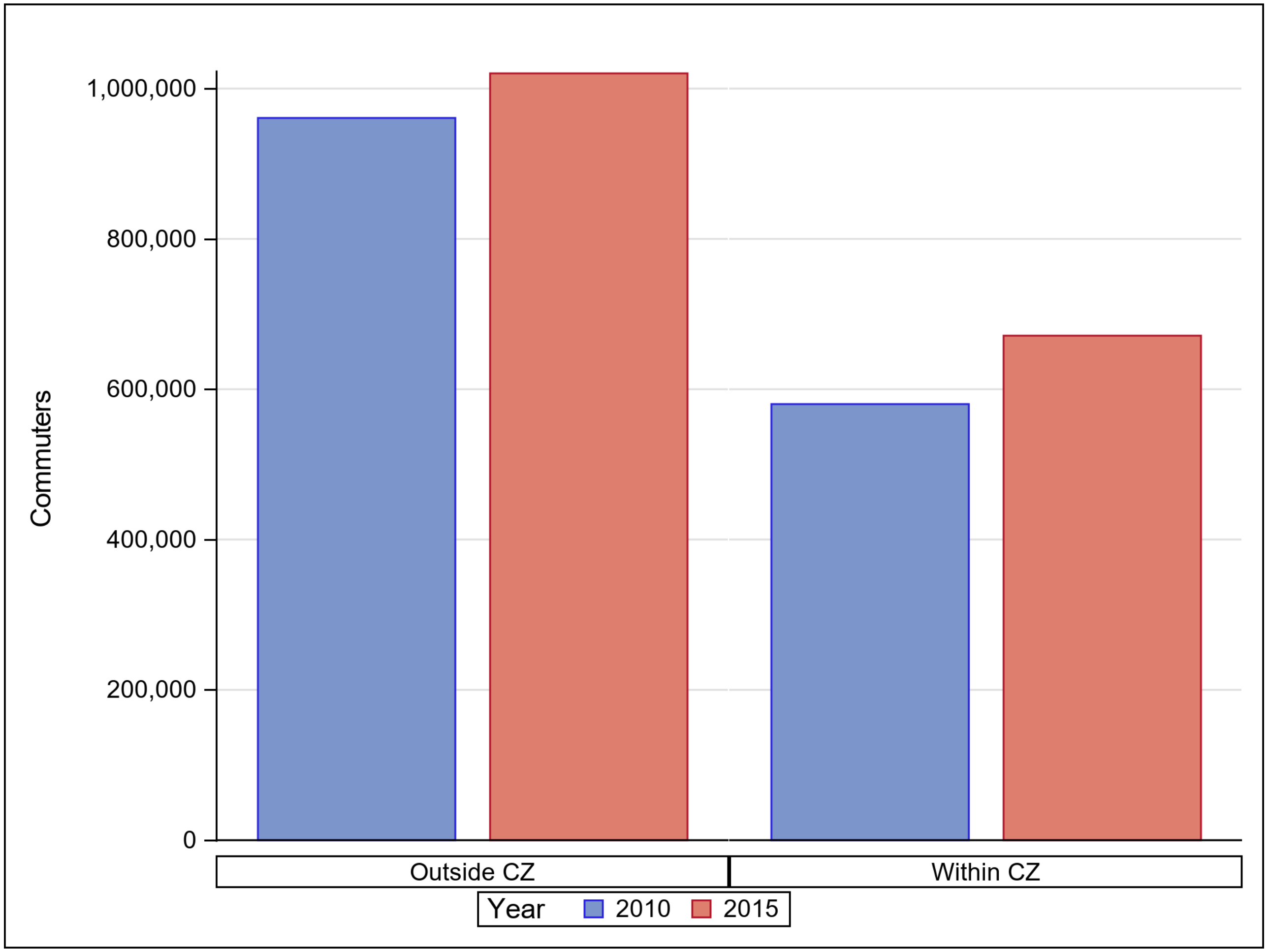

Figure 4.11: Commuting Between and Within CZs

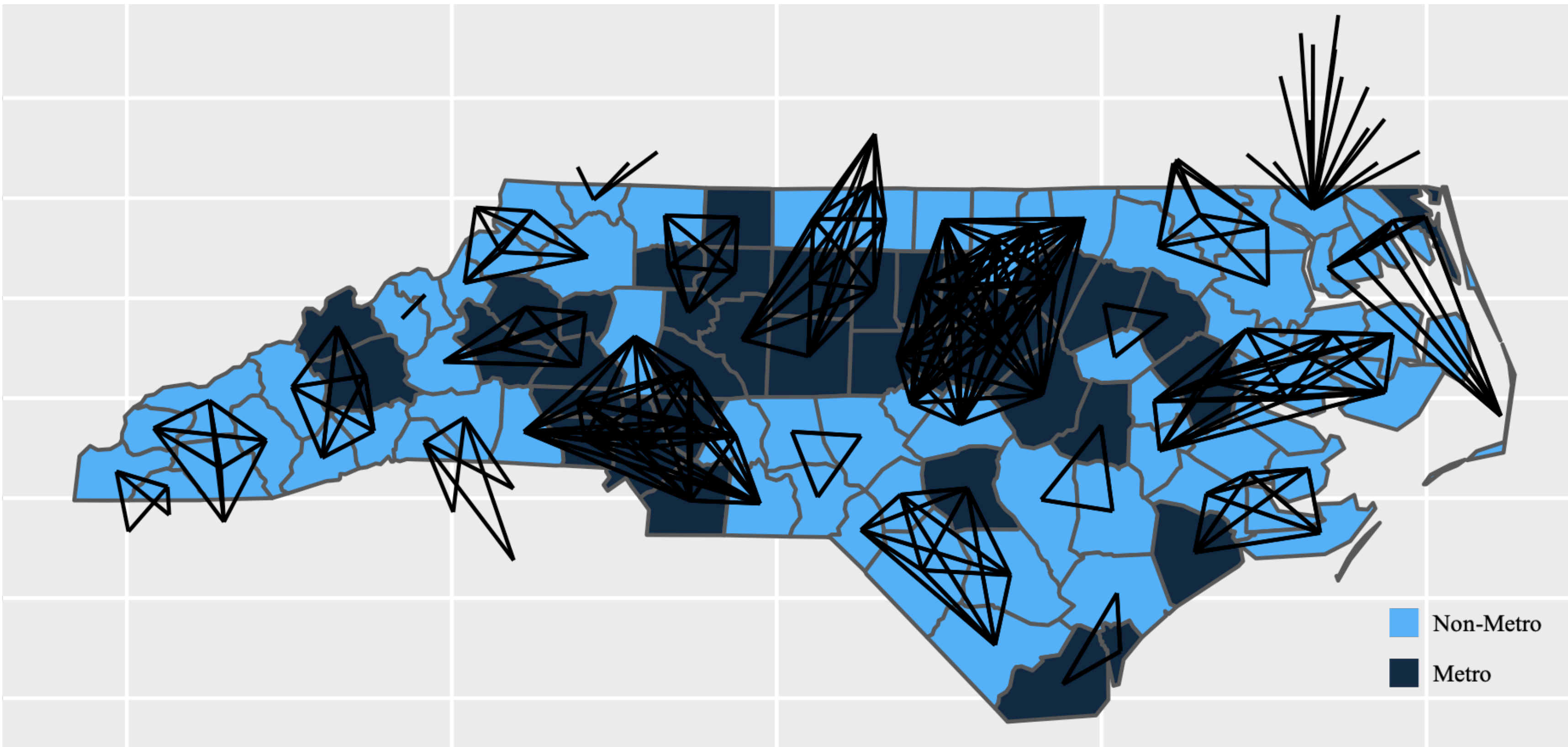

Figure 4.12: North Carolina