BIGNALL, NICHOLE M. Ph.D. Geography of Entrepreneurship: Non-Farm Proprietorship by U.S. County – Key Predictors. (2021)
Directed by Dr. Keith Debbage. 106 pp.

This three-article dissertation explores the geography of non-farm proprietorship (NFP) employment by U.S. County in 2016. NFP employment continues to be an important and emerging research area in the field of entrepreneurship. All three articles used data collected from the U.S. Census and Bureau of Economic Analysis and focused on identifying the key predictors that best explained why certain counties generated high shares of NFP employment. A stepwise regression analysis was conducted at three forms of county typologies; the 800 most populated counties in the U.S., 107 micropolitan counties, and 71 outlying metropolitan counties.

All three articles supported the idea that the geography of entrepreneurship is unevenly distributed by county. In each regression analysis, it appeared that the employment composition of the local labor pool played a more powerful role in shaping the geography of NFP than more aggregate socio-economic metrics like per capita income, level of education or median household income.

Key predictors included the share of the labor pool employed in real estate, rental and leasing (RRL) employment and construction employment which featured prominently in the final regression models in all three articles. RRL and construction employment may be a proxy for access to a particular type of capital for NFP workers that is tied to vibrant, growing land markets. The findings provide a disaggregated analysis at different county typologies that can help policymakers to better understand the key predictors that drive the local choices of entrepreneurs and help communities build more competitive local economies.

GEOGRAPHY OF ENTREPRENERUSHIP: NON-FARM PROPRIETORSHIP BY U.S. COUNTY – KEY PREDICTORS

by

Nichole M. Bignall

A Dissertation

Submitted to

the Faculty of The Graduate School at

The University of North Carolina at Greensboro

in Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

Greensboro

2021

Approved by

Dr. Keith Debbage
Committee Chair

DEDICATION

This dissertation is dedicated to all my family members, friends, and church family who encouraged, supported, and prayed me through this program. A special thank you and gratitude to my very supportive and loving husband Wes, our children Baisha and Stacia for constantly reminding me to trust in God and to remember that He has a plan for my life. To my loving parents Glasme and Winston Taylor and all my siblings, I will always be grateful for your support, time and prayers. I also dedicate this work in loving memory to my Daddy Daley.

APPROVAL PAGE

This dissertation written by Nichole M. Bignall has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

Committee Chair	Dr. Debbage
Committee Members	Dr. Johnson
	Dr. Sultana
	Dr. Knapp
	Mr. Cramer

October 14, 2021

Date of Acceptance by Committee

October 14, 2021

Date of Final Oral Examination

ACKNOWLEDGEMENTS

With gratitude and appreciation I would like to thank all the members of my Dissertation Committee for their individual and collective support throughout my dissertation journey. I am especially grateful to my Committee Chair Dr. Keith Debbage who has been a mountain of patience and knowledge, a wonderful mentor, a consistent support and guide throughout the dissertation process.

I am also grateful to Dr. Hall-Brown, for her kind words of encouragement and her hours of dedication helping me in the lab. To all my supportive colleagues, especially Jesse Lane, a dear friend, who has been an inspiration of positive thinking and forward looking – I am grateful for all your help, kind words, and encouragement, while helping me to stay the course to graduation.

To a great man in my life, my loving husband Wes, I thank you for being an unbelievable tower of strength, friend, and prayer partner.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I: INTRODUCTION

Since the late 1960s, the U.S. has seen a shift in traditional employing institutions (e.g., Fortune 500 companies) being credited as creators of new jobs, and instead, the majority of new business formations were being invented by small and medium-sized institutions (Drucker, 1985). Researchers and policymakers have become increasingly interested in the generation of new jobs in the U.S. when viewed from the spatial perspective. Numerous studies have investigated the role that entrepreneurship/self-employment plays in the invention of new jobs. According to Rupasingha and Goetz (2013), self-employment is an important trend in the economic development of local economies. Within the field of entrepreneurship, a number of crucial questions remain unanswered, including where these more entrepreneurial communities are more likely to be located, what factors outside the immediate entrepreneurial ecosystem provide a supportive environment for entrepreneurs, and how are communities on the fringe of central and more urbanized areas interconnected.

Over the years, considerable research attention has been devoted to better understanding the role that entrepreneurship and self-employment have played on economic development and job growth (Fritsch and Wyrwich, 2016; Backman and Lööf, 2015; Lin, 2010; Baycan-Levent et al., 2009; Kansas et al., 2009; Harvey, 2008), but most entrepreneurial studies have focused on the who and what of this unevenly distributed phenomenon (Mack, 2016; Stam, 2009). Although entrepreneurship has received a lot of research attention, “geography as a fundamental factor in the distribution of the people and factors that promote entrepreneurship” (p. 3) has received little attention in the literature (Mack, 2016). The “spatial conditionality” of entrepreneurship deserves more research attention. The constraints of the broader geography (i.e., job mix) that encircles the microscale entrepreneurial ecosystem influences the outcomes in shares of entrepreneurial activities. This study aims to better understand the spatial dimensions of entrepreneurial opportunities at different county typologies, thus providing a spatial (i.e., geographical) perspective.

The lack of a uniform definition for entrepreneurship has led to a several research studies using proxies within this area of investigation (Backman and Lööf, 2015). In the literature, proxies including self-employment, start-ups, and new firm formations have been used to better understand entrepreneurship and its possible relationships with economic growth and development (Rupasingha and Goetz, 2013; Goetz and Rupasingha, 2009; Shrestha et al., 2007; Goetz, 2003), however, few studies have paid attention to the continuously increasing phenomenon of non-farm proprietorship (NFP) employment. Non-farm proprietors are similar to wage and salary workers, in that they are full- or part-time owners of businesses, although small and unincorporated, who take risks, earn profits, or incur losses (Rupasingha and Goetz, 2013). This dissertation provides important contextual information regarding the rising importance of NFP employment. Based on BEA data, the U.S. saw an increase in NFP jobs from 13.8 million in 1980 to 45.6 million in 2019. NFP employment is an important area of inquiry; however, relatively little is known about this area of job creation in generating jobs or where those counties with highest shares of NFP employment are located.

In this dissertation study, NFP employment is used as a proxy for entrepreneurship and self-employment. Data for all three articles in this dissertation were obtained from the U.S. Census Bureau's American Community Survey and the Bureau of Economic Analysis (BEA) by county and subject to stepwise linear regressions. NFP employment data were analyzed to gain a better understanding of what shapes the spatial distribution of NFP employment by each of the three county typologies. Each article of this dissertation aims to identify those counties, at each county typology (i.e., most populated counties, micropolitan counties, and outlying metropolitan counties), that are most likely to demonstrate disproportionately high shares of NFP entrepreneurs or self-employed people, relative to those places with fewer such workers. In addition to identifying those counties exhibiting high shares of NFP workers, key socio-economic and demographic variables, outside the traditional entrepreneurial ecosystem, will be identified to best explain why certain counties generate high shares of NFP employment at each respective county scale. Furthermore, article one seeks to shed light on the extent that types of entrepreneurship (i.e., opportunity or necessity) may play on the uneven growth of self-employment at the more populated counties. Article two focuses on micropolitan counties, those places between the more urban and the more rural, classified by the Office of Management and Budget (OMB) as central counties with urban clusters of at least 10,000 but less than 50,000 (Helmer, 2008), and it will be argued that these causal variables are unique to this scale of analysis. The final paper of this dissertation extends the area of investigation by metropolitan counties and takes a more disaggregated look at outlying metropolitan counties. In this paper the extent to which outlying metropolitan counties with highest shares of NFP workers are linked through commute to their adjacent central and more urbanized core counties is discussed. Additionally, this dissertation study hopes to provide policy guidance for local communities looking for a better way forward in planning and economic development, by incorporating a geographical perspective in their analysis.

CHAPTER II: NON-FARM PROPRIETORSHIP EMPLOYMENT BY U.S. COUNTY

Introduction

Entrepreneurship and self-employment are increasingly recognized as crucial sources for generating jobs and contributing to economic growth, but frequently it can be a spatially uneven process (Henderson and Weiler 2010; Shrestha, Goetz, and Rupasingha 2007; Ács and Armington 2004). Some places create more entrepreneurial jobs and are more economically viable than others. Stam (2009) has argued that the creation of new products and services are “created somewhere” and are unevenly distributed over space because they are subject to different rates of diffusion. Understanding the geography of entrepreneurship has been put forward as crucial, as the proportion of workers employed as non-farm proprietors is increasing at a faster rate than conventional wage and salary workers (Debbage and Bowen 2018; Shrestha, et al., 2007). Mack (2016) has suggested that a better understanding of the distribution of the people and factors that promote entrepreneurship would aid in understanding why some places are more entrepreneurial than others.

Previous works have principally focused on the demographic characteristics and culture of the individual entrepreneur (Anggadwita et al., 2017; Lofstrom, 2017; Ramadani et al., 2017; Beladi and Kar, 2015; Lin, 2010; Baycan-Levent and Nijkamp, 2009; Kanas, van Tubergen and van der Lippe, 2009; Harvey, 2008) rather than the geographical distribution of entrepreneurship as a whole. For some U.S. counties, access to capital, culture and technology may represent entrepreneurial opportunity. In other counties, home-grown self-employment may be the only viable economic option, a strategy of last resort due to a stagnant local economy and/or lack of opportunities. In a case study of the Roanoke-Blacksburg region in the state of Virginia, differing types of entrepreneurship (high-growth firms, and main street and lifestyle businesses) and their specific growth-related requirements were revealed (Cowell et al., 2018). Fritsch and Wyrwich (2016) considered whether the existence of a persistent regional entrepreneurship culture is a possible consequence of both entrepreneurial role models and the diffusion of positive entrepreneurial attitudes in relation to different types of entrepreneurship–a so-called entrepreneurship of opportunity and entrepreneurship of necessity. The interplay of certain key human capital metrics (e.g. knowledge, skills, social connections) and broader socio-economic predictors (e.g. access to capital, incubators, maker spaces, other supporting services, environmental amenities) spatially vary and can create different entrepreneurial environments and opportunities. These entrepreneurial environments are ground zero for possible success and progressive economic growth in any community.

Here we use non-farm proprietorship (NFP) as a proxy for entrepreneurship and self-employment. Proprietorship data are widely used in entrepreneurial research (Debbage and Bowen, 2018; Rupasingha and Goetz, 2013; Goetz and Rupasingha, 2009; Shrestha, Goetz, and Rupasingha, 2007). NFP data were collected from the U.S. Bureau of Economic Analysis.

Although it has been argued, that the capturing of entrepreneurial opportunities by individuals is a key part of the entrepreneurial process and dependent on “the interaction between the individual attributes and the surrounding environment” (Stam, 2009, p. 2), this paper adds to this area of research by highlighting potential predictor variables of entrepreneurship at the county scale. We posit that the “spatial-conditionality” features of the broader community environment in a specific location can: (1) substantively affect the relationship between percent NFP employment and certain key predictors (Breitenecker and Harms, 2010); and (2) help generate a better understanding of why some areas are more entrepreneurial than others and thus exhibit a strong geographical component.

Regions and Spatial Attributes

Although there is no uniformity in the definition of entrepreneurship (Backman and Loof, 2015), it has been broadly associated with risk taking, profits, and economic growth. Entrepreneurship broadly defined has been a driving force of economic development though its effects have been spatially uneven (Debbage and Bowen, 2018, Mack, 2016, Goetz and Rupasingha, 2009). While past studies have yielded some important insights into entrepreneurship, unfortunately, little research has addressed the actual geography of entrepreneurship. Mack (2016, p.3) has argued that “only a very small portion of this literature examines geography as a fundamental factor in the distribution of the people and factors that promote entrepreneurship” and that much more research is needed for a better understanding of the spatial attributes “of the actors, factors, and processes that foster entrepreneurship” (p. 3). According to Mack (2016), more research is needed in the area of the entrepreneurial ecosystem, and the geographer’s tools and techniques are ideally structured to produce “comparative work,” and “research that evaluates the variability in ecosystem components over space and time.”

Within some entrepreneurial ecosystems local communities frequently lack the knowledge and needed resources to achieve success in their businesses. Cowell et al. (2018) found that there was a significant knowledge and service gap among some populations, such as minorities and those in rural areas. In this paper, we believe that the distinct attributes of each county's entrepreneurial patterns should be considered and studied to develop a better comprehension of the support systems available to entrepreneurs.

Although much of the research on the geography of entrepreneurial ecosystems is still relatively nascent, it is still crucial that we better understand why some U.S. counties generate more entrepreneurial opportunities than others. Doing so can help local communities to establish a sustainable entrepreneurial culture that can create a competitive local economy over the long term. In this paper, we focus on the broader contextual environment of the entrepreneurial ecosystem with the belief that such a perspective can inform how entrepreneurs respond to the opportunities (or lack of) they discover or co-create in an ecosystem. The term entrepreneurial ecosystems have gained increasing attention in the business literature particularly because of Feld's (2012) *Startup Communities: Building an Entrepreneurial Ecosystem in Your City,* but also due to more traditional academic research (e.g., Ács *et al.,* 2014; Audretsch and Belitski, 2017; and Spigel, 2017). Much of this literature has focused on the inner workings and detailed structure of the entrepreneurial ecosystem (e.g., firms, venture capitalists, banks, public sector agencies) and the related knowledge-spillovers that have triggered innovation and venture creation. However, as Liguori *et al.* (2018, p.87) have argued "entrepreneurial ecosystems have boundaries owing to the fact that ecosystems are tied to geography." Such a viewpoint supports the work of Florida *et al.* (2017) who argued that local communities are at the very heart of processes of innovation, entrepreneurship and creativity. In this paper, the main focus is understanding the external business environment that drives NFP employment differentials by U.S. county because pressures beyond the boundaries of the firm can contribute to a firm's success or failure. The urgency of this issue is well illustrated by the number of special issues recently published by business journals on entrepreneurial ecosystems including most recently in 2018 by the *Journal of Enterprising Communities.*

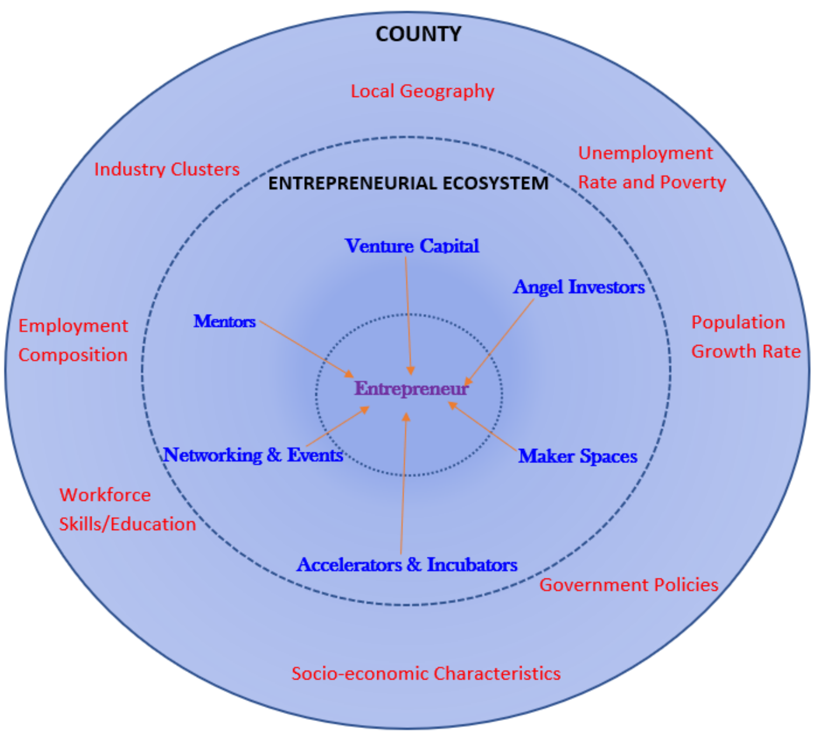
The literature already shows that at the MSA level, certain attributes are linked disproportionately to regions with high shares of entrepreneurs. Debbage and Bowen (2018) found that certain predictor variables played a key supporting role in shaping the disproportionate representation of shares of non-farm proprietors in certain metropolitan areas. Their findings indicated that the main predictor variables included a high percent of employment in finance, insurance and real estate (FIRE), percent Hispanic, median age, and median home value (MHV).

Even though the geography of entrepreneurship is considered complex (Backman and Loof, 2015), varying in strength through time, and dependent on specific variables (Debbage and Bowen, 2018), it has been shown to be a positive for economic growth where proprietors not only create new jobs for themselves, but also to the benefit of others (Goetz and Rupasingha, 2009), while positively affecting neighboring regions economically. Goetz and Rupasingha (2009), expressed that, "while proprietors cannot be equated with entrepreneurs per se, they arguably have more in common with this group than with wage-and-salary workers…" (p. 426) and are more willing to take on the risk of self-employment.

Family entrepreneurships share some similarities with those of sole proprietorships/non-family firms. According to Ratten et al. (2017), "the founders of a family business are often the most entrepreneurial" (p. 153) and even though the governance and management structures may differ, both types of firms do face decisions involving risk. Ramadani et al. (2017) in their qualitative research, presented six cases of women entrepreneurs in Kosovo who faced economic challenges, and out of necessity, were motivated in starting their businesses that would eventually include additional members of their family. Others have explored the role of race and ethnicity in shaping local entrepreneurial ecosystems. Fisher and Lewin (2018) found that a main reason Hispanics in the U.S. choose to be entrepreneurs or self-employed is because they can earn more being self-employed than through wage and salary work, which commonly offer more limited opportunities. They also found that certain groups of Hispanics, with high human capital (e.g., workers from Columbia and Southern South America) were pulled into self-employment because of non-monetary benefits such as a flexible work schedule and greater work autonomy, while others were pushed because of limited opportunities in the wage and salary sector.

Overall, it has been argued that entrepreneurs are not just individuals who are free to innovate and take risk, but that they also operate within complex ecosystems (Stam, 2009) that may substantially influence outcomes in both positive and negative ways. Spigel (2017) posits that, "ecosystems are defined by the connections between the attributes that produce them and the benefits they provide to the entrepreneurs," and that these "benefits and relationships can differ between regions" (p. 66). The entrepreneur at the center of this ecosystem can be influenced by several variables both within the entrepreneurial ecosystem itself and in the broader environment. In Figure 1, the key attributes of the entrepreneurial eco-system (such as maker spaces, accelerators and mentors) are more likely to directly impact individual entrepreneurs although the broader socio-economic climate of any given place can pre-determine outcomes. Consequently, these complex entrepreneurial ecosystems possess attributes that do not exist in singular of themselves, but rather play an influential role in helping to develop the other (Spigel, 2017) and as such may encourage and influence the individual entrepreneur. Curran (2010) supported the notion that there is a local embeddedness of networks in most entrepreneurial ecosystems and that they are situated in a broader culture and community (e.g., city, county, metropolitan area). These more broadly-based geographic employment clusters or talent pools can facilitate the broader exchange of knowledge and skillsets that can effectively either nurture or stymie innovation. In this paper, we focus on these broader socio-economic predictors rather than the detailed inner workings of the specific entrepreneurial ecosystem per se since county-wide labor pools and the broader composition of the local economy can substantially pre-determine the outcomes of any given ecosystem.