Resident Within CZ Commuting, 2015

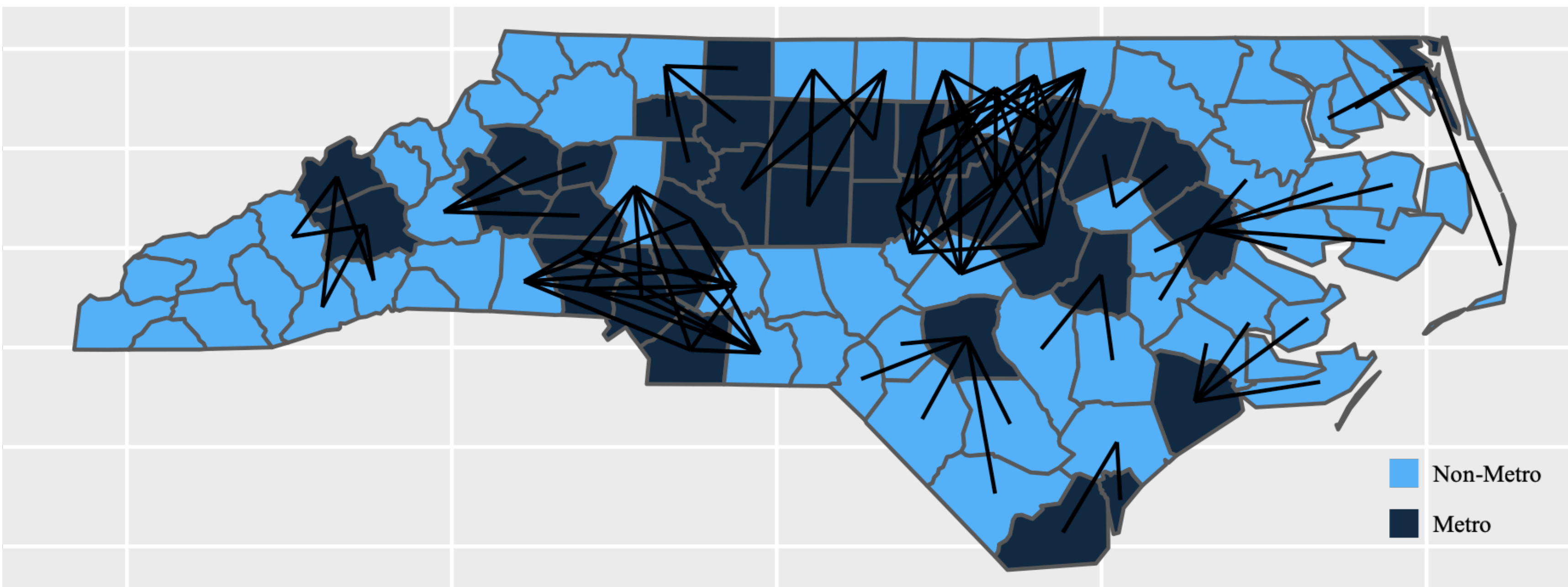

Figure 4.13: North Carolina Resident Within CZ Non-Metro to Metro Commuting, 2015

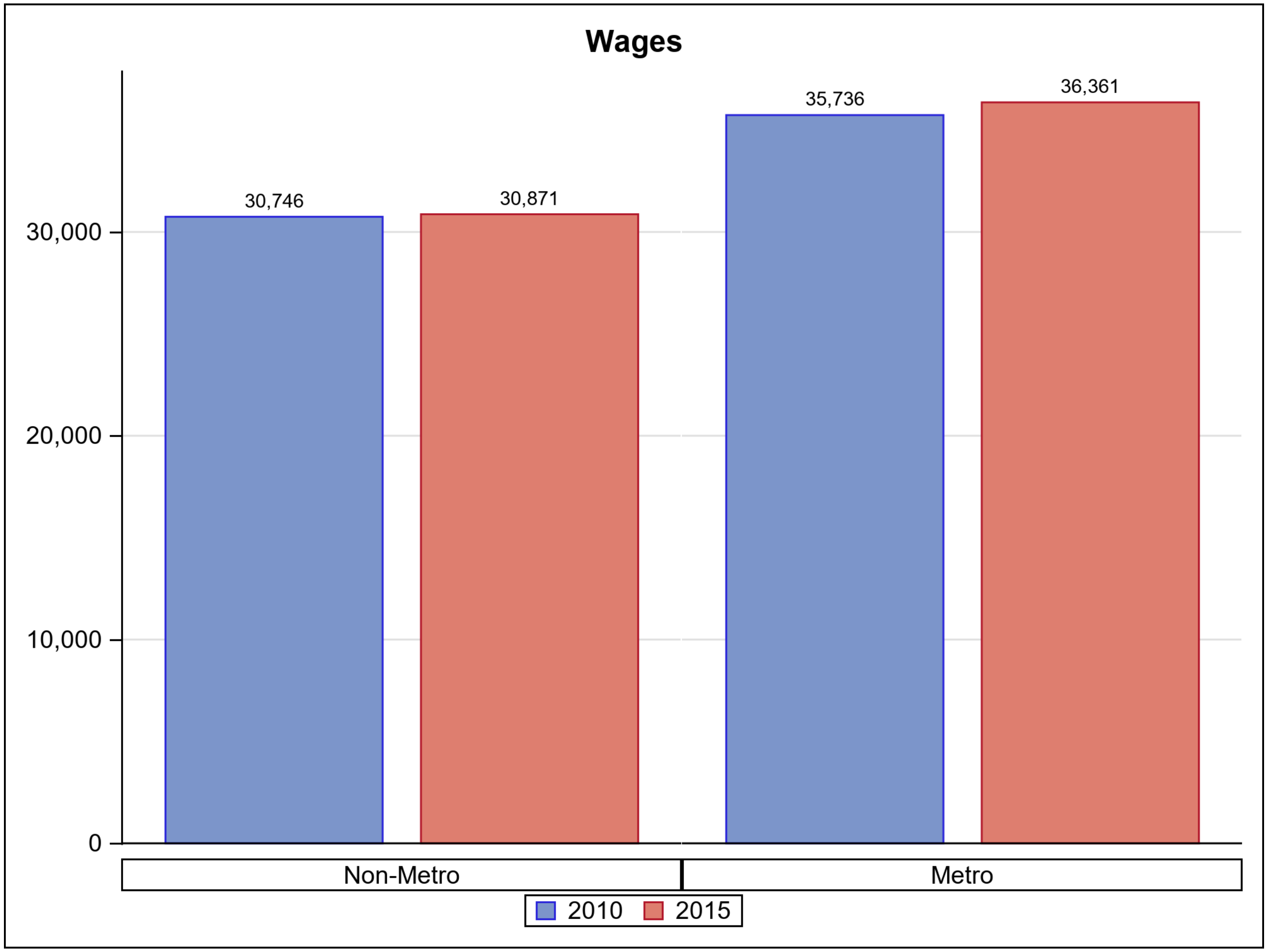

Figure 4.14: Mean Wages by Metro Designation and Year

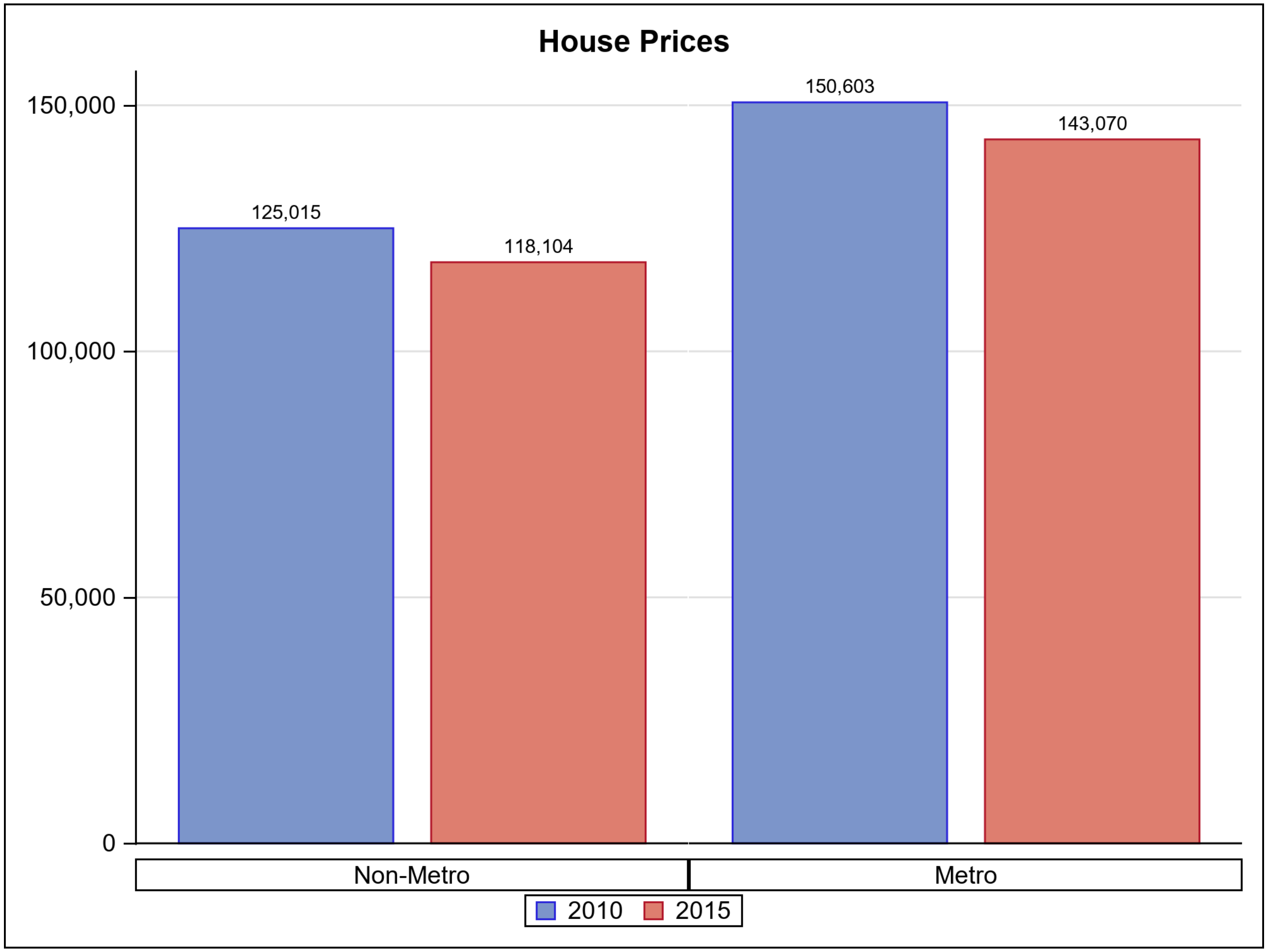

Figure 4.15: Mean House Prices by Metro Designation and Year

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Appendix A: Data and Variable Construction 57

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Appendix C: Ordinary Least Squares Results for All Counties 67

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Appendix A: Data and Variable Construction

Dependent Variables

There are four dependent variables in the system: in-commuting, out-commuting, unemployment, and labor force. The in-commuting and out-commuting variables come from the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program obtained via OnTheMap. LEHD collects Origin-Destination Employment Statistics (LODES) data from a variety of administrative and survey data to account for county-to-county movement. The core jobs data come from a voluntary federal-state partnership called the Local Employment Dynamics (LED) Partnership which was created in 1999 with the mandate to merge data from workers (who provide residential information) with data from employers (who provide unemployment insurance reporting and account information).