Figure 1. The County-Wide Ecosystem of the Entrepreneur



Research Design

Data were collected from the 2016 US Census Bureau: American Community Survey (ACS) and the Bureau of Economic Analysis (BEA). The data were obtained for counties in the contiguous United States and the District of Columbia and included only those counties with a population of 65,000 plus, as reported by the ACS annual survey. The special combination counties of Virginia were not included in the data set, since the BEA data matched poorly with the ACS counties. Additionally, the nondisclosure rule of the US Census limited data when a business' data values may be presumed due to a low number of observations. The final sample contained exactly 800 counties.

As previously stated, NFP is being used here as a proxy for entrepreneurship and self-employment. We used the Internal Revenue Service (IRS) definition of non-farm proprietorship, which stated that:

> A sole proprietorship is an unincorporated business that is owned by one individual who is required to file Schedule C (Form 1040) for profit or loss from a business. A partnership is the relationship existing between two or more persons who join to carry on a trade or business. A partnership must file an annual information return to report the income, deductions, gains, losses, etc., from its operations, on Form 1065 (U.S. Return of Partnership Income). Organized for profit, unincorporated, full and part-time sole proprietorships, partnerships, and other private nonfarm businesses are non-farm proprietorships (IRS, 2020).

Others (Cowell et al., 2018; Debbage and Bowen, 2018; Fisher and Lewin, 2018; Anggadwita et al., 2017; Ramadani et al., 2017; Goetz and Rupasingha, 2009) have contributed qualitative and quantitative research to the entrepreneurial literature. Our study helps to fill a gap by conducting quantitative research at the county level. In order to identify potential variables that would influence the shares of NFP employment by county, a combination of 31 independent variables were selected from the U.S. Census and the BEA based on the existing literature. The key predictors in the literature included median age, percent construction employment, race/ethnicity, unemployment rate, percent Hispanic, per capita income, and percent real estate and rental and leasing (RRL) employment, among others (Table 1).

Table 1. Dependent and Independent Variables and Descriptive Statistics

Variables	Mean	SD
% NFP employment [a]	21.2	5.5
Demographic [b]		
PGR 2015-2016	0.6	1.1
Median age (years)	38.7	4.7
%White	78.9	14.7
%Black	11.1	12.6
%Asian	3.3	3.9
%Hispanic	12.5	14.1
%Male	49.3	1.2
%Ffemale	50.7	1.2
% 65 years and older	15.8	4.2
% of population 25 years or older with only a high school diploma	28.9	6.7
% of population 25 years of age or older with a bachelor's degree or higher	29.1	10.3
% of households with broadband	84.8	6.3
Economic [b]		
Per capita income ($)	29,637	7,105
Median earnings ($)	31,844	6,632
Median household income ($)	57,754	15,087
Poverty rate (%)	13.9	5.3
Unemployment rate	5.8	2.1
% Housing stock, owner-occupied	66.4	9.0
Median home value ($)	203,797	116,885
Employment [a]		
% Construction	5.8	1.9
% Manufacturing	8.2	5.3
% Retail	11.1	1.9
% Information	1.3	0.8
% Finance and Insurance	4.4	2.2
% Real Estate, Rental and Leasing (RRL)	4.2	1.3
% Finance Insurance & Real Estate (FIRE)	8.6	2.8
% Education	2.0	1.4
% Health services	11.5	3.4
% Professional and Business Services	5.5	2.7
% Arts, Entertainment, and Recreation	2.1	0.9
% Accommodation and Food Services	7.7	1.9

Sources: [a] US Department of Commerce, BEA; [b] US Census Bureau: American Community Survey by county

A two-tailed Pearson correlation analysis was completed using all the variables to assess whether statistically significant relationships existed between NFP and each independent variable to reduce the potential for collinearity. Linear regression was then performed using a stepwise procedure to identify the most powerful predictors of NFP among the remaining independent variables.

Results and Discussion

Trends and Context

One of the most under-researched and least-studied labor market trends during the past three decades has been the ever-increasing growth of non-farm proprietorship jobs in the USA. The number of NFP workers more than tripled between 1979 and 2016 from 13.2 to 41.6 million. Furthermore, most of these jobs are geographically concentrated in metropolitan labor pools which account for approximately 90 per cent of all such workers (Debbage and Bowen, 2018). NFP employment growth has been triggered by several factors (e.g., deindustrialization, the rise of self-employment, and the emergence of scalable information technology). Less clear is which specific predictors best explain the geography of NFP at the county scale and whether this growth in self-employment is in response to opportunity or the result of necessity (such as layoffs).

The Geography of the Leading NFP Counties

In absolute terms, the largest NFP labor markets by county included Los Angeles County, CA (1.7 million workers), Cook County, IL (755,645 workers) and Harris County, TX (659,599 workers). Although the largest NFP markets by county tended to match the rank hierarchy of the most populated and largest employment labor pools in the nation, the geography of NFP employment was shaped by more than just critical mass. Nearly half of the 25 largest NFP labor pools by county were in either California (seven) or Texas (five) particularly in places with disproportionately large Hispanic populations including Los Angeles County, CA (48.5% Hispanic), San Bernardino County, CA (52.8%) and Bexar County, TX (59.9%).

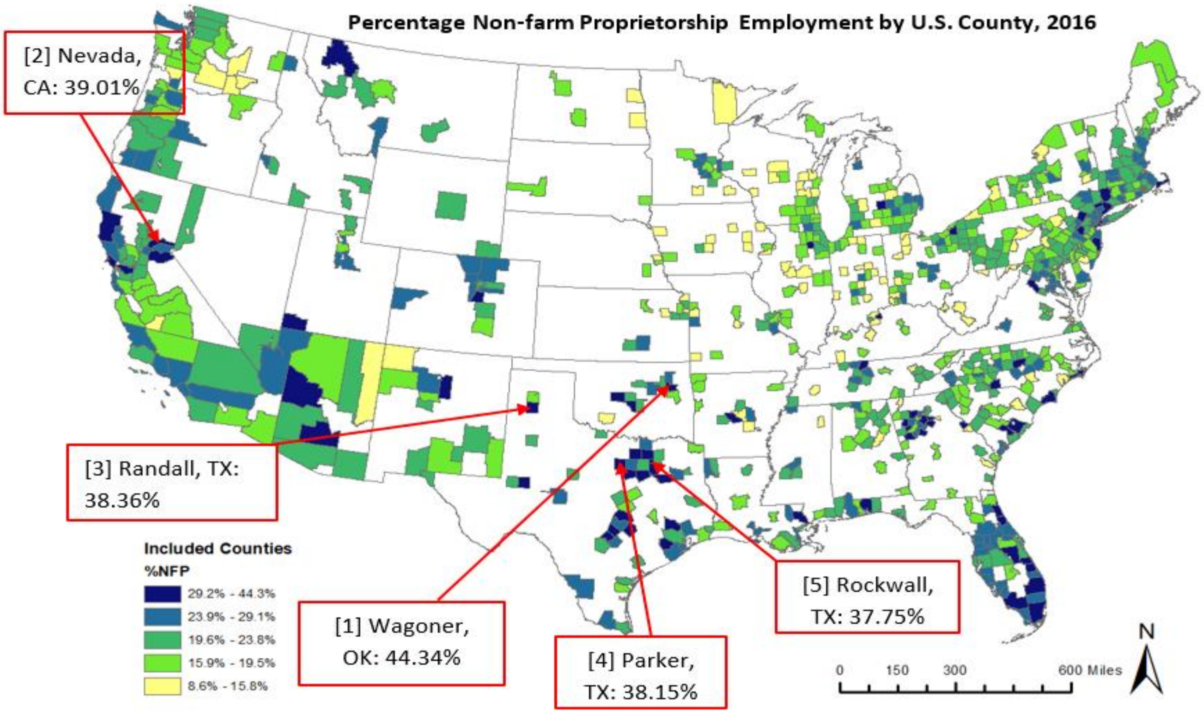
Furthermore, the relative geography of NFP employment suggested a radically different spatial outcome (Table 2 and Figure 2). In 2016, the percent share of NFP workers by county varied from a high of 44.3% in Wagoner County, OK to a low of 8.6% in Christian County, KY, with a mean of 21.2%

across all 800 counties included in this analysis. The top 25 counties with the highest relative NFP employment averaged a 35.6% share–nearly 15 percentage points higher than the overall average of 21.2% - although they tended to be much smaller counties in terms of total employment.

Table 2. Top 25 Counties Ranked by % NFP Employment 2016

Counties	NFP Employment	Total Employment	% NFP Employment
Wagoner County, OK	8,785	19,814	44.3
Nevada County, CA	21,272	54,524	39.0
Randall County, TX	21,055	54,890	38.4
Parker County, TX	23,577	61,804	38.2
Rockwall County, TX	18,402	48,745	37.8
Fort Bend County, TX	111,340	300,226	37.1
Marin County, CA	72,141	195,892	36.8
Cherokee County, GA	35,755	97,541	36.7
Newton County, GA	14,728	40,460	36.4
Paulding County, GA	14,329	39,736	36.1
Christian County, MO	11,067	30,698	36.1
Flagler County, FL	13,445	38,011	35.4
Henderson County, TX	10,812	30,720	35.2
Midland County, TX	4,8095	137,182	35.1
Denton County, TX	129,836	377,934	34.4
Henry County, GA	3,1363	92,791	33.8
Putnam County, NY	14,049	41,600	33.8
Canadian County, OK	18,031	53,768	33.5
Bastrop County, TX	10,328	30,801	33.5
Oldham County, KY	8,646	25,825	33.5
Chatham County, NC	8,347	24,939	33.5
Brunswick County, NC	16,711	50,184	33.3
El Dorado County, CA	29,397	88,419	33.3
Kings County, NY	359,141	1,081,888	33.2
Douglas County, CO	61,387	186,286	33.0
Top 25 Average	44,482	128,187	35.6
N=800 Average	44,470	207,779	21.2

Figure 2. Non-Farm Proprietorship Employment (%) by County, 2016

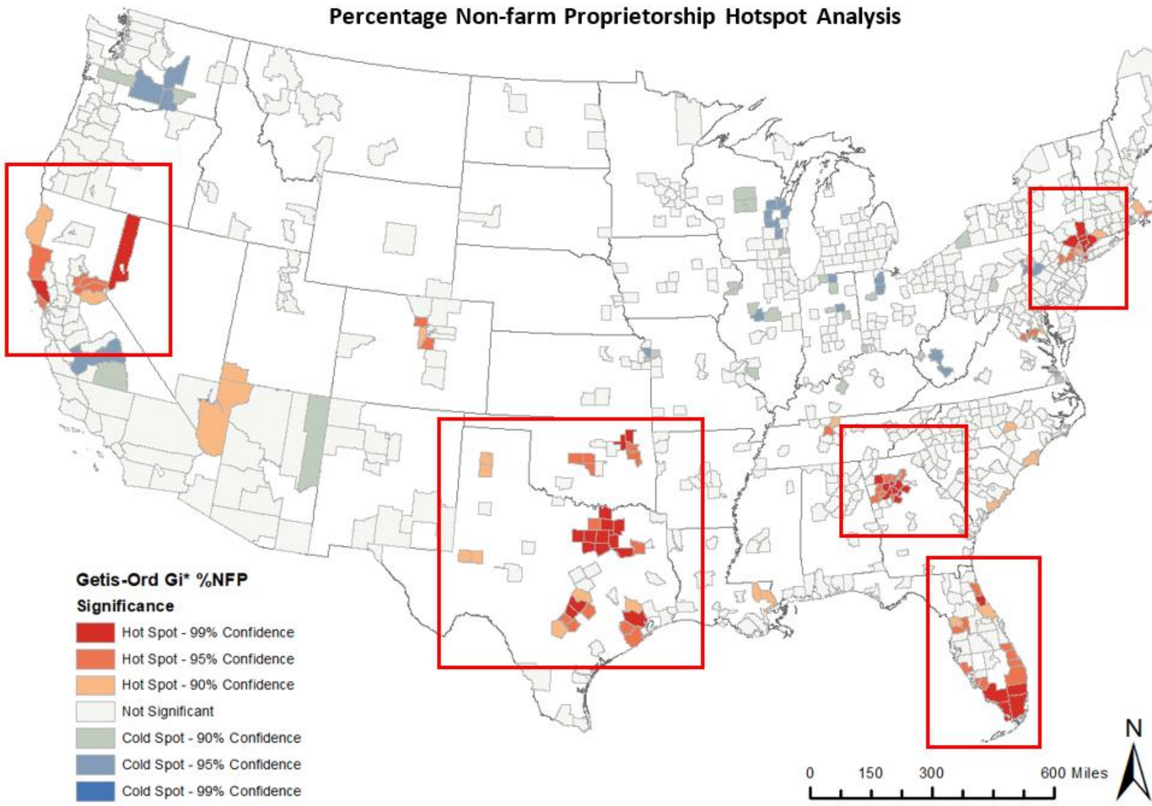


Ten of the top 25 counties in terms of percent NFP employment were in either Texas or Oklahoma. Many of these counties were small labor pools in absolute terms with disproportionately large Hispanic populations where barriers to entry were low, and fewer business regulations existed. Texas featured prominently with four of the top six highest percentage NFP counties including Randall County (38.4), Parker County (38.2), Rockwall County (37.8), and Fort Bend (37.1) although these were all relatively small labor pools with only Fort Bend County generating more than 24,000 NFP workers. Although most of the high ranking counties in terms of the relative share of NFP workers tended to be fairly small counties in absolute terms, one exception to this rule was Kings County, New York (i.e., Brooklyn) which generated the 24th highest share of NFP jobs at 33.2%, but was also substantive in absolute terms ranking 10th in terms of the total number of NFP workers (359,141) – a point to which we shall return later in this paper.

To identify clusters or *hotspots* of counties with especially high or low shares of NFP workers, and to assess quantitatively the strength of the observed relationship, a Getis-Ord Gi* statistic was performed (Figure 3). The statistic revealed that, in 2016, there existed five clusters of counties with NFP workers including some of the counties in the Atlanta and New York metropolitan area, south Florida, the south-central region of East Texas (e.g., Dallas, Houston and San Antonio) and East Oklahoma (e.g. the Tulsa area), and the northern California/Reno NV region. Most of the counties included in these clusters scored at the 95 to 99 percent confidence level in the Getis-Ord analysis indicating that the clusters are robust with less than a five percent probability ($p<0.05$) of occurring by random chance alone.

The results of this analysis confirmed that the distribution of entrepreneurship was highly uneven as proposed in previous studies (Mack, 2016; Stam, 2009). A majority of the counties that featured prominently in the five hotspots with disproportionate shares of NFP workers could be characterized as : 1) urban core counties (e.g., King County/Brooklyn, NY – 33.2%; and Miami/Dade, FL – 31.1%); 2) highly affluent bedroom suburbs of a major urban area (e.g., Marin County, CA – 36.8%, located north of San Francisco; and Rockwall County, TX – 37.5%, located to the east of Dallas), or 3) sparsely populated and/or poor communities (e.g., Wagoner County, OK – 44.3%; and Mendocino County, CA – 29.3%). Counties capable of generating disproportionate shares of NFP workers can be situated in a wide variety of socio-economic contexts. The implication is that any explanation of the underlying geography of entrepreneurship is unlikely to be straightforward.

Figure 3. Hot Spot Analysis of Percent Non-Farm Proprietorship Employment by Getis-Ord by Gi* by County, 2016



One of the uncommon urban county settings for NFP workers is Kings County/Brooklyn, NY, the only county in the dataset to rank in the top 25 for both absolute (10th) and relative (24th) NFP employment. According to the Office of the New York State Comptroller (2018), Brooklyn accounted for 24% of all private sector jobs created in New York City (NYC) between 2009 and 2017 and this increase was the greatest of all NYC's boroughs for that time period. More specifically, the NFP employment growth in Kings County was just over 100,000 from 2009-2017 (US BEA, 2009 and 2017), and eight neighborhoods in Brooklyn experienced private sector employment growth rates over 40% during this period (Office of the New York State Comptroller, 2018) including Borough Park (72%), Flatbush (68%), Williamsburg/Greenpoint (44%) and Bay Ridge (44). According to Curran (2010), against all odds, Kings County "small-scale manufacturers stay in neighborhoods such as Williamsburg through a combination of force of will, business and personal networks, flexibility and the need for a New York location" and Curran (2010) also suggested that place matters to the success of urban economies.

A recent report by the Center for an Urban Future (2019) indicated that of all the major tech hubs in the US, Brooklyn's start-up growth rate since 2008 was second only to San Francisco and they also argued that:

> Brooklyn is one of just a handful of regions across the country to capture a significant share of the growth occurring in the innovation economy – a set of industries fueled by technology, creativity, and invention that is driving much of the nation's high wage job gains. (Center for an Urban Future, 2019)

Much of this growth has been focused in downtown Brooklyn, the Dumbo Improvement District and the Brooklyn Navy Yard along with other emerging clusters including the creative campus of Industry City in Sunset Park. Most of the start-ups have been in media entertainment, commerce and shopping, financial services, and data and analytics. However, many of the other counties listed with a disproportionate share of NFP workers (Table 2) tended to be smaller markets with a wide variety of attributes, suggesting that the Kings County experience may not be operative for the broader spectrum of entrepreneurship ecosystems featured across the 800 counties analyzed in this paper.

Regression Analysis

Consequently, a stepwise linear regression analysis was performed to assess quantitively the potential relationships that might exist between NFP and select socio-economic variables by county. Diagnostic tests indicated that the regression models exhibited low multicollinearity among the independent variables and met the assumptions of linearity, normality and homoscedasticity. All models and independent variables were significant at the $p < 0.01$ level.

In the final regression model for 2016 (i.e., Model 4, Table 3), 60.0 percent of the variation in the percentage of NFP employment by county was accounted for by the percentage of the labor pool employed in both Real Estate and Rental and Leasing employment and Construction employment as well as percent Hispanic and Median Age. Debbage and Bowen (2018) found broadly similar results when examining the geography of NFP by metropolitan area.