For every year and origin-destination pair, LODES provides the number of workers making that commute. Each location is identified by a unique 5-digit FIPS number: the first two digits representing the state and the last three digits representing the county. I first eliminate all observations for those workers residing outside of the 100 NC counties or the 32 adjacent counties which lie in a commuting zone containing at least one NC county. I sort the dataset by residence, so the origin is the place of residence location and the destination is the place of work. I aggregate the number of workers with the same origin and destination FIPS, i.e., those who live in county i and work in county i, are considered "home workers." I also aggregate the number of workers with different origin and destination FIPS, i.e., those who live in county i and work in county j. These workers are considered "out-commuters." I then sort by place of work. Those whose origin and destination are different, i.e., those who work in county *i* and live in county *j* are considered "in-commuters." [23]

The next dependent variables come from using Local Area Unemployment Statistics (LAUS) county tables. The Bureau of Labor Statistics (BLS) uses a handbook method with Quarterly Census of Employment and Wages (QCEW) data, American Community Survey (ACS) data, and Current Population Survey (CPS) data to produce the LAUS county numbers for the labor force, employment, and the unemployment rate.

There are inconsistencies in aligning the LODES commuting numbers with the LAUS employment, labor force, and unemployment numbers. In comparing 5-year ACS commuting estimates with the LODES commuting data, the in-commuters and out-commuters appear very similar; it is the home-worker estimate in the LODES dataset that appears to be systematically underrepresented. For this reason, I take the LAUS employment number as given, subtract the LODES in-commuters estimate, and obtain a new number of home workers for a given county—essentially augmenting the number of home workers in the LODES dataset to include those that are seemingly not accounted for. I take the LAUS unemployment rate as given and use the augmented home worker number along with the LODES out-commuters to calculate the labor force number. [24] I then multiply the unemployment rate by this constructed labor force number. [25]

Finally, I difference the 2015 and 2010 values for in-commuters, out-commuters, unemployed, and labor force participants to obtain my dependent variables.

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[23] It should also be noted that commuting flows were restricted to within-CZ commuting to represent the average NC worker. This meant that, for example, the few workers living in Wake county and commuting to Washington, D.C. or New York are not counted in the commuting flows.

[24] lf=(hw+outcom)/(1-ur)

[25] unemp=ur*lf

Independent Variables

I take the LAUS employment number as given and difference the 2015 and 2010 values to obtain the employment growth variable. Other independent variables include CZ-level employment and labor force. USDA first developed commuting zones (CZs) and Labor Market Areas (LMAs) in 1980 as a way to better delineate local economies (Tolbert and Sizer, 1996). Nationally, there were 768 CZs in 1980, 741 CZs in 1990, and 709 CZs in 2000. I use the most recent designation (2000 update) with one notable exception. Graham County, in the 1980s and 1990s, shared a CZ with Jackson and Swain counties. In 2000, Jackson and Swain were subsumed into the same CZ as Macon and Rabun counties while Graham was left in a CZ unto itself. I manually code Graham County as a part of the Jackson/Swain/Macon/Rabun cluster for two reasons: (1) it makes intuitive sense that previous county relationships hold, and (2) because Renkow (2003) uses this designation. I adopt this designation in order to make as close a comparison as possible. I use the 2000 CZ delineation to sum the labor force and employment estimates for each CZ. I net out county estimates from its corresponding CZ for both 2010 and 2015. I then difference the two years to obtain the change in CZ employment and change in CZ labor force.

Obtained via American Fact Finder, I use the 2010 and 2015 ACS 5-year estimates to obtain median house value for owner-occupied housing units in USD. I use a GNP deflator of (218.1/237) to obtain the real, in 2010 dollars, house value in 2015. I then sum house values to the CZ-level after first netting out each county's individual value. In that way, the value of the Relative Housing Price reflects average housing costs in all other counties within the CZ. I then difference the 2015 and 2010 values to obtain the change in house price. This wage is also deflated, made into a measure relative to the CZ, and differenced in the same manner as the house value. I use the QCEW, which covers approximately 95 percent of American jobs, from BLS to obtain the total industry annual average pay in each county.

Lastly, I obtain the Rural Urban Continuum Codes (RUCC) from the U.S. Department of Agriculture (USDA). I use their delineation to account for metro (codes 1-3) and non-metro (codes 4-9) county differences. [26] RUCC codes have been updated on a periodic basis—1983, 1993, 2003, and 2013. I cannot use the most recent update (2013) because it occurred in the middle of the time period under consideration, so I look at the second most recent dataset (2003). There are several anomalies in the 2003 RUCC classification. As an example, Anson county was classified as a 6 (an urban population of 2,500 to 19,999, adjacent to a metro area) in 1983, 1993, and 2013; oddly, it was classified as a 1 (counties in metro areas of 1 million population or more) in 2003. Another example is Greene county which was classified as a non-metro county in 1983 (9), 1993 (8), and 2013 (8), but a metro county in 2003 (2). There are also several counties (Rowan, Lincoln, and Davidson) that are consistently coded as metro except for in 2003, when they are coded as non-metro. Because of these discrepancies and to make as best a comparison as possible to the Renkow (2003) data, I use the 1993 RUCC designation. I note the classification for eleven counties changed from non-metro to metro between the 1993 and 2013 code publication (which might be the most accurate except that I cannot use it due to timing issues). This group of counties includes: Craven, Gates, Haywood, Henderson, Hoke, Iredell, Jones, Pamlico, Pender, Person, and Rockingham counties.