Table 3. Regression Models Indicating Associations Between Socio-Economic Variables and NFP Employment (%) by County, 2016

Model	Variable	Model R^2	Unstandardized Coefficients b	Std. Error SE b	Standardized Coefficients β	p-value
1	Constant	.45	9.376	.527		<0.01
	% RRL		2.729	.117	.669	<0.01
2	Constant	.57	5.104	.556		<0.01
	% RRL		2.278	.108	.559	<0.01
	% Cons		1.095	.078	.370	<0.01
3	Constant	.58	4.652	.558		<0.01
	% RRL		2.256	.107	.553	<0.01
	% Cons		1.100	.077	.371	<0.01
	Hisp		.042	.009	.110	<0.01
4	Constant	.60	-.995	1.173		.397
	% RRL		2.128	.107	.522	<0.01
	% Cons		1.034	.077	.349	<0.01
	% Hisp		.059	.010	.155	<0.01
	Med age		.165	.030	.146	<0.01

Percent Real Estate and Rental and Leasing Employment As indicated by the variable's *b* coefficient, the relationship between percentage of real estate, rental and leasing (%RRL) employment and NFP is such that a 1 percent increase in the percentage of RRL employment is expected to result in a 2.1 increase in the percentage of NFP employment. The counties with the highest % RRL included Collier County, FL (9.33%), Cape May County, NJ (9.23%), Ocean County, NJ (8.88%), Horry County, SC (8.46%) and Flagler County, FL (8.43%) (Figure 4). By contrast, the average %RRL employment for all 800 counties was just 4.2%. Although many of the most highly concentrated RRL labor pools were frequently located in coastal, amenity-rich tourism-based county economies, the Getis-Ord Gi* analysis identified six RRL clusters (Figure 5). Three of these clusters seemed to mimic, in part, the geography of NFP (Figure 2) including the RRL clusters in South Florida, the New York metropolitan area and the northern California/Reno, NV region.

Figure 4. Real Estate and Rental and Leasing Employment (%) by County, 2016

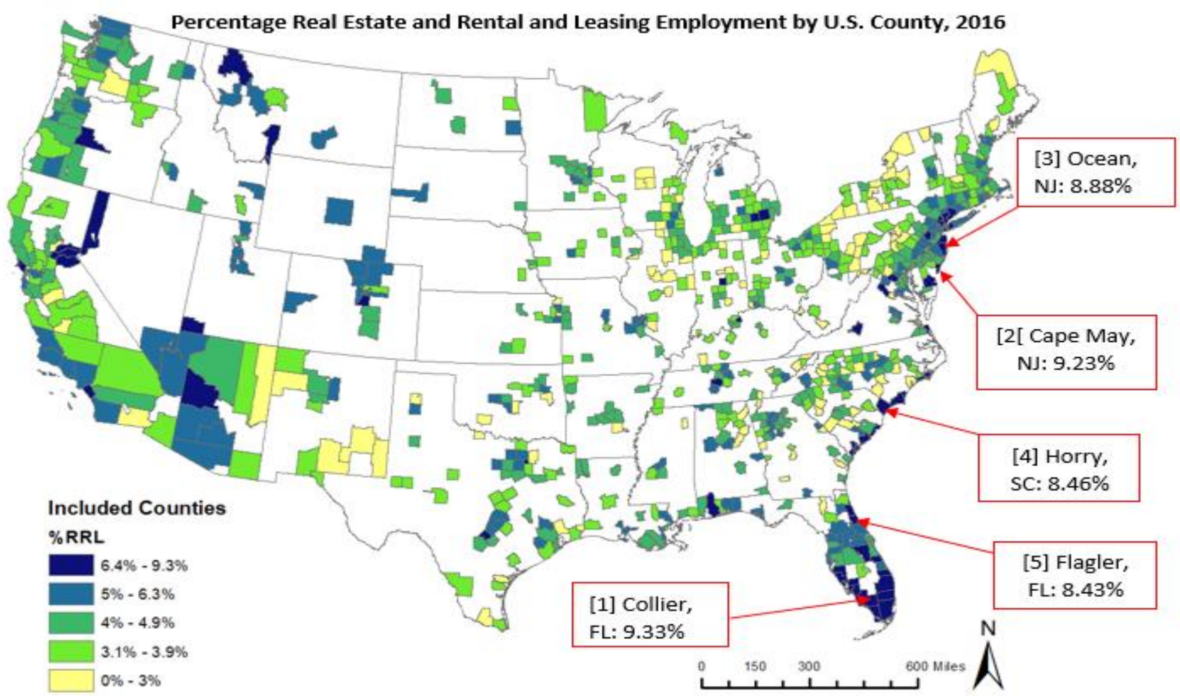
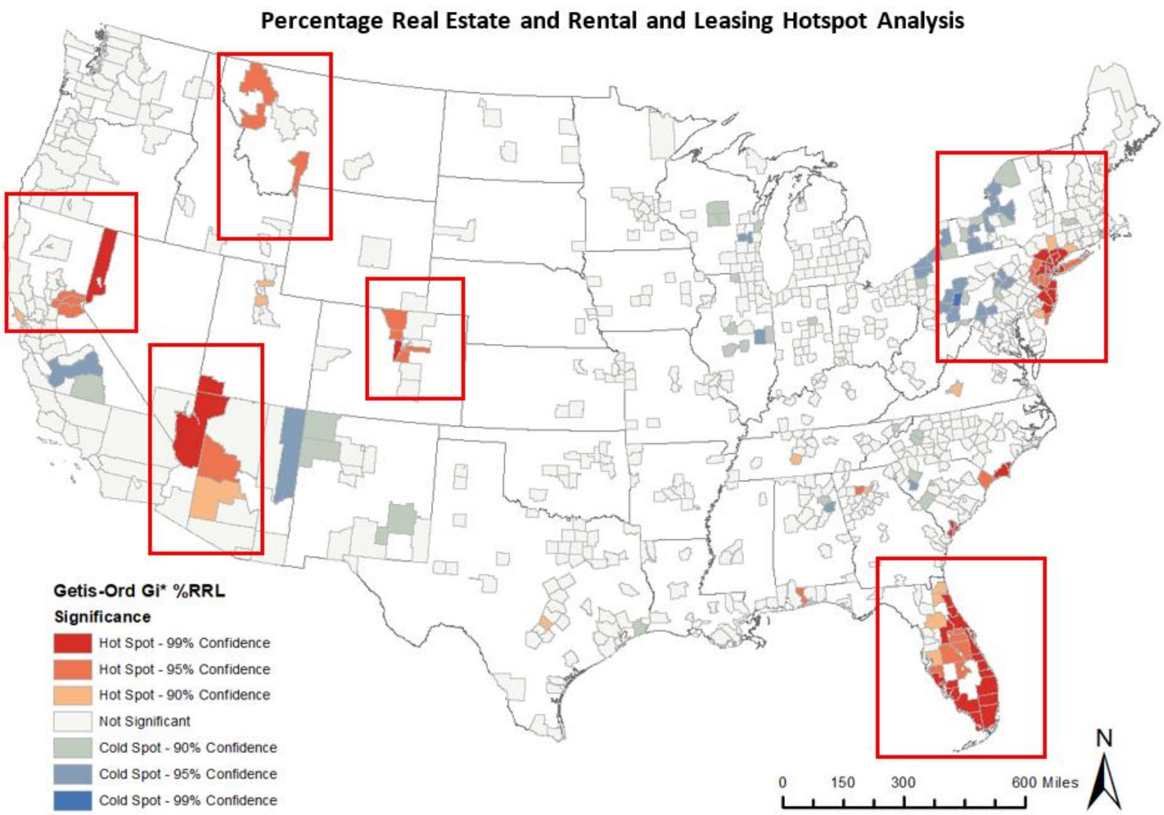


Figure 5. Hot Spot Analysis of Percent Real Estate and Leasing Employment by Getis-Ord Gi* by County, 2016



Research by Rupasingha and Goetz (2013) and Debbage and Bowen (2018) has suggested that places with a disproportionate share of workers in finance, insurance and real estate (% FIRE) tended to be more likely to attract large shares of NFP workers. They both argued that % FIRE acted as a proxy for access to loan capital and other financial services which, in turn, can enhance the growth of self-employment rates particularly given the crucial need to access capital when beginning a business.

However, we found that it was % RRL – a sub-category of FIRE – that featured prominently in the final regression model suggesting that any explanation may need to be more nuanced. RRL includes establishments that rent or lease their own assets to others (e.g., car rental companies and parts of the sharing economy), as well as establishments engaged in managing real estate and operating real estate investment trusts. The suggestion here is that % RRL may be a proxy for access to a particular type of capital, one that is tied up in vibrant land markets particularly in places with urban and tourism-related economies. In Kings County/Brooklyn, it has been suggested that a key contributor to the boom in self-employment has been the emergence of a significant number of start-ups specializing in proptech – digital technology that aides in the management, selling, renovating, buying or renting of real estate property through, for example, apps, electronic keys, smart homes and other buildings, and online financing (Dvorkin, 2019). Although more research is needed before definitive explanations can be offered, the dominance of the % RRL variable in the regression models was clear in Models 1-4 in Table 3 and in the high standardized coefficient scores.

Percent Construction Employment The regression analyses not only identified RRL as a key predictor in shaping the geography of NFP by county but also highlighted the important role that construction jobs can play in shaping the spatial distribution of NFP workers. The unstandardized regression coefficient suggests that if the percent of construction workers increased by one percent, then the share of NFP employment would increase by 1.03 percent. The counties with the highest percent of their labor pools in construction employment included San Patricio County, TX (17.3%), Ascension Parish, LA (16.3%), Calvert County, MD (14.7%), Walton County, GA (13.2%) and Brazoria County, TX (12.8%) compared to an average for all 800 counties of just 5.75% (Figure 6). After the Great Recession of 2008/9, many construction markets rebounded across the United States providing numerous self-employment opportunities. Goetz and Rupasingha (2009, p.435) have found that "many construction workers are self-employed, and this trend seems to be increasing over time." The Getis-Ord Gi* analysis identified five clusters of construction workers which included counties located in eastern Texas (Dallas, Houston and San Antonio areas), eastern Oklahoma (Tulsa area), and in the Atlanta metropolitan area (Figure 7) which matched well with the geography of NFP by county (Figures 2 and 3).

Figure 6. Construction Employment (%) by County, 2016

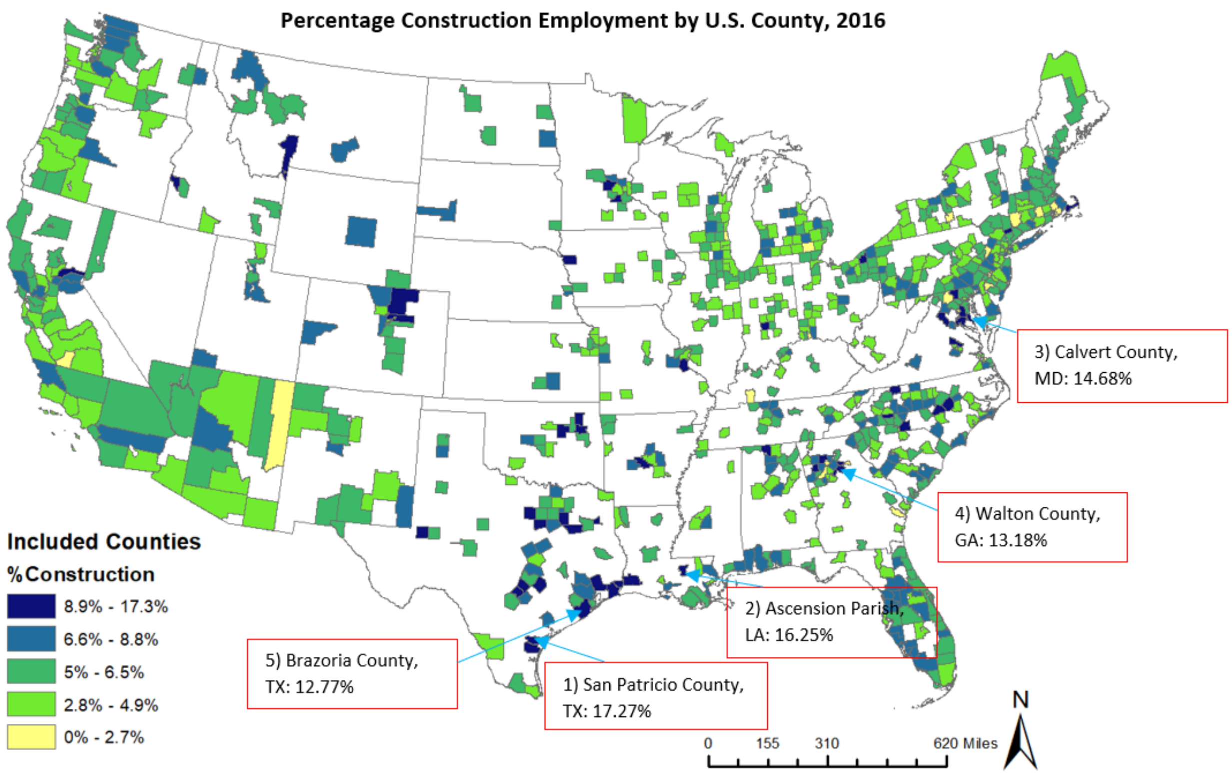
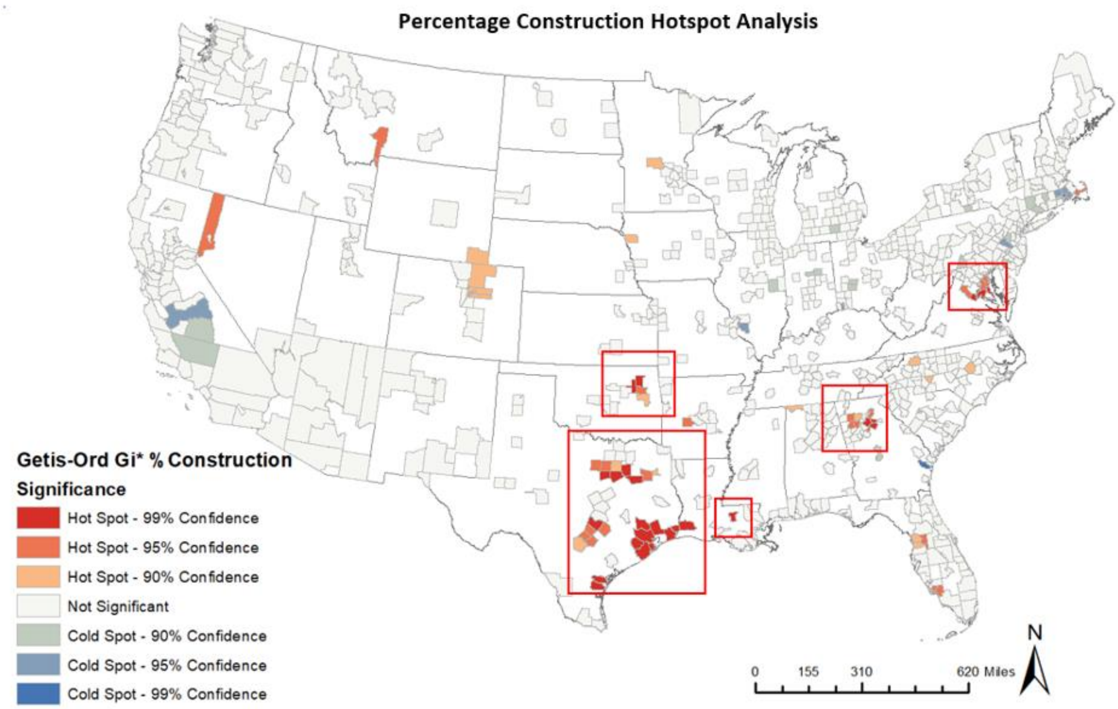


Figure 7. Hot Spot Analysis of Percent Construction Employment by Getis-Ord Gi* by County, 2016



In 2016, the most active industrial construction markets during the first quarter in the United States included Dallas (#1) (in terms of square footage), Atlanta (#4) and Houston (#6) (Statista.com, 2017). Similar trends applied in the office and residential construction markets. The skilled labor shortages that plagued construction companies during the post-recession growth years provided new entrepreneurial opportunities. Non-farm proprietorships and partnerships were established during this time to provide "just-in-time" construction work crews during peak demand. It should also be noted that the construction employment hotspots identified in Figure 7 complement rather than duplicate those identified for RRL (Figure 5) suggesting additional explanatory power as it relates to the regression analysis.

Percent Hispanic The third variable to enter the final regression model (Table 3 and Model 4) was the percentage of the population classified as Hispanic suggesting that the spatial variation of NFP jobs by county is also influenced by race and ethnicity. The unstandardized regression coefficient indicated that if the percentage of the population that is classified as Hispanic increased by one percentage point, then the share of the labor pool in NFP by county increased by 0.06 percent. Although this is a modest change, in recent years, the number of Hispanic entrepreneurs in America has grown exponentially. Between 2007 and 2012, the growth rate of both non-employer and employer Latino firms nearly outpaced the growth rate of white, Asian and black-owned firms combined (Orozco *et al.*, 2017). In 2016, the counties with the highest percentage Hispanic included Webb County, TX (95.5%), Hidalgo County, TX (91.8%), Cameron County, TX (89.4%), Imperial County, CA (83.7%), and El Paso County, TX (82.2%) (Figure 8) compared to an average of just 11.8% for all 800 counties. Not surprisingly the Getis-Ord Gi* analysis identified three substantive Hispanic clusters in the southwestern United States in California and Texas but also identified more geographically confined clusters in south Florida, New York and the Pacific Northwest (Figure 9).