Instruments

To account for the endogenous variables, Renkow (2003) uses county population, county area, and population density as part of his instrument set. I also include these variables along

[26] Additionally, non-metro counties can be further delineated to either adjacent (codes 4, 6, and 8) or non-adjacent counties (codes 5, 7, and 9).

with the 5-year ACS change in employment and commuting estimates. The population, area, and density data come from the 2010 Decennial Census (obtained via Social Explorer). County population is total population; county area is calculated as land area in square meters; and population density is calculated as the average number of people per square mile.

I use the 5-year ACS estimates of commuting flows for the periods 2006-2010 and 2011-2015. These estimates are period-estimates such that they represent the commuting characteristics of the population over a specific data collection period. For instance, the data in the 2010 ACS 5-year estimates have been combined from interviews starting January 1, 2006 through December 31, 2010. Similar to LODES, the data is organized with a pair of FIPS, identifying place of residence and place of work, and corresponding number of workers making that commute. I strip out any residence counties that are not in NC or within a NC commuting zone. As with the LODES dataset, I calculate home workers, in-commuters, and out-commuters with the 5-year ACS survey data. Although the 5-year ACS directly provides the labor force, employment, and unemployment estimates for each county, for internal consistency, I use the methodology implemented with the LODES and LAUS data to calculate labor force and unemployment numbers. I use the unemployment rate—along with the commuting numbers—to determine an estimate for employment.

Multi-year estimates cannot be used to say what is going on in any particular year in the period, only what the average value is over the full period; for this reason, I cannot obtain accurate numbers or statistics for a specific year, e.g., 2010 and 2015, but I do use these data to produce variables used in my instrument set. I difference the 2011-2015 employment and 2006-2010 employment estimate to obtain the change in employment. I do the same for in-commuting and out-commuting numbers and use these three change estimates to instrument for the change in employment, in-commuting, and out-commuting between 2015 and 2010.

Appendix B: List of Counties Grouped by Commuting Zone

County Name	State	CZ
Duplin County	NC	559
Sampson County	NC	559
Wayne County	NC	559
Montgomery County	NC	528
Moore County	NC	528
Richmond County	NC	528
Ashe County	NC	482
Avery County	NC	482
Watauga County	NC	482
Wilkes County	NC	482
Johnson County	TN	482
Mitchell County	NC	402
Yancey County	NC	402
Polk County	NC	361
Rutherford County	NC	361
Cherokee County	SC	361
Spartanburg County	SC	361
Union County	SC	361
Cherokee County	NC	357
Clay County	NC	357
Towns County	GA	357
Union County	GA	357
Beaufort County	NC	298
Greene County	NC	298
Hyde County	NC	298
Lenoir County	NC	298
Martin County	NC	298
Pitt County	NC	298
Tyrrell County	NC	298
Washington County	NC	298
Bertie County	NC	261
Halifax County	NC	261
Hertford County	NC	261
Northampton County	NC	261
Greensville County	VA	261
Emporia city	VA	261
Alamance County	NC	248

Caswell County	NC	248
Davidson County	NC	248
Guilford County	NC	248
Randolph County	NC	248
Rockingham County	NC	248
Pittsylvania County	VA	248
Danville city	VA	248
Alexander County	NC	246
Burke County	NC	246
Caldwell County	NC	246
Catawba County	NC	246
McDowell County	NC	246
Carteret County	NC	182
Craven County	NC	182
Jones County	NC	182
Onslow County	NC	182
Pamlico County	NC	182
Bladen County	NC	162
Columbus County	NC	162
Cumberland County	NC	162
Hoke County	NC	162
Robeson County	NC	162
Scotland County	NC	162
Alleghany County	NC	150
Carroll County	VA	150
Grayson County	VA	150
Galax city	VA	150
Camden County	NC	147
Chowan County	NC	147
Currituck County	NC	147
Dare County	NC	147
Pasquotank County	NC	147
Perquimans County	NC	147
Edgecombe County	NC	146
Nash County	NC	146
Wilson County	NC	146
Anson County	NC	138
Cabarrus County	NC	138
Cleveland County	NC	138
Gaston County	NC	138
Iredell County	NC	138

Lincoln County	NC	138
Mecklenburg County	NC	138
Rowan County	NC	138
Stanly County	NC	138
Union County	NC	138
Graham County	NC	123
Jackson County	NC	123
Macon County	NC	123
Swain County	NC	123
Rabun County	GA	123
Davie County	NC	112
Forsyth County	NC	112
Stokes County	NC	112
Surry County	NC	112
Yadkin County	NC	112
Brunswick County	NC	110
New Hanover County	NC	110
Pender County	NC	110
Buncombe County	NC	91
Haywood County	NC	91
Henderson County	NC	91
Madison County	NC	91
Transylvania County	NC	91
Chatham County	NC	87
Durham County	NC	87
Franklin County	NC	87
Granville County	NC	87
Harnett County	NC	87
Johnston County	NC	87
Lee County	NC	87
Orange County	NC	87
Person County	NC	87
Vance County	NC	87
Wake County	NC	87
Warren County	NC	87
Gates County	NC	39
Gloucester County	VA	39
Isle of Wight County	VA	39
James City County	VA	39
Mathews County	VA	39
Middlesex County	VA	39