Figure 8. Hispanic (%) by County, 2016

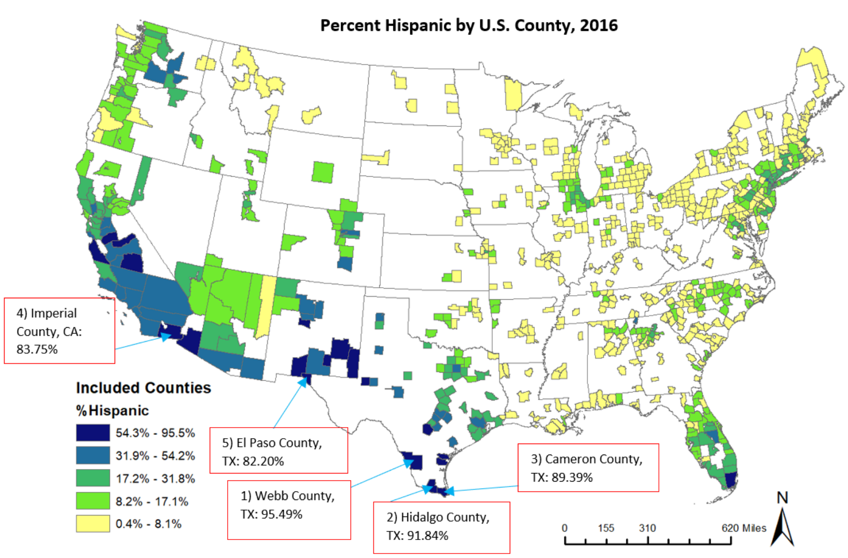
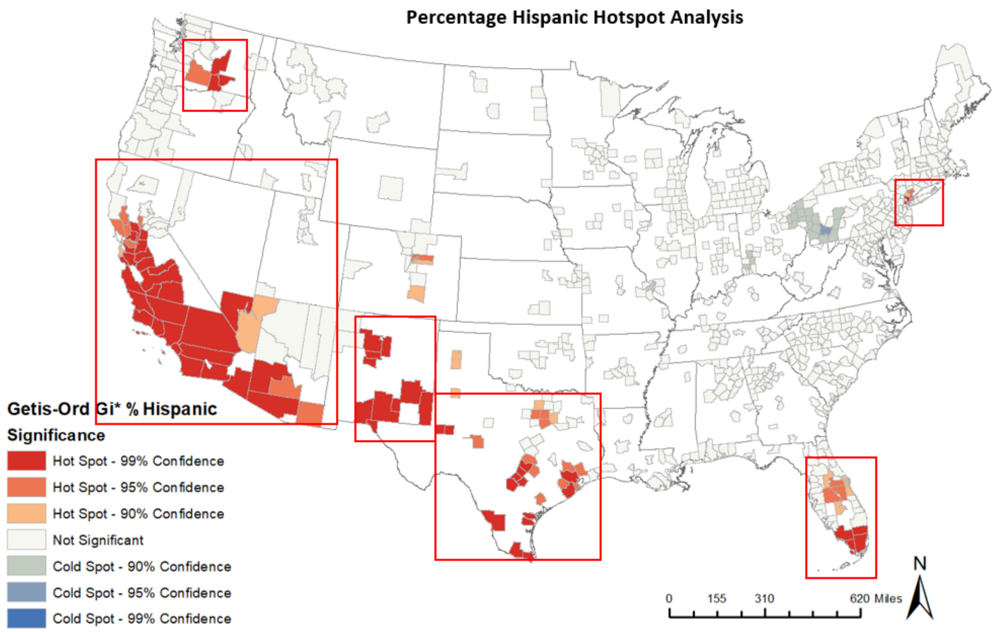


Figure 9. Hot Spot Analysis of Percent Hispanic Getis-Ord Gi* by County, 2016



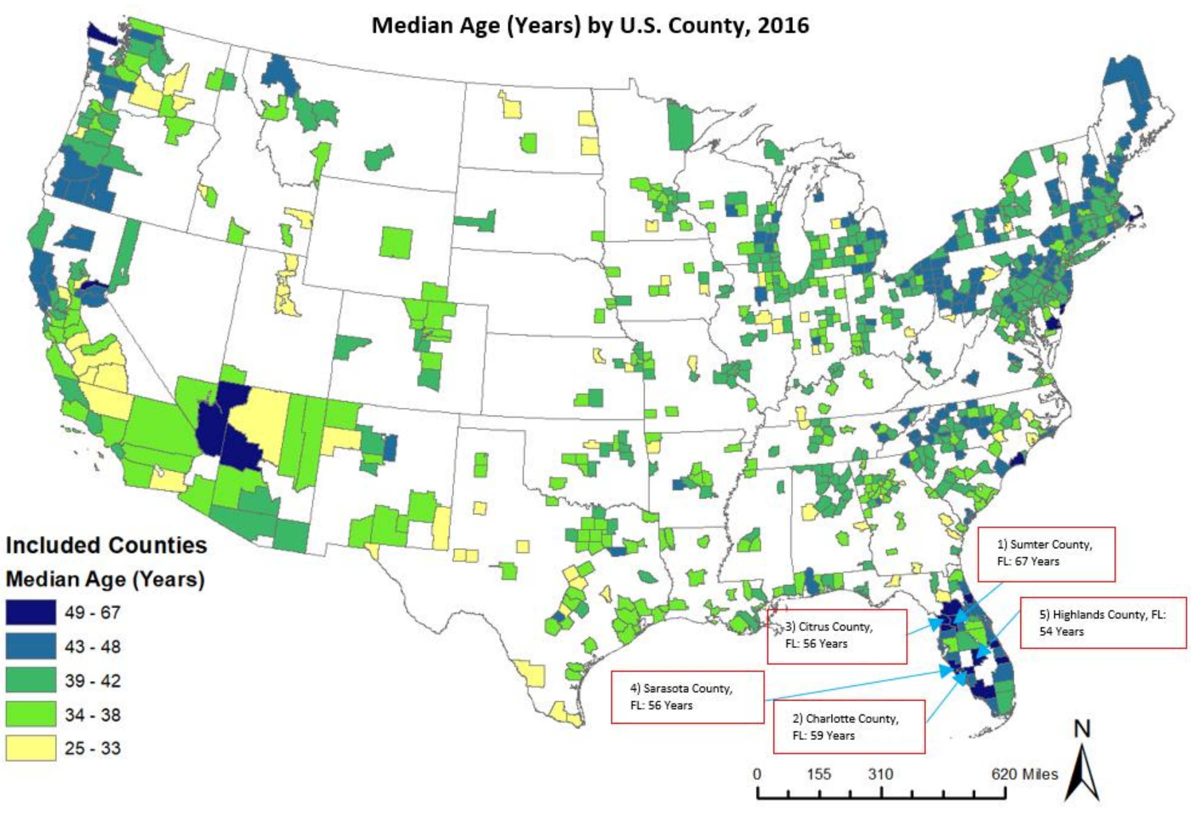
Orozco *et al.* (2017) have argued that Hispanic NFP workers tend to be disproportionately entrepreneurial relative to other ethnic groups because of their highly engaged networking behaviors and strong family histories of entrepreneurship. However, a review conducted for the Kauffman Foundation by Bradford and Mijid (2016) found that Hispanic entrepreneurs tended to experience lower success rates in starting new businesses, had a greater propensity to enter business lines with low entry barriers and experienced lower business survival rates. Valdez (2014) has echoed these concerns when she argued that many Mexican American entrepreneurs may be pursuing an entrepreneurship of last resort when she suggested that they were "more likely to engage in business ownership to combat unemployment or underemployment in the general labor market; they are basically providing themselves with a job in the absence of other labor market opportunities." It is posited by Fisher and Lewin (2018) that if push and pull factors continue to encourage the growth of Hispanic entrepreneurs, "Hispanic self-employment is likely to rise considerably" and that it is "imperative to identify policies and programs that support the success and contribution of Hispanic small business owners to their local communities and the US economy" (pg. 1068).

It is important to note, however, that Hispanic or Latino entrepreneurs are a heterogenous group. Cuban Americans, for example, report much higher rates of business ownership than Mexican Americans, in part, because the post-Castro Cuban migrants largely comprised a professional and managerial class that geographically concentrated in compact ethnic enclaves, particularly in Miami-Dade County and places like "Little Havana" located immediately west of downtown Miami. Much like Brooklyn, Miami-Dade County is a substantive NFP labor pool in both relative and absolute terms with a 31.3% share and more than 500,000 NFP workers.

Median Age The final predictor variable to enter the regression model was median age. The unstandardized regression coefficient suggested that if the median age increased by one year, then the share of NFP employment would increase by 0.17 percent. The median age varied from a high of just over 67 years in Sumter County, FL to a low of 24.6 years in Utah County, UT compared to a mean of 38.7 years across all 800 counties. Fifteen of the 25 counties with the oldest median age were in Florida including Charlotte County (58.5), Citrus County (56.4), Sarasota County (55.5), and Highlands County (54.4) (Figure 10). One of the counties that stands out is Flagler County located north of Daytona Beach on the east coast of Florida is noteworthy as it had the eleventh highest median age (51.1 years), the fifth highest share of RRL workers (8.4%) and ranked twelfth in %NFP (35.4%). Other counties with high median ages and disproportionately large NFP labor pools included Nevada County, CA (50.2 years and 39.0 % NFP), Brunswick County, NC (53.4 and 33.3%), and El Dorado County, CA (46.1 and 33.3%).

Much of the research on the connection between median age and NFP suggests that self-employment rates increase with age. Goetz and Rupasingha (2009, p. 428) have suggested that this trend reflects "both greater experience levels and potential age discrimination in the labor market." In an analysis of older entrepreneurs in New York City, Messina (2018) has argued that many "are pushed toward self-sufficiency in the face of a daunting labor market for older workers or the inability to afford retirement" (p. 6). Others have suggested that the increased popularity of part-time self-employment among the elderly is a way to supplement income or even avoid taxes.

Figure 10. Median Age (Years) by County, 2016



Conclusion

NFP's can be a powerful determinant of the economic landscape, but this metric has not received much attention in the entrepreneurship or geography literature despite the uneven geographic distribution of NFP employment. Prior research on the geography of entrepreneurship has also highlighted the need for more spatially disaggregated analyses to better understand the key predictors that lie behind the locational preferences of entrepreneurs. Such research has profound public policy implications for communities because the theory of both agglomeration economies and industry clusters suggest that entrepreneurs located in counties with a disproportionate share of NFP workers can benefit from external economies of scale. Policy makers in these sorts of communities need to focus on cultivating labor pools with the sorts of transferrable skills and knowledge spillovers that can grow the value creation and social embeddedness of their NFP economy. Such an approach will include nurturing the interconnections that exist in geographically concentrated clusters of NFP workers especially between specialized suppliers, service providers, companies in related industries and associated institutions. Such work will likely include forming targeted workforce development programs, building mentoring networks and guiding broad-based visioning strategies to help further cultivate an NFP identity in each county.

In this paper, we found that an unusually high percent of NFP workers were concentrated in just five clusters of counties located in the Atlanta and New York metropolitan areas, south Florida, the south-central region of eastern Texas and Oklahoma, and the northern California/Reno, NV region. Those counties that generated disproportionately large NFP labor pools tended to be situated in a wide variety of milieu suggesting that any explanation of the geography of NFP would not be straightforward. Based on a stepwise regression analysis, the relative share of NFP employment by U.S. county seemed to be best explained by county-wide ecosystems that have disproportionately large RRL and Construction labor pools, a high % Hispanic population, and high median age. These findings largely confirm the work of Debbage and Bowen (2018) who uncovered similar trends and explanations in an analysis of the geography of NFP at the metropolitan scale. What this suggests is that although many forms of entrepreneurship are essentially unique embedded local events, the key predictors that best explain the spatial distribution of NFP appear to be fairly consistent across different geographic scales of analysis.

The combination of socio-economic predictors captures both an entrepreneurship of opportunity (e.g., vibrant land markets and access to capital) and an entrepreneurship of necessity or last resort (e.g., low-skilled immigrant populations and aging populations) where their effects on local development and economic growth are clearly different. These tensions are apparent even in one of our exemplar counties–Kings County/Brooklyn, NY–which generated unusually large absolute and relative shares of NFP workers. While Brooklyn has been relatively successful in attracting young talent and stimulating employment in both the NFP and RRL sectors, it also is a county facing significant challenges particularly regarding income inequalities, affordability issues, and acute poverty especially in low-income, immigrant communities within the county.

The opportunity-necessity dichotomy can be interpreted differently depending on the county in question, but for theorists and policymakers alike, it is important that we not "lump" these different types of entrepreneurs together when looking to create jobs by promoting NFP. Current policies aimed at stimulating entrepreneurship rarely make a distinction between opportunistic and necessity-driven entrepreneurial logics. Cowell et al. (2018) found that innovation-driven enterprises (IDEs) alongside small- and medium-sized enterprises (SMEs) are needed in an ecosystem and that they each have specific needs. We concur with Cowell et al. (2018) that the different requirements and support needs of each type of entrepreneurship, within an ecosystem should be considered by policymakers. An innovation-based entrepreneurship of opportunity where access to capital and vibrant land markets is vital will require very different policy initiatives relative to an entrepreneurship of last resort dominated by an aging, immigrant community that may lack foundational workforce skills. From training programs and tax incentives to business accelerators and mentoring activities, NFP support programs must be designed differently for innovative, scalable start-ups than for more conventional small businesses where more fundamental workforce development programs may be more important. For example, while Latino entrepreneurship has grown rapidly in recent years, substantial barriers still exist that keep Hispanic-owned NFP's from reaching their full potential. These include issues regarding limited collateral value, poor or limited credit histories, low literacy rates and a culturally ingrained fear of government and established institutions (Federal Reserve Bank of Minneapolis, 2011).

Future avenues of research should develop a more detailed understanding of which counties can be best characterized as being part of either an opportunity-based or necessity-based NFP employment cluster. Several counties in this paper stand out as potential case studies for this sort of research including Kings/Brooklyn County, NY and Miami/Dade County, FL. However, the range of NFP county "hot-spot" case studies is diverse and includes a mix of suburban bedroom counties, and several sparsely populated and/or relatively poor counties in addition to the more conventional urban core counties. Finally, it would be helpful to conduct a more disaggregated scale of analysis within specific counties to better understand the geography of NFP at a more refined scale of analysis to see if significant spatial differences exist *within* each county.

CHAPTER III: NON-FARM PROPRIETORSHIP EMPLOYMENT BY MICROPOLITAN COUNTY

Introduction

It is well established in the literature that entrepreneurship can contribute positively to economic growth (Henderson and Weiler, 2010; Stam, 2009; Acs and Armington, 2004). In a recent article, Kline et al., (2020) referred to entrepreneurs as "some of the most significant change agents in development" (p. 15). Although there is no universal definition of entrepreneurship (Backman and Lööf, 2015), non-farm proprietorship employment (NFP) has been commonly used as a proxy to better understand the determinants of growth and spatial distribution of entrepreneurship and self-employment (Bignall and Debbage, 2020; Debbage and Bowen, 2018; Goetz and Rupasingha, 2009). Since the Great Recession, non-farm proprietorship (NFP) employment has played an increasingly important role in local economies growing by 25.5% from 35.5 million workers in 2009 to 44.6 million workers in 2018 (BEA, 2020). Rupasingha and Goetz (2013) argued that, although non-farm proprietors are not a perfect direct measure for entrepreneurship, they are full-time or part-time owners of small businesses who organize and operate a business, take risks, earn profits, or incur losses. In this sense, NFPs have more in common with entrepreneurs than with conventional wage and salary workers employed by larger, more formal businesses.

Much of the research on NFP employment has tended to focus geographically on either metropolitan areas, large urban counties, or rural counties. However, little research has been conducted on micropolitan counties – those places that commonly straddle the urban-rural divide – where rates of growth and change can be quite dramatic. The Office of Management and

Budget (OMB) has classified Micropolitan Areas as places that include central counties that have urban clusters with a population of at least 10,000 but less than 50,000 (Helmer, 2008) that may also include additional outlying counties if they have strong commuting ties to the central county hosting the largest urban cluster (Spell, 2019; Brown et. al., 2004). Micropolitan Areas are commonly located adjacent to larger, more densely settled Metropolitan Areas where they frequently function as bedroom-commuter or spillover suburbs. However, some Micropolitan Areas are located some distance from neighboring Metropolitan Areas and many of these have unique, "stand-alone" local economies. Additionally, many micropolitan communities are unevenly distributed, "fringe communities" (Kline et al., 2020) that have been under-researched with respect to the geography of entrepreneurship. As such, this geography of "micropolitan opportunity", while less well understood, is of increasing interest to policymakers and researchers.

Here, we use NFP employment as a proxy for entrepreneurship and self-employment to gain a better understanding of what influences the spatial distribution of NFP in these micropolitan counties. The contribution of this paper is twofold. First, we examine the spatial variation of the percent share of NFP employment by micropolitan county to better understand which places generate disproportionately high and low rates of entrepreneurial opportunity. Second, we utilize stepwise regression to identify the key socio-economic variables that best explain the micropolitan geography of NFP. We argued that some of the key causal variables that shape the geography of NFP employment by micropolitan county are unique to this scale of analysis. In addition, the paper provides policy guidance for micropolitan communities looking to establish a competitive advantage for their local entrepreneurial ecosystems that can enhance the overall quality of life.

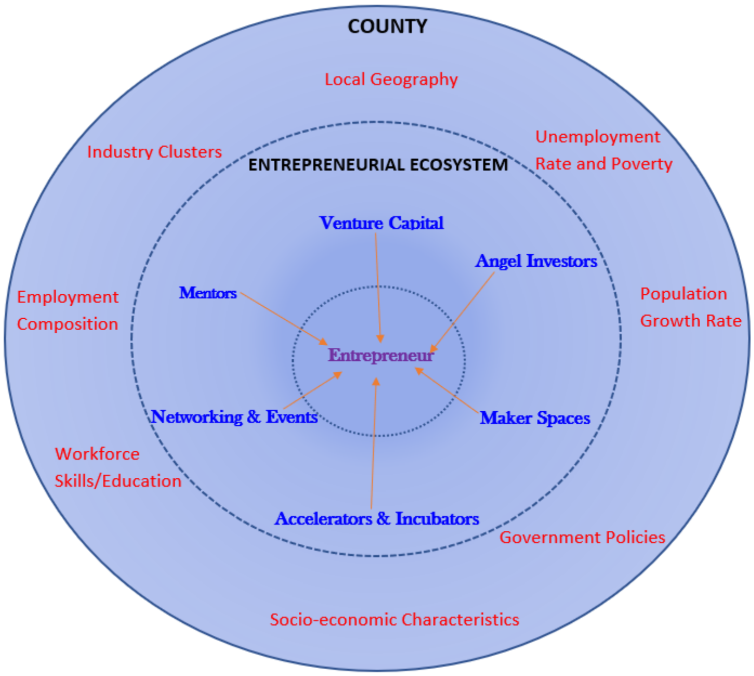
Literature Review

Entrepreneurship does not have a univocal definition (Faggian, 2017), and according to Drucker (1985), "there has been total confusion over the definitions of 'entrepreneur' and 'entrepreneurship'" (p. 21), it has not suffered from a lack of extensive research (Lofstrom, 2017; Qian, 2016; Backman and Lööf, 2015; Baycan-Levent and Nijkamp, 2009; Harvey, 2008; Acs and Armington, 2004). Research devoted to understanding economic development, entrepreneurship and population change has tended to focus on metropolitan areas; traditional areas of labor in-migration since the Industrial Revolution (Vias et al., 2002). However, to better understand what shapes the geography of NFP, Mack (2016) argued that "much more work is required to unpack the spatiality of the actors, factors and processes that foster entrepreneurship" (p. 3). While past research has yielded numerous insights, little research has addressed the actual geography of entrepreneurship and much more research is needed to better understand the spatial attributes of the key players that shape each community's entrepreneurial ecosystem.

In this paper, we focus on the broader-based contextual impact of the entrepreneurial ecosystem (Figure 11). While much of the existing literature has focused on the inner workings of entrepreneurial ecosystems (e.g., firms and start-ups, the role of venture capital, banks, maker spaces, public institutions) and related knowledge spillovers, in this paper, the focus is on better understanding the broader scale external business environment that can drive NFP employment differentials by U.S. micropolitan county. These more broadly based geographic employment clusters or talent pools by county can facilitate the broader exchange of knowledge and skillsets that can effectively either nurture or stymie innovation (e.g., employment composition, demographics, population growth rate). Answers to these questions are important because pressures beyond the boundaries of a firm can contribute to a firm's eventual success or failure (Liguori *et al.*, 2018; Florida *et al.*, 2017; Stam, 2009).