Southampton County	VA	39
Surry County	VA	39
York County	VA	39
Chesapeake city	VA	39
Franklin city	VA	39
Hampton city	VA	39
Norfolk city	VA	39
Poquoson city	VA	39
Portsmouth city	VA	39
Suffolk city	VA	39
Virginia Beach city	VA	39
Williamsburg city	VA	39
Hopewell city	VA	14

Appendix C: Ordinary Least Squares Results for All Counties

Table C.1: Ordinary Least Squares Results for All Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
County Employment	0.502***	-0.087**	-0.182***	0.642***
	(0.035)	(0.041)	(0.013)	(0.020)
County Labor Force	-0.258***	0.383***		
	(0.0520)	(0.061)		
CZ Employment		0.018***	-0.006**	0.009*
		(0.003)	(0.003)	(0.004)
CZ Labor Force	0.012***			
	(0.00)			
Relative Wage	-1995.93	817.73	-2968.09	-488.09
	(2291.10)	(2720.13)	(2902.50)	(4569.41)
Relative Housing Price	408.32	-629.30		1546.10
	(1370.82)	(1627.45)		(2729.38)
Metro	-197.317	1052.177***	-1519.72***	-683.652
	(241.212)	(288.216)	(303.733)	(479.027)
Intercept	-412.928***	74.969	-905.362***	-997.066***
	(145.886)	(179.202)	(179.703)	(282.941)
Adjusted R-Square	0.934	0.808	0.787	0.926
F Value	236.180	70.68	92.54	248.49
N	100	100	100	100

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.

Appendix D: First- and Second-Stage Results for All, Metro and Non-Metro Counties

Table D.1: First-Stage Regression Results for All Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
Lagged Population	0.013**	0.003	-0.021***	-0.000
	(0.006)	(0.004)	(0.003)	(0.008)
Lagged Density	1.397	1.315	-0.642	5.055*
	(2.297)	(1.716)	(1.100)	(2.985)
Lagged Area	-0.968	0.168	-0.002	0.277
	(1.196)	(0.893)	(0.572)	(1.553)
Lagged Employment	0.099***	0.030	0.055	0.786***
	(0.080)	(0.060)	(0.038)	(0.104)
Lagged In-commuting	0.743	-0.040	-0.052	-1.170***
	(0.257)	(0.192)	(0.123)	(0.333)
Lagged Out-commuting	0.017	0.982***	0.311***	1.600***
	(0.190)	0.142	(0.091)	0.247
CZ Labor Force	-0.027	-0.084***	0.072***	-0.032
	(0.027)	(0.020)	(0.013)	(0.035)
CZ Employment	0.026	0.075***	-0.058***	0.032
	(0.018)	(0.014)	(0.009)	(0.024)
Relative Housing	-654.47	-909.70	907.40	1079.93
	(2,179.50)	(1628.28)	(1043.09)	(2831.81)
Relative Wage	2,152.50	1257.87	-2819.75	2266.08
	(3,605.15)	(2693.37)	(1725.40)	(4684.15)
Metro	-684.534	170.252	-81.586*	-966.850
	(428.696)	(320.273)	(205.170)	(557.001)
Intercept	-385.258	-863.318*	323.645	-957.991
	(590.017)	(440.795)	(282.377)	(766.606)
Adjusted R-Square	0.843	0.818	0.927	0.925
F Value	49.300	41.540	115.670	111.480
N	100	100	100	100

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.

Table D.2: Second-Stage Regression Results for All Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
County Employment	0.392***	-0.067	-0.183***	0.650***
	(0.049)	(0.055)	(0.013)	(0.021)
County Labor Force	-0.100	0.348***		
	(0.074)	(0.082)		
CZ Employment		0.018***	-0.006**	0.009*
		(0.003)	(0.003)	(0.004)
CZ Labor Force	0.010***			
	(0.004)			
Relative Wage	-1630.97	911.95	-2926.29	-751.36
	(2,413.46)	(2,728.85)	(2905.26)	(4576.74)
Relative Housing Price	62.98	-611.86		1632.78
	(1,445.42)	(1,634.09)		(2732.02)
Metro	-33.883	1,050.320***	-1511.57***	-735.83
	(257.438)	(293.022)	(304.70)	(480.92)
Intercept	-257.731	40.911	-905.031***	-999.009***
	(160.664)	(187.810)	(179.713)	(283.141)
Adjusted R-Square	0.920	0.794	0.782	0.923
N	100	100	100	100

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.

Table D.3: First-Stage Regressions for Metro and Non-metro Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
		Metro		
Lagged Population	0.017	-0.0056	-0.017***	-0.016
	(0.015)	(0.008)	(0.006)	(0.016)
Lagged Density	0.946	4.133	-1.662	10.337*
	(5.486)	(2.910)	(2.223)	(5.938)
Lagged Area	-2.792	3.734	0.199	5.744
	(4.687)	(2.486)	(1.900)	(5.074)
Lagged Employment	0.055	0.128	-0.023	0.957***
	(0.177)	(0.094)	(0.072)	(0.192)
Lagged In-commuting	0.972*	-0.177	0.040	-1.636***
	(0.530)	(0.281)	(0.215)	(0.573)
Lagged Out-commuting	-0.239	0.892***	0.512***	1.579***
	(0.401)	(0.213)	(0.163)	(0.434)
CZ Labor Force	-0.045	-0.172***	0.110***	-0.118
	(0.075)	(0.040)	(0.030)	(0.081)
CZ Employment	0.047	0.146***	-0.089***	0.103*
	(0.050)	(0.027)	(0.020)	(0.054)
Relative Housing	8731.14	-647.54	543.21	-3,871.140
	(12,305.38)	(6,527.73)	(4,987.33)	(13,320.14)
Relative Wage	7,456.90	-2,077.95	-7,940.34	11,335.86
	13,145.49	(6,973.40)	(5,327.83)	(14,229.53)
Intercept	-1,159.600	-3,221.80**	402.662	-5,340.64*
	(2,484.992)	(1,318.234)	(1,007.160)	(2,689.917)
Adjusted R-Square	0.817	0.874	0.915	0.940
F Value	16.200	24.540	37.790	54.260
N	35	35	35	35

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.

Table D.3: First-Stage Regressions for Metro and Non-metro Counties Continued

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
		Non-Metro		
Lagged Population	0.017**	0.022**	-0.036***	-0.003
	(0.007)	(0.008)	(0.005)	(0.018)
Lagged Density	-3.685	-2.827	5.206**	5.130
	(3.099)	(3.891)	(2.552)	(8.179)
Lagged Area	-0.834	-1.323	1.056*	-0.276
	(0.643)	(0.808)	(0.530)	(1.698)
Lagged Employment	0.172**	0.194**	0.159***	0.562***
	(0.069)	(0.086)	(0.057)	(0.181)
Lagged In-commuting	-0.001	-0.147	-0.049	0.153
	(0.156)	(0.196)	(0.128)	(0.411)
Lagged Out-commuting	0.233*	0.479***	0.046	0.796**
	(0.118)	(0.148)	(0.097)	(0.312)
CZ Labor Force	-0.010	-0.000	0.039***	0.037
	(0.011)	(0.014)	(0.009)	(0.029)
CZ Employment	0.011	0.007	-0.033***	-0.023
	(0.008)	(0.010)	(0.006)	(0.020)
Relative Housing	-699.75	379.87	623.32	1432.76
	(700.94)	(880.13)	(577.27)	(1849.91)
Relative Wage	562.32	1991.43	-516.35	1242.72
	(1267.52)	(1591.55)	(1043.89)	(3345.22)
Intercept	141.177	149.94	-186.50	-274.14
	(315.362)	(395.984)	(259.723)	(832.303)
Adjusted R-Square	0.507	0.625	0.864	0.277
F Value	7.570	11.690	41.610	3.450
N	65	65	65	65

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.

Table D.4: Second-Stage Regressions for Metro and Non-metro Counties

Variable	In-commuting	Out-commuting	Unemployment	Labor Force
		Metro		
County Employment	0.495***	-0.053	-0.179***	0.648***
	(0.071)	(0.080)	(0.020)	(0.033)
County Labor Force	-0.252**	0.321**		
	(0.107)	(0.120)		
CZ Employment		0.030***	-0.002	0.023**
		(0.006)	(0.007)	(0.011)
CZ Labor Force	0.026***			
	(0.008)			
Relative Wage	-12,078.40*	-7955.71	-8166.79	-9620.49
	(7,044.13)	7930.54	(8816.65)	(14236.44)
Relative Housing Price	2,135.15	-4367.99		-2657.30
	(6,151.33)	(6891.61)		(12490.48)
Intercept	-804.057*	628.830	-2576.55***	-2265.560***
	(402.826)	(497.467)	(465.000)	(756.875)
Adjusted R-Square	0.936	0.814	0.733	0.931
N	35	35	35	35
		Non-Metro		
County Employment	0.388***	0.486***	-0.622***	0.537***
	(0.070)	(0.091)	(0.100)	(0.128)
County Labor Force	-0.027	0.074		
	(0.095)	(0.118)		
CZ Employment		0.004**	-0.002	-0.000
		(0.002)	(0.003)	(0.004)
CZ Labor Force	0.002			
	(0.002)			
Relative Wage	818.72	2378.97	724.50	2488.21
	(1144.85)	(1426.13)	(2126.63)	(2735.03)
Relative Housing Price	-617.32	226.26		1960.82
	(631.71)	(787.67)		(1475.64)
Intercept	0116.280	-123.636	-605.343***	-671.879***
	(92.323)	(115.353)	(127.81)	(164.372)
Adjusted R-Square	0.566	0.672	0.495	0.288
N	65	65	65	65

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels respectively.