In the broader literature on entrepreneurship, metropolitan areas, as well as larger urban areas and some smaller rural areas have tended to be the primary areas of focus. A large majority of "start-up communities" have tended to thrive in dense agglomerative metropolitan economies where entrepreneurs and NFP workers can benefit from both external economies of scale and knowledge spillovers that can grow the value creation and social embeddedness of entrepreneurial ecosystems. On the other hand, some entrepreneurial ecosystems have tended to thrive in smaller, rural economies that have developed intimate and unique support systems grounded in face-to-face contact, trust, and community visioning. Before summarizing some of the limited research that has concentrated exclusively on the geography of entrepreneurship and NFPs by micropolitan county, this literature review will first concentrate on the bulk of the research that has traditionally analyzed NFP employment by Metropolitan Area and large urban county, as well as across the urban-rural continuum.

Figure 11. The County-Wide Ecosystem of the Entrepreneur



NFP Employment by Metropolitan Area and Large Urban Counties

The spatial distribution of economic opportunity and entrepreneurship remains a substantive and rapidly emerging arena of research interest no matter whether it is focused on urban or rural areas. However, many studies have yielded some important insights into the socio-economic impact of entrepreneurship within metropolitan spaces. A recent example of this sort of research is provided by Carree et al. (2015) who examined the geography of self-employment and job generation rates by U.S. metropolitan area. They argued that while sole proprietorship data may not perfectly reflect the notion of innovative activity, it is one of the simplest and least expensive business structures to establish. They also found that nine out of the ten metropolitan areas with the highest total employment growth rates also had self-employment rates well above the national average. Conversely, they pointed out that nine of the ten slowest growing metropolitan areas had a below average self-employment rate. However, Carree et al. (2015) also argued that while self-employment can contribute to economic growth and the reduction of unemployment, it is also true that unemployment can also lead to increased self-employment rates if unemployed individuals find it difficult to find conventional wage and salary employment.

In one of the more recent studies of NFP employment by metropolitan area, Debbage and Bowen (2018) found that metropolitan areas with high shares of NFP workers tended to predominate in Florida, the Northeast, and the West Coast. Based on a regression analysis, they also found that the key causal variables included a high share of finance insurance and real estate (FIRE) workers, high median age, disproportionately large Hispanic populations, and high median home value. They argued that the geography of NFP by metropolitan area seemed to be shaped by a combination of predictors that captured both "out-of-necessity" self-employment (e.g., low-skilled Hispanic and aging populations) and a self-employment of opportunity (e.g., access to capital through bank loans and equity loans partly generated by high home values). Their findings suggest that the uneven growth of NFP at the metropolitan scale may not necessarily be a response to opportunity but instead a result of necessity because of layoffs or the lack of opportunity in some metropolitan economies. Rupasingha and Goetz (2013) uncovered similar findings in their analysis of self-employment rates by U.S. counties. They also found that higher shares of employment in FIRE can spur NFP employment growth.

Bignall and Debbage (2020) partly confirmed some of these trends at a more disaggregated scale of analysis in a study that analyzed the geography of NFP for 800 of the most populated counties in the U.S. They found that the share of NFP employment by county was highly uneven with significant clusters in Atlanta, New York, eastern Texas and Oklahoma, south Florida, and northern California. Bignall and Debbage (2020) also found that the key regression predictors of percent NFP employment by county included disproportionately large labor pools employed in Real estate and Rental and Leasing (RRL) as well as the Construction sector, disproportionately large Hispanic populations, and high median age. Although their findings suggested that explanations of the geography of NFP were consistent across different geographic scales of analyses (i.e., metropolitan areas versus counties), they also uncovered notable differences. Bignall and Debbage (2020) found that %RRL – a sub-category of FIRE – featured more prominently in their regression analysis than in Debbage and Bowen's (2018) analysis of metropolitan areas. They argued that %RRL may be "a proxy for access to a particular type of capital, one that is tied up in vibrant land markets particularly in places with urban and tourism-related economies" (p. 594). Additionally, they found that the share of workers employed in the Construction sector played a key role in shaping NFP labor pools by county, in part, because many construction markets rebounded after the Great Recession creating numerous self-employment opportunities. Earlier work by Goetz and Rupasingha (2009) came to similar findings concluding that "many construction workers are self-employed, and this trend seems to be increasing over time" (p.435).

NFP Employment Across the Urban-Rural Continuum

Several scholars have examined the role of entrepreneurship or self-employment across the full spectrum of the U.S. urban-rural continuum. Goetz (2003) attempted to understand the causes and consequences of proprietorship growth in rural America. He focused on what he called dependent counties (i.e., those counties with a disproportionately high share of NFP employment). Goetz (2003) found that proprietorship employment had been growing rapidly since 1969, although the spatial distribution of NFP was highly uneven across space and time.

He found that the share of proprietorship employment had increased from 13.5% to 18.0% from 1969-2000 particularly in several Tennessee counties, the Northeast states, and Idaho. Goetz (2003) also found that counties with a disproportionate share of owner-occupied homes, higher median home value, aging populations, more construction and service employment shares, and a higher natural amenities index experienced higher relative growth rates in proprietor employment.

Other studies also found self-employment or proprietorship to be important elements of rural economic growth. Markeson and Deller (2012) examined the role of local amenities in rural areas and its potential impact on proprietorship growth from 2000 to 2008. They found that proprietorship growth was largely spatially clustered in a small number of U.S. rural counties, and that spatial spillover effects mattered, although proprietorship growth was higher in those areas with particular climate attributes (i.e., warm and dry climates). In effect, Markeson and Deller (2012) argued that the effect of climate on quality of life may be enough to attract individuals who wish to start new firms. However, they also found that the economic structure of each county mattered along with higher levels of education, ethnic make-up, and levels of income when attempting to better understand proprietorship growth rates. For example, Markeson and Deller (2012, p.99), found that a higher concentration of employment in the construction industry (where firms are frequently structured as proprietorships) generated positive and “statistically significant direct and indirect spatial spillover effects” (p.99). Goetz and Rupasingha (2009) uncovered similar findings in their analysis of NFP employment of U.S. counties where a greater concentration of construction employment was associated with more rapid growth in self-employment rates although their analysis included both rural and urban counties.

Shrestha et al. (2007) attempted to “systematically and comprehensively test for the effect of proprietorship formations on overall job creation in the U.S. economy” (p. 147) based on an exhaustive analysis of 3,035 metropolitan and non-metropolitan counties from 1985-2004. They argued studies of proprietorship formation and job growth had been virtually non-existent up to that point, and they found that self-employment or proprietorship rates are associated with faster job growth than in the wage and salary sector, and that the effect is statistically significant. Shrestha et al. (2007) also found that certain socio-demographic factors had a positive effect on job growth including the share of the adult population with a college degree and counties rich in amenities. By contrast, they also found that increased ethnic diversity reduced job growth which they indicated was likely a “contrary and potentially controversial finding in the current immigration debate” (p.162).

Tsvetkova et al. (2017) examined the geography of self-employment in more than 2,700 counties located in large and small metropolitan areas, micropolitan areas and rural counties. They focused on how a community’s position in the urban-rural continuum might impact economic trends in various industries. Tsvetkova et al. (2017) found that responses to either economic changes or shocks to local self-employment varied and were influenced by the county’s location in the hierarchy. Self-employment in lower-tier metropolitan counties was not affected by nearby larger MSA growth, but wage and salary employment was affected strongly and positively by growth in MSAs with a population of at least 1.5 million. Micropolitan counties were found to create more self-employed jobs than rural counties when there was a positive economic change. Unlike rural counties, they argued that self-employment in micropolitan counties did not seem to be overly affected by economic changes in nearby large MSAs. By contrast, they found that self-employment growth in surrounding rural counties was hampered if a nearby MSA was large and rapidly growing. Tsvetkova et al., (2017) suggested that rural counties with higher shares of workers with only high school diplomas may be a sign of an economy favoring 'out-of-necessity entrepreneurship' due, in part, to a lack of jobs in the formal wage and salary sector.

NFP Employment by Micropolitan County

Although considerable research has been focused on the geography of NFP in metropolitan areas, counties and across the urban-rural continuum, only a limited amount of research has focused exclusively on micropolitan areas and micropolitan counties. Cortes et al. (2015) provided some context for this sort of research in their analysis of the fastest and slowest growing micropolitan areas. They examined how population and income growth and volatility rates over time impacted the employment composition of micropolitan areas.   Cortes et al. (2015) found that employment changes in specific sectors lead to population growth while job growth in the suburbs had a positive impact on population growth in micropolitan areas. Concernig income growth, they found that certain sectors had differential effects including health care, professional services, and construction. In terms of volatility, Cortes et al. (2017) found that changes in construction employment were a major source of instability for micropolitan areas given the "boom-bust" nature of construction cycles although sectors such as health care and finance and insurance tended to have a more moderating or stabilizing effect. They also found that only employment changes in the construction industry had direct and significant effects on income growth although they provided no explanation. Overall, although Cortes et al. (2017) provided a useful framework for better understanding growth and change in micropolitan areas, they were largely silent regarding what role NFP employment might play in micropolitan area economies.

Liu et. al., (2020) partly remedied this shortfall in the literature in their recent analysis of general and high-tech start-up rates by micropolitan area. They pointed out that "while scholars have extensively studied regional variation in entrepreneurial activities, most existing studies focused on metropolitan areas…" (p. 1) and that "limited efforts have been made to study varying new firm formation across small and medium-sized urban communities" (p.1). Such a deficiency is problematic, they argued, because the geography of NFP employment by micropolitan county may well exhibit different patterns and explanations relative to metropolitan or rural counties. Liu et al. (2020) found that micropolitan areas generated a higher average number of new single-unit establishments per 10,000 employees (a surrogate measure for NFP formation) than metropolitan areas particularly in construction, retail trade, transportation and warehousing, and accommodation and food services. Furthermore, Liu et al. (2020) pointed out that only the construction sector generated a positive and significant relationship with start-ups in general. Construction has been previously identified in the literature as a significant predictor of NFP employment and having a direct and significant effect on income growth (Bignall and Debbage, 2020; Cortes et al., 2015; Markeson and Deller, 2012; Goetz and Rupasingha, 2009). Liu et al. (2020) also found that population growth and human capital are positively associated with both general and high technology entrepreneurship in micropolitan areas.

Overall, although entrepreneurship and NFP can play an important role in urban and regional development, only limited efforts have been made to understand the geography of NFP by micropolitan county. In this paper, we will attempt to partly remedy this deficiency by identifying those micropolitan counties with disproportionately high shares of NFP employment and isolating the key causal triggers that best explain this unique geography of opportunity. We focus on the broader socio-economic predictors because county-wide labor pools and the broader composition of the local economy can substantially pre-determine the outcomes of any given entrepreneurial ecosystem.

Methods

Our study expands from the work of Bignall and Debbage (2020) who examined the geography of NFP for 800 of the most populated counties in the U.S. In this paper, we focus exclusively on the 107 micropolitan counties included in the Bignall and Debbage (2020) analysis to better understand the key predictors that lie behind the locational preferences of entrepreneurs located solely in micropolitan economies. Most of these micropolitan counties were located adjacent to larger metropolitan areas, in part, because many micropolitan areas act as spillover communities that are functionally linked to larger, nearby metropolitan economies (i.e., 92 of the 107 micropolitan counties in this study).

U.S. county data were collected from the U.S. Census Bureau: American Community Survey (ACS) (U.S. Census Bureau, 2019) and the U.S. Bureau of Economic Analysis (BEA) (U.S. Bureau of Economic Analysis, 2109). The data were obtained for counties in the contiguous USA and the District of Columbia and included only those micropolitan counties with a population of 65,000 plus, as reported by the ACS annual survey. As a result, the 107 micropolitan counties included in our analysis are some of the largest populated micropolitan communities in the U.S. The special combination counties of Virginia were not included in the data set, as the BEA data matched poorly with the ACS counties. Additionally, the nondisclosure rule of the US Census limited data when a business' data value may be presumed due to a low number of observations.

In this paper, NFP is used here as a proxy for entrepreneurship and self-employment. We used the U.S. Internal Revenue Service definition of NFP which stated that:

> A sole proprietorship is an unincorporated business that is owned by one individual who is required to file Schedule C (Form 1040) for profit or loss from a business. A partnership is the relationship existing between two or more persons who join to carry on a trade or business. A partnership must file an annual information return to report the income, deductions, gains, losses, etc., from its operations, on Form 1065 (U.S. Return of Partnership Income). Organized for profit, unincorporated, full and part-time sole proprietorships, partnerships, and other private nonfarm businesses are non-farm proprietorships. (IRS, 2020)

We only include counties that are classified by the OMB as micropolitan counties that effectively captures economically functional small to medium-sized cities (or urbanized areas) between 10,000 and 50,000 and the surrounding counties where residents largely travel to the urban core to work. We initially identified 27 potential independent variables (Table 4) expected to exhibit some relationship with NFP by micropolitan county. The selection of this initial cohort was largely based primarily on previous research (Liu *et al.*, 2020; Bignall and Debbage, 2020; Debbage and Bowen, 2018; Caree *et al.*, 2015; Goetz and Rupasingha, 2009; Shrestha *et al.*, 2007). Along with a group of demographic and economic indicators, employment composition by major industry is also included as a measure of employment specialization to assess whether a particular mix of jobs is systematically linked to the geography of NFP by micropolitan county. All the included industries are defined based upon the North American Industry Classification System (NAICS) and represent all the major industry components of the micropolitan labor pool.

Table 4. Dependent and Independent Variables and Descriptive Statistics

Variables	Mean	SD
%NFP employment	20.2	4.6
Demographic [a]		
% PGR 2015-2016	0.1	0.97
Median age (years)	40.3	4.7
% White	84.8	13.6
% Hispanic	7.6	9.8
% Male	49.8	1.7
% Female	50.2	1.7
% 65 years and older	17.8	3.3
% of population 25 years or older with only a high school	33.9	6.8
diploma	21.9	7.5
% of population 25 years of age or older with a bachelor's	80.5	7.5
degree or higher		
% of household with broadband		
Economic □		
Per capita income ($)	24,991	4,859
Median earnings ($)	27,159	4,003
Median household income ($)	47,061	8,789
Poverty rate (%)	16.5	5.76
Unemployment rate (%)	6.3	2.6
%Housing stock, owner-occupied	68.4	6.1
Median home value ($)	148,52	66,64
	3	1
Employment [a]		
% Construction	5.4	1.4
% Manufacturing	10.3	6.4
% Retail	11.7	1.5
% Information	1.0	0.5
% Finance and Insurance	3.3	1.2
% Real estate, rental, and leasing (RRL)	3.5	1.2
% Finance insurance and real estate (FIRE)	6.7	1.8
% Professional and business services	3.2	1.4
% Arts, entertainment, and recreation	1.7	1.3
% Accommodation and food services	7.9	2.9

Notes: [a]US Department of Commerce, BEA; □ US Census Bureau: American Community Survey by micropolitan county, 2016

A correlation analysis was completed using all the variables prior to performing linear regression to reduce the potential for collinearity in the regression by identifying statistically significant correlations between the independent variables. Among each pair of variables with a high degree of correlation, the one least correlated with NFP was chosen for elimination. Linear regression was then performed using a stepwise procedure to identify the most powerful predictors of NFP among the remaining independent variables.

Results and Discussion

Trends and Context

One of the most substantive and overlooked labor market trends in recent decades has been the rapid rise in NFP employment in U.S. micropolitan economies. From 2003 to 2018, NFP employment in micropolitan areas increased approximately 28% from 2.4 million to 3.1 million jobs (BEA, 2020). While NFP employment by metropolitan area, large urban county or rural county is fairly well understood, little is known about what factors shape the geography of NFP employment by micropolitan county. Many micropolitan counties lack a diverse industrial base, and their economies often depend on only one or a few industries (Mulligan and Vias, 2006). Furthermore, given the proximity of many micropolitan areas to larger metropolitan areas, some micropolitan economies may experience "spread effects" and knowledge spillovers creating unique NFP opportunities in some micropolitan counties. Conversely, other micropolitan counties may suffer from a lack of resources as the adjacent metropolitan economy potentially draws human capital and business away from the nearby peripheral communities (i.e., "backwash effects").

Leading NFP Micropolitan Counties

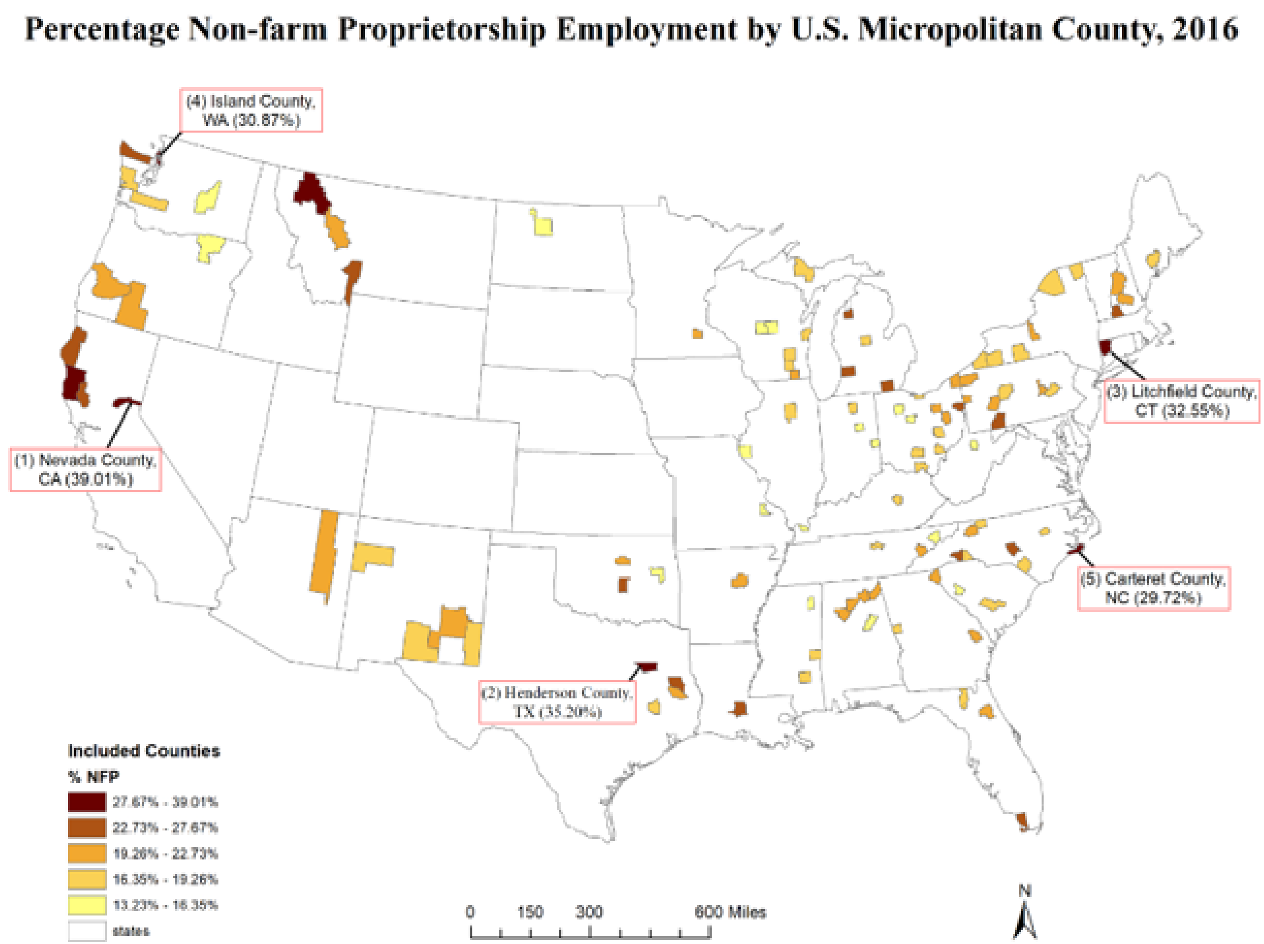
In absolute terms, the largest NFP labor markets by micropolitan county included Litchfield County, CT (31,460 NFP workers), Gallatin County, MT (22,630), Nevada County, CA (21,272), Merrimack County, NH (20,241) and Humboldt County, CA (18,865) which all rank well above the average of 9,137 NFP workers per county (for the 107 micropolitan counties included in this analysis). The largest NFP labor pools tended to match well with the rank hierarchy of the most populated and the largest employment labor pools. For example, Litchfield County, located midway between the New York and Boston metropolitan areas, was the most populated county in the dataset as well as having the largest absolute NFP labor pool. However, the geography of NFP employment was shaped by more than just critical mass.

The relative (%) geography of NFP employment suggested a radically different spatial outcome (Table 5 and Figure 12). In 2016, the percent share of NFP workers by micropolitan county varied from a high of 39% in Nevada County, CA to a low of 13.23% in Hancock County, OH, with a mean of 20.2% across all 107 counties included in this analysis. The top 15 counties with the highest relative NFP employment had an average share of 29%, nearly 9 percentage points higher than the overall average for all 107 counties. Ten of the top 15 counties were located in just four states including California (4), Washington (2), North Carolina (2), or Montana (2) suggesting that certain places may be more likely to generate disproportionately large shares of NFP workers than others.

Table 5. Top 15 Micropolitan Counties Ranked by % NFP Employment, 2016

Counties	NFP employment	Total employment	%NFP employment
Nevada County, CA	21,272	54,524	39.0
Henderson County, TX	10,812	30,720	35.2
Litchfield County, CT	31,460	96,660	32.5
Island County, WA	10,632	34,444	30.9
Carteret County, NC	10,630	35,765	29.7
Flathead County, MT	18,761	63,851	29.4
Mendocino County, CA	14,375	49,085	29.3
Monroe County, FL	17,190	62,124	27.7
Gallatin County, MT	22,630	82,134	27.5
Lake County, CA	6,489	24,409	26.6
Humboldt County, CA	18,865	71,598	26.3
Moore County, NC	13,054	50,677	25.8
St. Landry Parish, LA	9,275	36,578	25.4
Grand Traverse County, MI	17,775	70,804	25.1
Clallam County, WA	8,103	33,703	24.0
Averages			
Top 15	15,422	53,138	29.0
N=107	9,137	44,744	20.2

Figure 12. Non-Farm Proprietorship Employment (%) by Micropolitan County, 2016



While the counties featured in Table 5 and Figure 12 generated unusually high shares of NFP workers, they also tended to be large absolute labor markets. The top 15 counties averaged 15,422 NFP workers per county compared to 9,137 workers for all 107 counties. In terms of total employment, similar trends applied. Several counties stood out in both relative and absolute terms. The leading NFP county in relative terms including Nevada County (39.0%) and Litchfield County (32.5%) were also two of the three largest NFP employment markets in absolute terms out of all 107 counties.

The uneven distribution of percent NFP employment in Figure 12 suggests that micropolitan counties capable of generating disproportionate shares of NFP workers can be situated in a wide variety of socio-economic contexts. However, a majority of the micropolitan counties with disproportionate shares of NFP workers that featured prominently could be characterized as:

- Exurban counties with significant “overspill” effects (e.g., Nevada County, CA; -39.1%; Henderson County, TX – 35.20%; Moore County, NC – 25.76%)

- “Standalone” counties with distinct urban identities (e.g., Gallatin County, MT – 27.55%; Clallam County, WA – 24.04%)

- “Standalone”, low density counties with no distinct urban identity (e.g., Flathead County, MT – 29.38%; Lake County, CA – 26.58%; Humboldt County, CA – 26.35%; Mendocino County, CA – 29.29%; Grand Traverse County, MI – 25.10%)

- Relatively unique counties that were exceptions to the above rules (e.g., Litchfield County, CT -32.55%; Monroe County, FL – 27.67%; Island County, WA – 30.87%; St. Landry Parish, LA).

The exurban counties with significant “overspill” effects tended to be those micropolitan counties that were functionally linked to a nearby, larger metropolitan area. These included counties that were typically part of a larger Combined Statistical Area (CSA) where, based on Federal Government regulations, the employment interchange between the micropolitan county and the adjacent metropolitan area was at least 15 percent. In this sense, these micropolitan counties essentially function as overlapping NFP labor pools with neighboring metropolitan areas. A good example of this is Nevada County located in northern California. Although much of the county is situated within the scenic Tahoe National Forest, the southwestern part of the county is just a 30 to 45-minute commute from the northeastern suburbs of the Sacramento metropolitan area. According to Spiral Internet (2014), community leaders in Nevada County “value livability and work-life balance as much as economic development” and see their community as “thriving” (p. 1). The report goes on to state that, in part, due to the development of Spiral’s gigabit fiber optic Internet network, the county was being hailed as “a destination for entrepreneurs and high growth companies seeking a superior work-life balance in one of the most scenic areas of the county" (p. 2).

By contrast, the second group of counties included functionally "stand alone" counties with distinct urban identities that were not part of a larger CSA commute field. A good example of this typology included Gallatin County, MT which has experienced significant population growth (e.g., 3.6% from 2015 to 2016) and included the city of Bozeman with a population of nearly 50,000 – one of the largest cities included in our analysis. In recent years, Bozeman has emerged as a rapidly growing entrepreneurial hotspot with its unique ecosystem. In a Kauffman Foundation funded analysis of Montana's entrepreneurial ecosystem, Motoyama et al. (2017) found that Bozeman exhibited high levels of entrepreneurial activity indicating that the rate of innovation compared favorably with many larger, more highly regarded, metropolitan areas. They found that Bozeman was successfully generating spinoff activities, high-growth companies and private equity investments that had been leveraged by dense networks of active local support organizations. Motoyama et al. (2017) reported that "Montana entrepreneurs perceived that the quality of life was the gravity force for both the employers (entrepreneurs) and employees, and it contributed to the high retention rate of workforce" (p. 15).

A third type of county included "stand alone" counties with lower population densities and little urban identity. A good example is Flathead County located southwest of Glacier National Park in the northwestern part of Montana. In 2019, the largest city in the county was Kalispell with a population under 25,000. Despite this county's *relatively* isolated geographic setting, nearly 30 percent of the workforce in 2016 was engaged in some form of NFP. Almost 9% were employed in construction, possibly a response to the county's continuous increase in population. In recent years, the rapid population growth in Flathead County, especially in the city of Kalispell, has presented local officials, real estate agents, and residents with substantial challenges including increased demand for housing, shortages in building supplies, a lack of affordable housing, and congestion (Scott, 2020).

Finally, other micropolitan counties tended to be exceptions to the rule that defied attempts at a more broadly based classification. This included places like Litchfield County, CT centrally located within the densely populated Boston-New York corridor. Other exceptions included micropolitan counties that are part of larger island archipelagos such as the ironically named Island County, WA located in the Puget Sound; Monroe County, FL that comprises the Everglades National Park and Florida Keys; and Carteret County, NC situated in the Emerald Isle and Cape Lookout Outer Banks region of coastal North Carolina. Many of these sorts of counties have such unique settings that any explanation of the underlying geography of entrepreneurship by micropolitan county for all 107 counties included in our analysis is unlikely to be straightforward given the diversity of county settings and varied entrepreneurial ecosystems.

Regression Analysis

Consequently, a stepwise linear regression analysis was performed to assess quantitively the potential relationships that might exist between NFP and select socio-economic variables by micropolitan county. Diagnostic tests indicated that the regression models exhibited low multicollinearity between the independent variables and met the assumptions of linearity, normality, and homoscedasticity. All models and independent variables were significant at the $p < 0.01$ level. In the final regression model for 2016 (i.e., Model 3 in Table 6), 68% of the variation in the percentage of NFP employment by micropolitan county is accounted for by the percentage of labor pool employed in Construction, percentage of the population employed in Real estate and rental and leasing (RRL) and the percentage of the Population age 65 and older.

Table 6. Regression Models Indicating Associations Between Socio-Economic Variables and NFP Employment (%) by Micropolitan County, 2016

Model	Variable	Model R^2	Unstandardized coefficients	Std. error SE b	Standardized coefficients β	p-value
1	Constant	0.56	6.921	1.242		<.001
	% Construction		2.416	.225	.746	<.001
2	Constant	0.63	5.861	1.172		<.001
	% Construction		1.878	.224	.580	<.001
	% RRL		1.144	.274	.314	<.001
3	Constant	0.68	.660	1.805		0.716
	% Construction		1.834	.230	.566	<.001
	% RRL		1.018	.260	.280	<.001
	% 65 Plus		.333	.091	.223	<.001

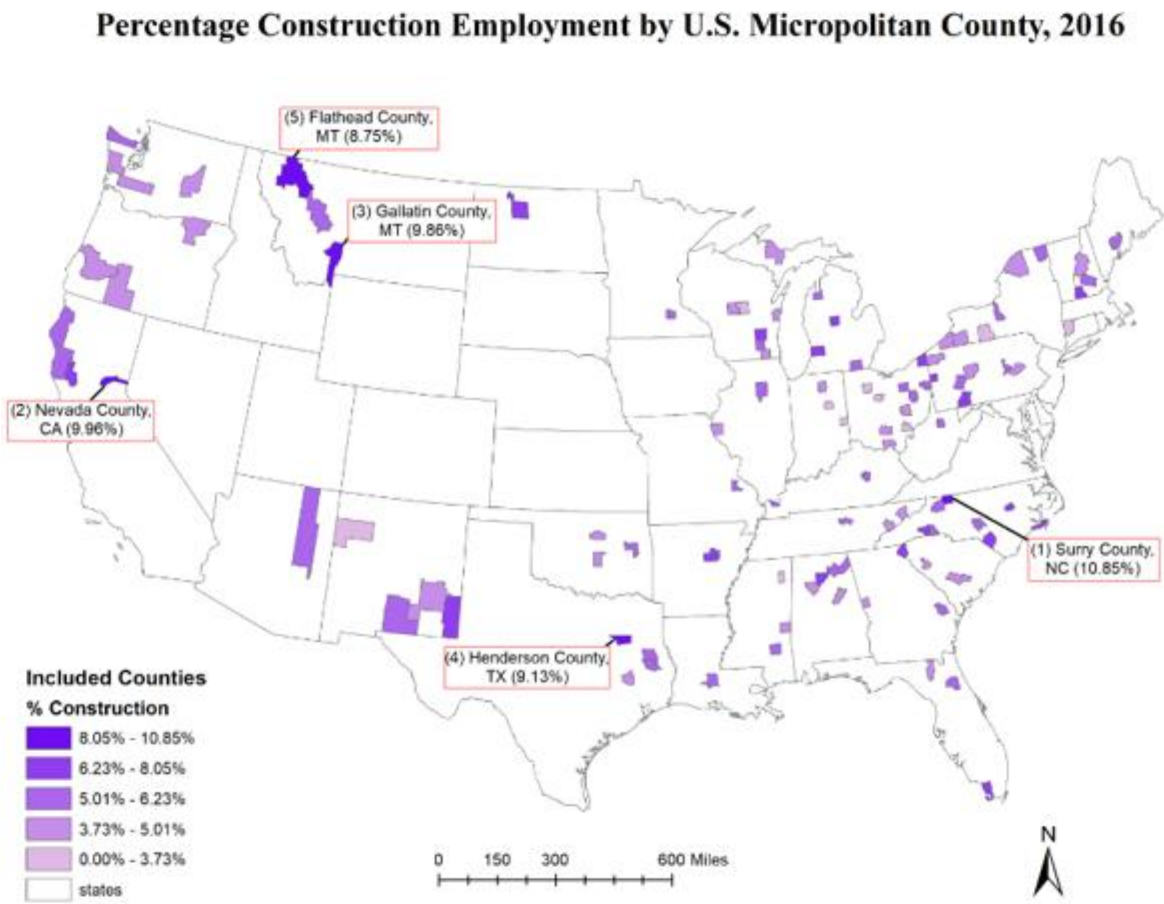
Note: The regression analysis included n=94 counties due to a small number of missing values for some counties.

Percent Construction Employment

As indicated by the variable's *b* coefficient, the relationship between percent Construction employment and NFP is such that a 1% increase in Construction employment is expected to result in 1.83% increase in the percentage of NFP employment. The counties with the highest percent Construction employment included Surry County, North Carolina (10.85%), Nevada County, California (9.96%), Gallatin County, Montana (9.86%), Henderson County, Texas (9.13%), and Flathead County, Montana (8.75%) (Figure 13). By contrast, the average construction employment for all 107 micropolitan counties in this analysis was just 5.39%. Top ranked Surry County, NC had more than twice the average workers employed in construction.

Nevada County, CA stood out as a county with the second highest share of construction workers by micropolitan county while also ranking first in the share of NFP workers. Although Nevada County did not escape the effects of the 2008/9 Great Recession, the county did experience notable employment growth from 2007 through 2016 creating numerous self-employment opportunities (Nevada County Economic & Demographic Profile, 2018). Additionally, “the percentage of Nevada County’s total earnings derived from the construction sector was over three times the statewide average…” (p. 25). These findings correlate favorably with the earlier findings of Bignall and Debbage (2020, p. 594) who argued that “the skilled labor shortages that plagued construction companies during the post-recession growth provided new entrepreneurial opportunities.” It should also be noted that the construction employment hotspots identified in Figure 13 (e.g., Gallatin, Henderson, and Flathead) match up well with those counties experiencing high shares of NFP workers. Although more research is needed before definitive explanations can be offered, the dominance of the % Construction variable in the regression models was clear in Models 1-3 in Table 6 and in the high standardized coefficient scores.

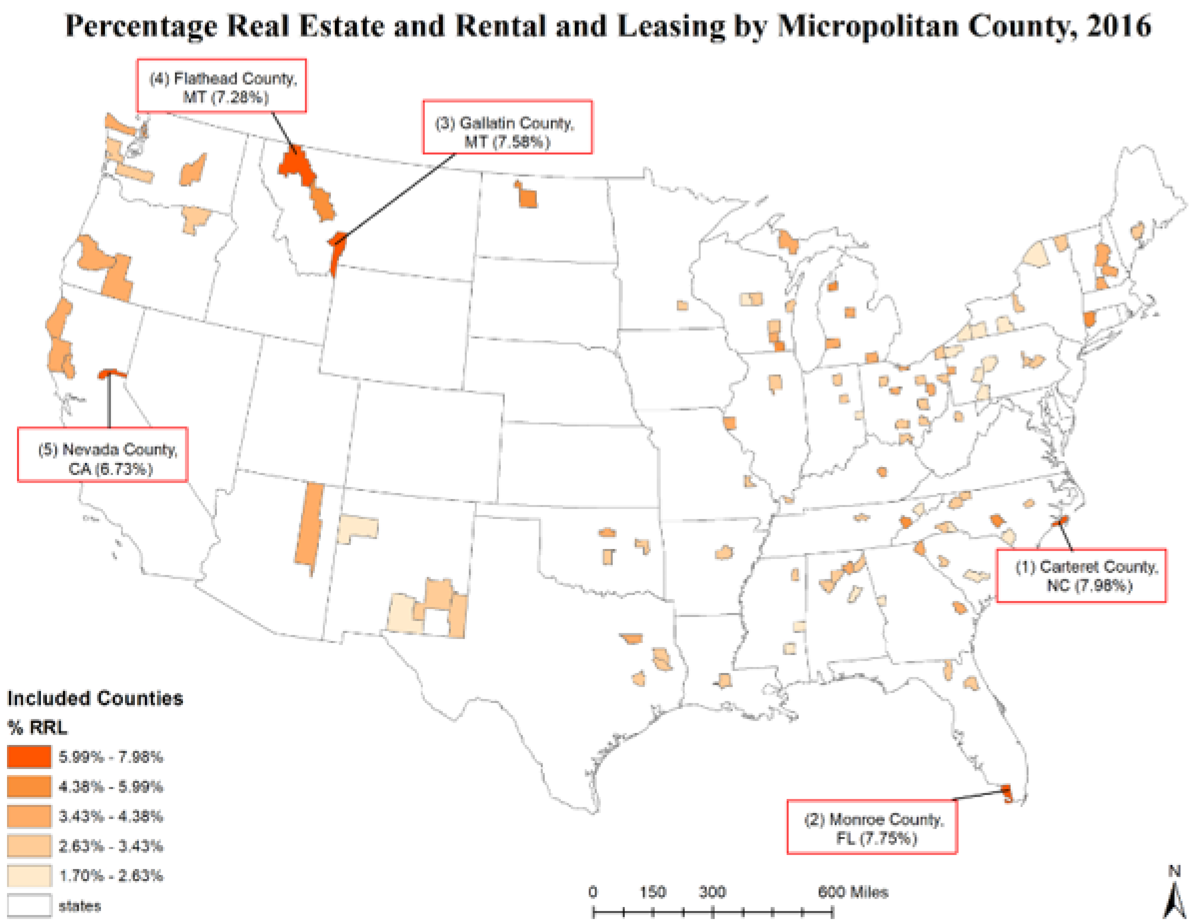
Figure 13. Construction Employment (%) by Micropolitan County, 2016



Percent Real Estate, and Rental and Leasing Employment (RRL)

The regression analysis not only identified % Construction as a key predictor in shaping the geography of NFP by micropolitan county but also highlighted was the percent of the labor pool employed in RRL. The unstandardized regression coefficient suggested that if RRL employment increased by 1% then the share of NFP workers would increase by 1.02% (Table 6). The counties with the highest percent of their labor pool employed in RRL included Carteret County, NC (7.98%), Monroe County, FL (7.75%), Gallatin County, MT (7.58%), Flathead County, MT (7.28%) and Nevada County, CA (6.73%) (Figure 14). By contrast, the average %RRL employment for all 107 micropolitan counties was just 3.48%. Many of the most highly concentrated RRL labor pools were frequently located in amenity-rich, tourism-based county economies grounded in either beach tourism (e.g., Carteret County, NC and Monroe County, FL) or National Parks and National Forests (e.g., Flathead County, MT, and Nevada County, CA). Our findings are consistent with previous research by Bignall and Debbage (2020) showing that RRL was a significant predictor in shaping the geography of NFP by county. The suggestion here is that %RRL may be a proxy for access to a particular type of capital, one that is tied up in vibrant land markets with active construction activity. Our analysis found that the geography of RRL matched up well with the geography of NFP with four of the top five NFP (%) micropolitan counties also ranking very high in the share of RRL employment (e.g., Carteret County, NC which ranked first in percent RRL at 7.98%, and Nevada County, CA which ranked 5th in percent RRL at 6.73%). In our view, these findings suggest the possibility that scenic amenities in micropolitan counties can be useful tools for attracting capital and skilled labor that is likely to engage in NFP employment suggesting a need for more research into how specific local amenities might shape the geography of NFP. Both Goetz (2003) and Markeson and Deller (2012) have suggested that counties with higher natural amenities indexes and certain climate attributes tend to experience higher relative growth rates in proprietor employment.

Figure 14. Real Estate and Rental and Leasing Employment (%) by Micropolitan County, 2016

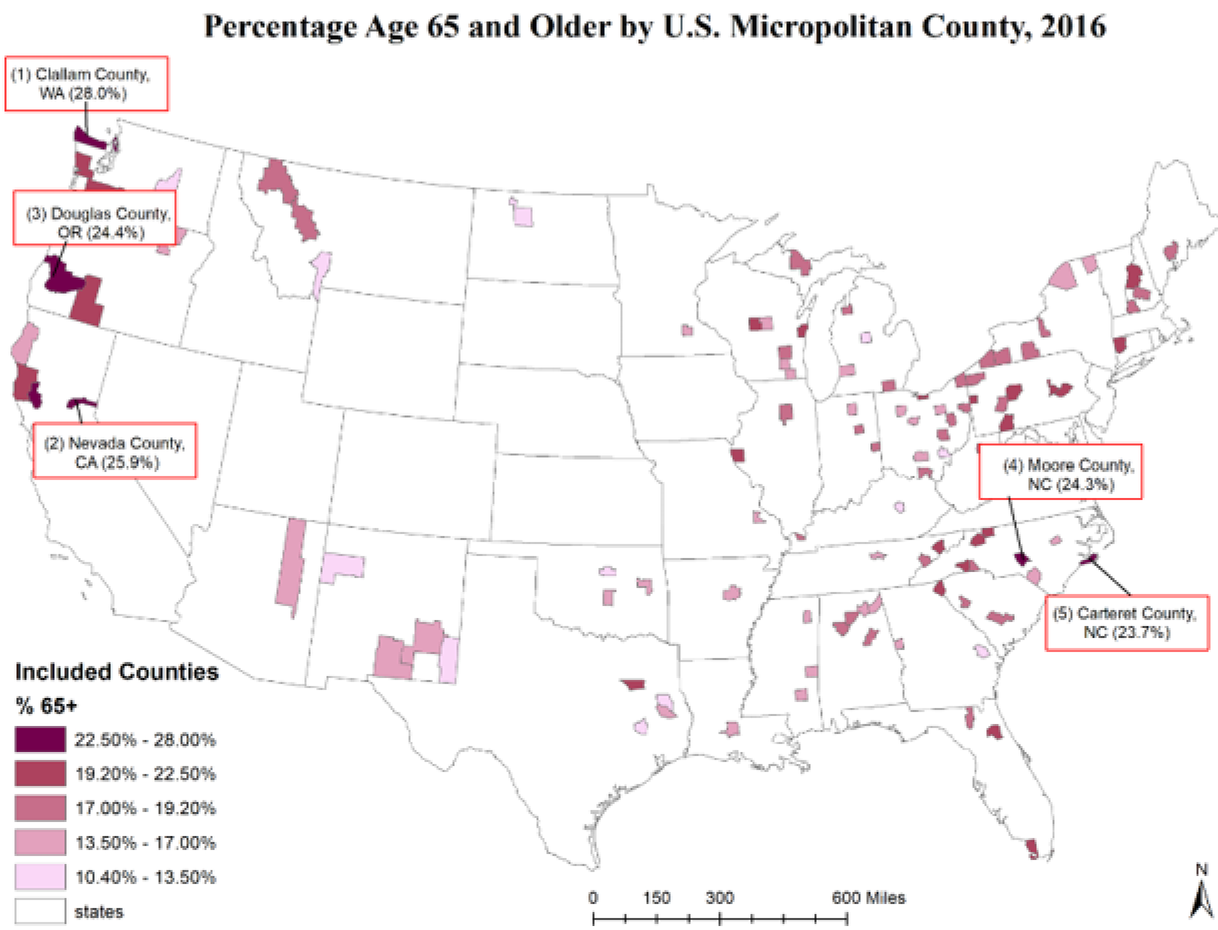


Percent 65-Plus

The final predictor variable to enter the regression model highlighted the important role that percent elderly can play in shaping the spatial distribution of NFP workers. The unstandardized regression coefficient suggested that if there is a 1% increase in the population of those age 65 or older, the share of NFP employment would increase by 0.33% (Table 6). The average percentage aged 65-plus varied from a high of 28% in Clallam County, WA to a low of 10.4% in Lea County, NM with a mean of 17.8% across all 107 micropolitan counties. The five leading micropolitan counties with the highest share of elderly included Clallam County, WA

(28%); Nevada County, CA (25.9%); Douglas County, OR (24.4%); Moore County, NC (24.3%), and Carteret County, NC (23.7%) (Figure 15). The geography of the elderly by micropolitan county seemed to match up well with the geography of NFP workers since eight of the top 15 counties for shares of NFP employment (i.e., Clallam County, WA; Nevada County, CA; Moore County, NC; Carteret County, NC; Island County, WA; Lake County, CA; Monroe County, FL; Henderson County, TX) were also ranked in the top 15 micropolitan counties with the highest percent shares of population age 65 and older. Much of the research on the connection between percent elderly and NFP suggests that self-employment rates increase with age. Goetz and Rupasingha (2009, p.428) have suggested that this trend reflects "both greater experience levels and potential age discrimination in the labor market." Others have suggested that the need for a better life-work balance and the increased popularity of part-time self-employment among the elderly is a way to supplement income or even avoid taxes.

Figure 15. Age 65 and Older (%) by Micropolitan County, 2016



Nevada County, CA – the county with the highest % NFP workers – stood out as an illustrative example of a micropolitan county that has benefited from having a population that is disproportionately elderly (i.e., 25.9%) Although Nevada County's population is said to have fluctuated over the years, in 2016 the County saw "its greatest proportional increases in those aged 65 to 74 years (80 percent), those aged 85 years and older (57 percent), and those aged 55 to 64 years old (20 percent)" (Nevada County Economic & Demographic Profile, 2018, p.1). Although primary personal income in Nevada County came from work earnings, dividends, interest, rent and commuter income, the county did see a "a significantly larger portion of Nevada County's personal income derived from retirement and veterans benefits when compared to the statewide average" (Nevada County Economic & Demographic Profile, 2018, p. 22). In communities with a substantial population of elderly persons, the economy of the community may benefit from those with retirement funds available for investments in local entrepreneurial ventures or as collateral to acquire credit (Hipple, 2010; Karoly, 2004).

Conclusion

Non-farm proprietorship (NFP) employment is an increasingly important determinant of entrepreneurial economic development in U.S. counties. Despite the uneven geographic distribution of NFP employment, most NFP studies have tended to focus on metropolitan areas, large urban areas, and/or largely rural areas. Relatively little is understood about the economic development of micropolitan areas, places commonly situated between the more urban and the more rural. Many micropolitan counties tend to be situated near metropolitan areas and as such, can benefit from positive spillover effects. By contrast, other micropolitan counties tend to be located a substantial distance from any large urban cluster which can lead to the development of relatively unique entrepreneurial ecosystems. As policymakers and stakeholders in micropolitan communities continue to seek ways to improve their county's economy and competitiveness, a better understanding of the key factors that contribute to NFP growth and change can only help elevate our understanding of micropolitan-based entrepreneurial ecosystems.

Our findings revealed that micropolitan counties that generated disproportionately large labor pools of NFP workers were highly unevenly distributed, but could still be generally categorized into at least four major typologies including exurban counties, "standalone counties" with clear urban identities, "standalone counties" that lacked any substantive urban identity, and counties that were exceptions to these general rules. We argued that exurban counties with strong commuter ties to nearby metropolitan areas may be benefiting from "overspill effects" that have encouraged NFP development in places like Nevada County, CA and Moore County, NC while more “standalone counties” such as Gallatin County, MT and Clallam County, WA have tended to develop relatively unique NFP and entrepreneurial identities.

Based on a stepwise regression analysis, the relative share of NFP employment by micropolitan county seemed to be best explained by micropolitan-based ecosystems that generated disproportionately large Construction and RRL labor pools and an aging population. The combination of predictors seems to capture an entrepreneurship of opportunity grounded in vibrant land markets particularly in places with high quality of life and amenity with an appeal to retirees. These findings largely confirm the work of Debbage and Bowen (2018) and Bignall and Debbage (2020) who analyzed the geography of NFP at different geographic scales of analysis (i.e., metropolitan areas and heavily populated, largely urban counties). The implication here is that while much entrepreneurial activity comprises essentially unique embedded local events, the key macro predictors that best explain the spatial distribution of NFP seem consistent across different geographic scales of analysis.

The challenge for micropolitan communities that have successfully attracted a disproportionate share of NFP workers is that elevated levels of entrepreneurial activity and vibrant RRL and Construction labor pools may encourage economic development that generates higher population densities and fewer natural amenities. While many of the more “successful” micropolitan counties have managed to maintain an attractive work-life balance that has attracted investment capital, rapid growth also can contain the seeds of its own destruction; careful planning and smart growth needs to be at a premium if such communities are to maintain their competitive advantage.

Future avenues of research should include case studies of some of these more successful micropolitan communities. Several counties in this paper stand out as potential case studies for this sort of research including Gallatin County (Bozeman, MT) and Nevada County, CA. However, the range of NFP micropolitan "hot spot" case studies is diverse and includes a mix of typologies. We are also aware that our research captures only those micropolitan counties with larger populations. It is possible that there are smaller populated micropolitan counties that may have divergent experiences when attempting to cultivate NFP labor pools. Overall, we hope this paper spurs more discussion on the various economic development strategies that can stimulate NFP employment in micropolitan America.

CHAPTER IV: NON-FARM PROPRIETORSHIP EMPLOYMENT BY OUTLYING METROPOLITAN COUNTY

Introduction

Since French economist J. B. Say, around 1800, first offered the following definition of what an entrepreneur does, - ‘shifts economic resources out of an area of lower and into an area of higher productivity and greater yield’ - (as quoted in Drucker, 1985, p. 21), much has been written about the entrepreneur, the phenomena of entrepreneurship, and the closely related concept of self-employment (Aparicio et al., 2020; Liu et al, 2020; Backman and Lööf, 2015; Liu et al., 2014; Lin, 2010; Kanas et al., 2009; Stam, 2009; Harvey, 2008; Acs and Armington, 2004). As local economies seek ways in which to become more urbanized and economically viable, entrepreneurship continues to be of interest to academics, policymakers, and local officials. Over the years, a great deal of this research has been focused on entrepreneurship and its related value to the metropolitan economy (Spigel, 2017; Liu et al., 2014; Baycan-Levent and Nijkamp, 2009; Acs and Armington, 2004). Even so, much research has also addressed the role entrepreneurship/self-employment in shaping non-metropolitan and more rural economies (Tsvetkova et al, 2017; Markeson and Deller, 2012; Goetz, 2003). More recently, research concerning those spaces situated between the more rural and the more urban – micropolitan areas – have warranted research attention as the importance of their economic and environmental futures have become more apparent (Liu et. al, 2020; Cortes et al., 2015; Mulligan and Vias, 2006; Brown et. al, 2004; Vias et al., 2002). According to Rupasingha and Goetz (2013), self-employment can diversify local economic development and be an avenue for enhanced quality of life. However, important questions remain unanswered regarding the role of entrepreneurship/self-employment in the more outlying, more suburban counties of metropolitan and micropolitan areas that are neither largely rural nor largely urban in their make-up. According to the U.S. Census, an outlying metropolitan county is defined as a county with strong commuting ties to the central county or counties of the urban core of metropolitan or micropolitan statistical areas. In this paper, it is expected that entrepreneurial activities in these outlying metropolitan counties will display different patterns from either the central counties of metropolitan areas or the more rural economies that lie outside the more urbanized cores of America's metropolitan areas.

In the literature, the uneven distribution of entrepreneurial activities across geographic space (Mack, 2016) has revealed that certain factors play a more significant role in the advancement of entrepreneurship depending on locational attributes (Debbage and Bowen, 2018). Spigel (2017) describes entrepreneurial ecosystems as having interplay among regional attributes (cultural, social, and material) influenced by economic and unique historical processes. Understanding economic factors, processes, and qualities of local economies, while investing in the development of local businesses, are useful strategies for the enhancement of local economic growth (Rupasingha and Goetz, 2013). Given all this, a better understanding of entrepreneurship/self-employment growth in outlying metropolitan counties would likely be beneficial in developing more effective intrametropolitan economic relations, while cooperatively encouraging and supporting local entrepreneurs as they identify opportunities within outlying metropolitan marketplaces (Spigel, 2017; Drucker, 1985).

Throughout the paper I use non-farm proprietorship (NFP) employment, by county, as a proxy for entrepreneurship and self-employment. In recent years, NFP employment has increased nearly 10% from 41 million jobs in 2016 to almost 46 million in 2019 (BEA, 2020) and a growing body of literature has examined entrepreneurial activities using proprietorship data (Bignall and Debbage, 2020; Debbage and Bowen, 2018; Rupasingha and Goetz, 2013; Shrestha et al., 2007). NFP data for this current paper were collected from the U.S. Bureau of Economic Analysis. The overall purpose of this paper is two-fold. First, I examine the spatial variation of the percent share of NFP employment by outlying metropolitan county to better understand which places in the suburban ring around the substantially urbanized core generate disproportionately high and low rates of entrepreneurial opportunity. Second, I will utilize stepwise regression to identify the key socio-economic and demographic variables that best explain the geography of NFP in suburban, metropolitan America. It will be argued that the geography of NFP by outlying metropolitan county will generate explanations and distributions that may not necessarily apply to other geographic scales of analysis (e.g., rural or more urban settings).

Literature Review

NFPs, although a growing trend as an economic strategy for development, is nevertheless a more recently and emerging research area in the field of entrepreneurship. However, proxies such as self-employment and NFP have been used in the literature to better understand entrepreneurship, in part, because of the difficulty in determining a universal definition of what comprises entrepreneurship (Backman and Lööf, 2015). Most NFP-based studies have focused on economic development in rural and larger metropolitan areas (Bignall and Debbage, 2020; Debbage and Bowen, 2018; Rupasingha and Goetz, 2013; Goetz and Rupasingha, 2009; Shrestha, Goetz and Rupasingha, 2007; Goetz, 2003). Other research has focused on the value of entrepreneurship/self-employment/NFP to local economies along the rural-urban continuum (Bignall and Debbage, 2020; Cowell et al., 2018; Tsvetkova et al., 2017; Carree et al., 2015; Chi and Marcouiller, 2013; Brown et al, 2004), but little attention has focused on NFP employment in the outlying counties of metropolitan areas.

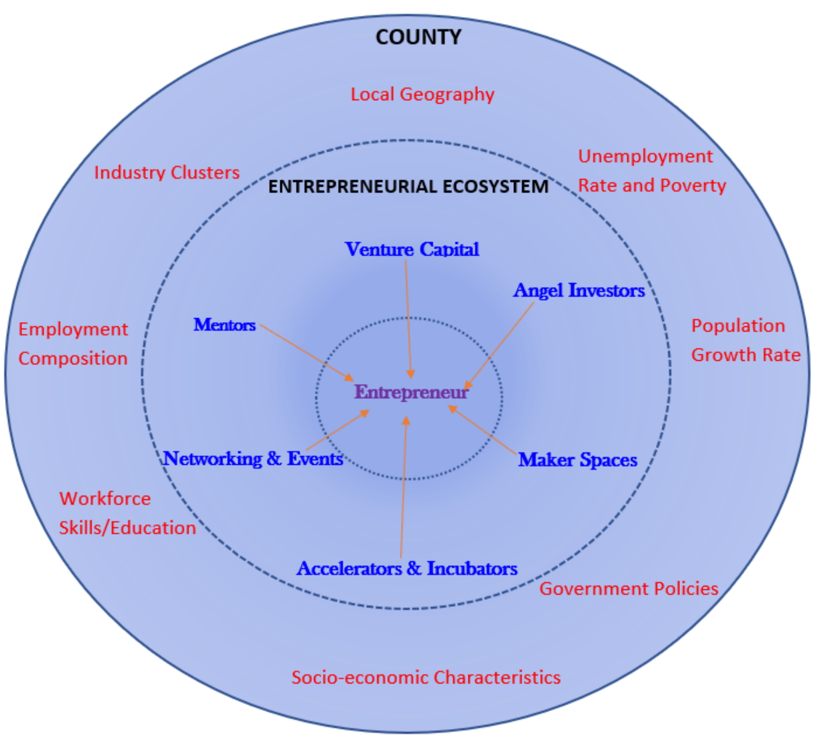
In their study of entrepreneurs and job growth at the county level, Henderson and Weiler (2010) found that between 1991-2001, entrepreneurial activity was positively linked to employment growth. They claimed that the benefits of entrepreneurship "are likely to accrue over a much longer time span than do the benefits of industrial recruitment" (p. 27). Rupasingha and Goetz (2013) looked at the effects of self-employment activities at the county level in metropolitan and non-metropolitan areas between 1970 and 2000, and in a similar vein, found that self-employment was positively associated with employment growth. Rupasingha and Goetz (2013) suggested that policymakers and local economic development practitioners should prioritize strategic investments in NFPs. Using NFP as a proxy for self-employment, their results revealed that urban counties with higher employment shares in finance, insurance, and real estate (FIRE), grew faster in total full- and part-time employment. They believed the results from their empirical study provided strong support "for pro-small, local business prescription to accelerate local economic growth..." (p. 158).

Other studies have also yielded some important insights into economic development in urbanized areas, and their functional connections with peripheral, more outlying- communities within a metropolitan area. The following section will provide discussions from the existing literature that deal with the benefits and challenges of economic development that best leverage the intra-urban connections of outlying metropolitan counties with their more centrally located urbanized cores.

According to Gardner and Marlay (2013), "employment areas that have developed on the urban fringe within the past few decades have begun to take on many of the high-order functions once exclusively located in downtown area, such as entertainment, commerce, and services" (p. 795). They identified various employment centers within U.S. metropolitan areas by employing tract-to-tract commuting data from the Census to identify high-employment census tracts and then delineate clusters of tracts with similar job densities around these cores. What they found is that, on average, larger metropolitan areas have more employment clusters including New York and Los Angeles with 42 and 41 clusters, respectively. Gardner and Marlay (2013) also found that approximately 17% of metropolitan employment were in outlying clusters some distance from the traditional downtown, and that most people actually work outside these employment clusters. These findings give some support to the notion that most metropolitan areas have become "edgeless cities" where employment is scattered among a variety of locations within a metropolitan area including within its outlying metropolitan counites.

Debbage and Bowen (2018), in their study of U.S. metropolitan statistical areas (MSAs) explored why certain MSAs had generated disproportionately more entrepreneurial activity than others. Their research looked at the post-Great Recession years of 2010-2014. Using NFP as a proxy measure for entrepreneurship, Debbage and Bowen (2018) found FIRE amongst other variables, to be a key predictor of percent NFP employment. Debbage and Bowen (2018) proposed that percent FIRE may very well be acting as a proxy for access to loan capital and other financial services. In a more disaggregated analysis of 800 of the most populous metropolitan counties in the contiguous U.S., Bignall and Debbage (2020) argued that several key factors outside the entrepreneurial ecosystem (e.g., industry clusters, employment composition, government policies, local geography; socio-economic characteristics), can be major determinants of the geography of entrepreneurship in metropolitan counties (Figure 16). They found that percent RRL, a sub-category of FIRE, among other socio-economic variables, to be the main predictor of percent NFP employment (Bignall and Debbage, 2020). Bignall and Debbage (2020) suggested that "percent RRL may be a proxy for access to a particular type of capital, one that is tied up in vibrant land markets particularly in places with urban and tourism related economies" (p. 12). By focusing on outlying metropolitan counties in this paper, I hope to expand the scope of analysis beyond just metropolitan areas in the aggregate or the most populous counties in the U.S. to the outlying suburban fringe counties where change in NFP employment level can be the most dramatic in relative terms. In this way, I can determine if predictors like the share of FIRE or RRL workers in a local economy are key determinants of NFP employment at a different scale of geographic analysis.

Figure 16. The County-Wide Ecosystem of the Entrepreneur



Kline et al. (2020), in their study of the entrepreneurial ecosystem/climate in tourism based fringe communities, found that these outlying communities "are increasingly having to negotiate the complexities of transitioning, natural, built, economic, political, social, and cultural landscapes" (p. 15). They stated that tourism being "a major economic driver" (p. 6) has led to amenity migration trends in the study area of Moore County, NC that differentiated the local area from nearby counties. The work of Kline et al. (2020) reminds us that planning for development and growth in outlying counties frequently includes decisions not only related to local interests, but also to those matters of interest related to functionally linked areas through, for example, journey to work trip patterns. Since outlying metropolitan counties are by definition linked to the central counties of any given metropolitan or micropolitan area by their commuting ties, it makes sense to focus on the interconnectedness of central and outlying counties.

For example, in an analysis of growth patterns and downtowns in Florida, Marshall (2002) argued that, "encouraging development at the fringes has generally pushed workers and homeowners away from the city-center toward the newer suburbs, requiring new homes, schools, and services" and "an imbalance of development in outlying metropolitan areas causes a flight of financial capital and people" (p. 1518) from city-centers, and "threatens cities because it drains the dynamic personal relationships, working activities, and leisure pursuits that give the city its distinctive character" (p. 1519). In this way, local policymakers, government officials, and stakeholders of central cities/counties may very well benefit from a better understanding of economic changes in outlying areas, as these economies have been shown to positively affect and be positively affected by economic changes within the other (Oh, 2008). In this paper, I will argue that the encouragement of redevelopment and the repurposing of city-center resources through innovative economic development may possibly come by way of self-employment growth in both the suburbs and city-centers.

Previous studies have yielded evidence that counties are affected by the economic activities of neighboring counties (Shrestha et al., 2007). Likewise, where formal wage and salary employment becomes difficult to acquire, metropolitan workers may turn to self-employment if they are negatively affected by the economic changes of neighboring metropolitan communities. In a study of self-employment in American metropolitan areas, Oh (2008) explored "how changing economic forces in a sub-territory (such as the central city) of a metropolitan area affect a shift in self-employment in an adjacent sub-territory (such as the suburban ring) and vice versa" (p. 1774). The research data were from the 1980s and 1990s and the analysis included 602 metropolitan areas and their related central cities and suburban rings. The study proposed that "metropolitan or intrametropolitan economic transformation [i.e., declining manufacturing employment, increasing proportion of college graduates, a declining unemployment rate, or a rising poverty rate] is a driving-force for local self-employment change" (p. 1784). Overall, it was found that a decline in manufacturing employment produced an increase on self-employment on all three urban levels. In addition, decline in public sector employment in the suburbs was found to produced a positive effect in suburban self-employment. Contrary to central-city economic forces on suburban areas, the study found that an increase in suburban college graduates, growth in suburban manufacturing employment and suburban public sector employment all had positive impacts on central-city self-employment change. However, the study did not claim that suburban and central-city economies are two independent markets within a metropolitan area, instead it found that the central-city was more dependent on the economic well-being of the suburb than vice versa (Oh, 2008). The central-city can benefit from the suburb's economic vitality and those living outside the central-city (i.e., the suburbs) can take advantage of resources and the benefits of the central-city "due to significant reductions in transportation costs and advances in technology" (Kosmopoulou et al., 2007, p.4). For this reason, it is important to better understand the economic interconnectedness of the suburbs and the central-city and journey-to-work, patterns since commuting is a major part of this interrelationship.

As modern living outside a central community does not limit/deny one access to resources found in the more urbanized central areas (Kosmopoulou et al., 2007), this economic relationship is important. The economic vitality of outlying metropolitan areas provides economic support to the central city and economic spillovers from central cities affect outlying areas (Oh, 2008; Shrestha et al., 2007); and as such, the interconnectedness (e.g., via commuting) of central and outlying metropolitan counties should be expected to exhibit economic associations providing benefits for each other.

Methods

The purpose of this paper is to identify those outlying metropolitan counties that generate disproportionately high percent shares of NFP employment. The research in this paper expands on earlier work by Bignall and Debbage (2020) that analyzed the geography of NFP employment for 800 of the most populated counties in the U.S. but failed to differentiate between central and outlying metropolitan counties. In this paper, I focus exclusively on the 71 outlying counties included in the prior Bignall and Debbage (2020) analysis of metropolitan counties. The current analysis was undertaken to determine if the geography of entrepreneurship and the related predictors are significantly different when related to a landscape of opportunity that is more suburban (i.e., outlying county) than urban (i.e., central county).

Using data from the 2016 U.S. Census Bureau American Community Survey (ACS) and the Bureau of Economic Analysis (BEA), the present study employed a quantitative research design to investigate county data for outlying metropolitan counties in the contiguous US. Special combination counties of Virginia that did not match well with Census ACS and BEA county datasets, along with any other non-matched counties were not included in this analysis. As reported by the ACS annual survey, only counties of 65,000 and greater in population were included. In addition, where a business' data values may be presumed due to a low number of observations the nondisclosure rule of the U.S. Census limited data.

NFP employment is used as a proxy for entrepreneurship or self-employment in this paper. I used the IRS definition of proprietorship, which states:

> A sole proprietorship is defined by the Internal Revenue Service as an unincorporated business that is owned by one individual who is required to file Schedule C (Form 1040) for profit or loss from a business. An existing relationship between two or more persons who join to carry on a trade or business is considered a partnership. As such, the partnership must file an annual information return to report the income, deductions, gains, and losses, etc., from its operations, on Form 1066 (U.S. Return of Partnership Income). Organized for profit, unincorporated, full- and part-time sole proprietorships, partnerships, and other private nonfarm businesses are non-farm proprietorships (IRS, 2020).

The units of analysis used in this study are outlying metropolitan counties. The U.S. Census Bureau delineates outlying counties to be economically tied to the core counties of metropolitan or micropolitan areas as measured by labor-force commuting. Most commonly, outlying counties are included if at least 25% of workers living in the county commute to the central counties of the metro- or micropolitan area or if 25% or more of those living in central counties commute to work in the outlying county.

With respect to the statistical analysis, a correlation analysis was conducted between the dependent variable, percent NFP employment, and selected independent socio-economic and demographic variables to evaluate the strength of their relationships. Twenty-eight independent variables were originally selected for the regression analysis grounded in the literature, but the final dataset for the regression analysis included only 61 outlying metropolitan counties due to missing data for some of the independent variables. Descriptive statistics were calculated for each of the remaining variables and the dependent NFP variable (Table 7).

In addition, to determine the strength of the functional linkage between the outlying metropolitan counties and their related central counties, journey to work trip flow data from the U.S. Census was analyzed between each of these counties. Each outlying county was paired with its corresponding central county/counties' commuting percentage(s) and the outlying county's commuting linkage with the central core counties was categorized as *very strong, strong, medium, weak, or very weak* based on an analysis of the share of the outlying workforce that commutes to the central county or counties. This quantitative approach provided a way to better understand how the geography of entrepreneurship by outlying metropolitan county is potentially linked to the underlying functional ties with the central county.

Table 7. Dependent and Independent Variables and Descriptive Statistics

Variables	Mean	SD
%NFP employment	24.2	4.8
Demographic [a]		
% PGR 2015-2016	1.4	1.32
Median age (years)	39.4	3.9
% White	82.8	10.4
% Hispanic	9.9	10.8
% Male	49.4	1.2
% Female	50.6	1.2
% 65 years and older	15.6	3.2
% of population 25 years or older with only a high school	31.35	5.7
diploma	25.1	8.0
% of population 25 years of age or older with a bachelor's	85.0	5.5
degree or higher		
% of household with broadband		
Economics [b]		
Per capita income ($)	28,437	5,963
Median earnings ($)	32,470	5,913
Median household income ($)	59,226	13,77
Poverty rate (%)	12.5	2
Unemployment rate (%)	5.6	4.3
%Housing stock, owner-occupied	71.5	1.7
Median home value ($)	180,05	7.3
	5	82,30
		9
Employment [a]		
% Construction	6.8	2.0
% Manufacturing	10.3	6.2
% Retail	11.3	1.7
% Information	0.9	0.4
% Finance and Insurance	3.6	1.3
% Real estate and rental and leasing (RRL)	4.0	1.2
% Finance insurance and real estate (FIRE)	7.6	2.2
% Educational	1.5	1.1
% Healthcare Services	9.1	2.6
% Arts, entertainment, and recreation	1.8	0.8
% Accommodation and food services	7.2	1.8

Notes: [a] US Department of Commerce, BEA; [b] US Census Bureau: American Community Survey by outlying metropolitan county, 2016

Results and Discussion

In 2007, there were 34.5 million nonfarm proprietor jobs and by 2019 this number had increased to 45.7 million (BEA, 2021). Despite NFP employment being an important area of inquiry and a growing sector of the economy, relatively little is known about the geography of non-farm proprietorship employment, especially in outlying metropolitan counties.

The geography of entrepreneurship by outlying metropolitan county is expected to be much different from larger more populated, urbanized, and central counties. From the original 800 counties included in the study by Bignall and Debbage (2020), the 71 outlying metropolitan counties were extracted to provide a more disaggregated analysis of the entrepreneurial activities of this rapidly changing suburban milieu. When compared to the largest 800 populated counties analyzed by Bignall and Debbage (2020), the 71 outlying metropolitan counties yielded some notable differences as highlighted in Table 8. The outlying more suburban counties tended to generate a higher percent share of NFP workers (24.2% vs 21.2%), experienced a more rapid population growth rate and tended to be less diverse than the most populated 800 counties analyzed by Bignall and Debbage (2020). They were found to be more affluent based on a comparison of median household income levels. They were also more likely to be homeowners and tended to generate a higher share of jobs in construction employment in part, because of intense suburban overspill out of the metropolitan core counties and the proliferation of greenfield sites and lower land costs.

Table 8. Descriptive Statistics for Non-Farm Proprietorship Employment (%) and Other Metrics: Average Difference Between Larger Populated Counties and Outlying Metropolitan Counties, 2016

Variable	Largest Populated Counties (n=800)	Outlying Metropolitan Counties (n=71)
NFP %	21.2	24.2
Population Growth Rate (2015/6)	0.6	1.4
% White	78.9	82.8
% Hispanic	12.5	9.9
Median Household Income ($)	57,754	59,226
% Owner-Occupied	66.4	71.5
% Construction Employment	5.8	6.8

Source: BEA, U.S. Census Bureau and Bignall and Debbage (2020)

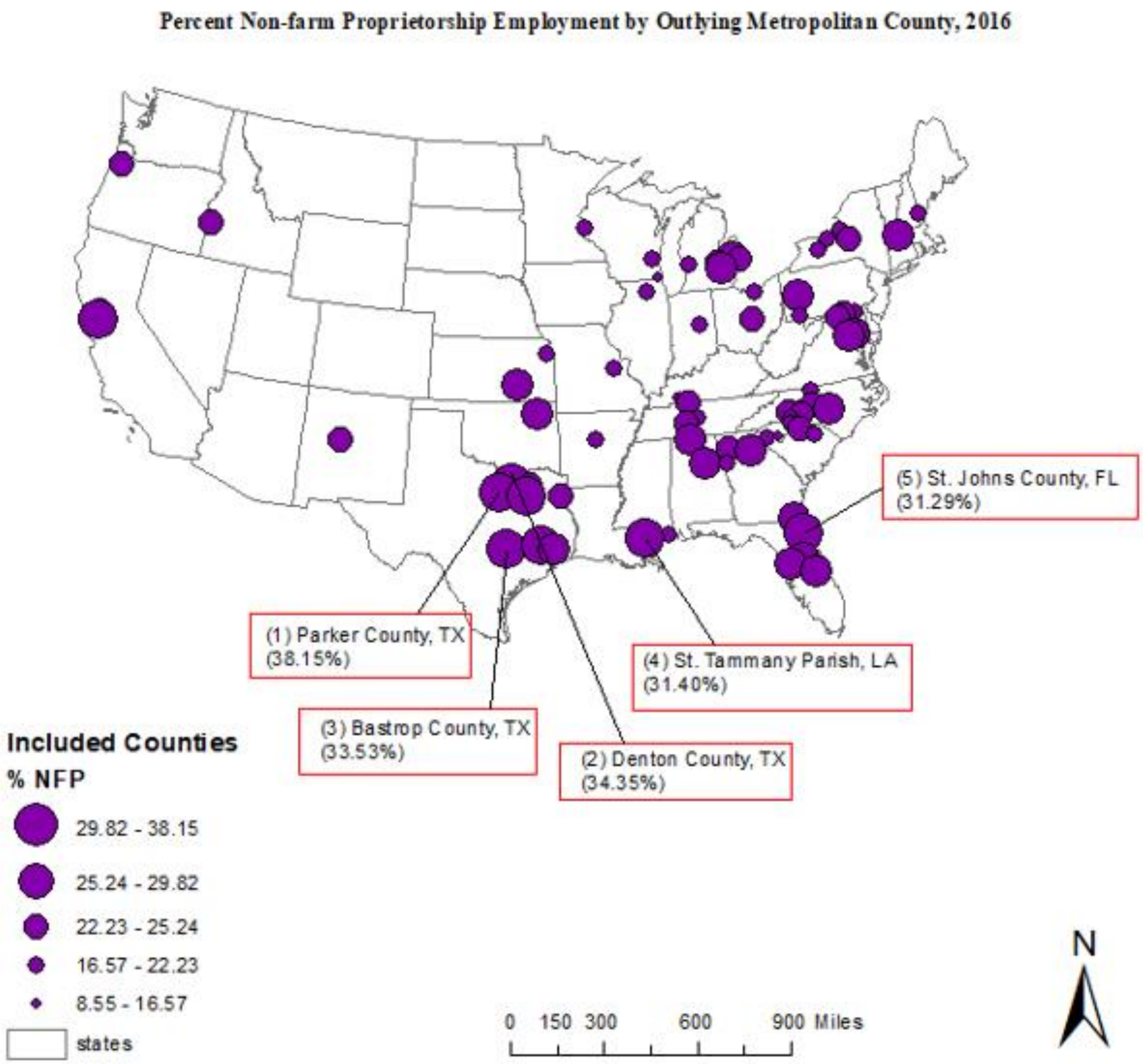
The Geography of the Leading Non-Farm Proprietorship Outlying Metropolitan Counties

The largest NFP labor pools by outlying metropolitan county in absolute terms included; Contra Costa, CA (168,896 NFP workers), Denton County, TX (129,836), Montgomery County, TX (82,055), St. Tammany Parish (43,419) and Osceola County, FL (40,498). The overall average absolute values varied from a high in Contra Costa County of nearly 170,000 NFP workers to a low of 4,628 in Laurens County, SC with a mean of 19,839 workers for all 71 outlying counties included in this paper. A closer inspection of the relative (%) geography of NFP employment suggests a radically different spatial configuration (Table 9 and Figure 17). Table 9 shows the top 10 outlying metropolitan counties ranked by percent NFP employment for 2016. The uneven distribution of shares of NFP employment is illustrated in Figure 17. The map shows most outlying metropolitan counties to be located in the eastern half of the U.S. The top five outlying metropolitan counties for percent NFP employment were all located in the South, with three located in the state of Texas. In 2016, the percent share of NFP workers by outlying county varied from a high of 38.1% in Parker County, TX to a low of 8.5% in Christian County, KY, with a mean of 24.2% across all 71 outlying metropolitan counties included in this analysis. The top 10 counties with the highest relative NFP employment averaged a 32% share – nearly 8 points higher than the overall average of 24.2%. They also tended to be much larger counties in terms of total employment. Seven of the top 10 outlying metropolitan counties for percent NFP were either in the state of Texas (5) or in the state of Florida (2).

Table 9. Top 10 Outlying Metropolitan Counties Ranked by % NFP Employment, 2016

Outlying County and Largest Metropolitan City by Population	NFP employment	Total employment	%NFP employment
Parker County, TX – Fort Worth	23,577	61,804	38.15
Denton County, TX – Dallas	129,836	377,934	34.35
Bastrop County, TX – Austin	10,328	30,801	33.53
St. Tammany Parish, LA – New	43,419	138,260	31.40
Orleans	34,055	108,829	31.29
St. Johns County, FL – Jacksonville	82,055	265,163	30.95
Montgomery County, TX – Houston	15,482	50,536	30.64
Kaufman County, TX – Dallas	168,896	556,047	30.37
Contra Costa County, CA – Oakland	40,498	135,789	29.82
Osceola County, FL – Orlando	8,162	27,633	29.54
Barrow County, GA - Atlanta			
Averages			
Top 10	55,631	175,279	32.0
N=71	19,839	78,405	24.2

Figure 17. Non-Farm Proprietorship Employment (%) by Outlying Metropolitan County, 2016



Parker County, TX had the highest percent NFP employment (i.e., 38.1%) in this study, but it is a relatively small NFP labor pool in absolute terms (just 23,577 NFP workers). By contrast, Denton County, TX had the second highest share of NFP workers (34.5%) but is also the second largest NFP labor pool in absolute terms (129,836). According to the 2020 Census, Denton County is the seventh most populous county in Texas. It has a population of nearly one million and is located just northwest of Dallas County, the second most populous county in Texas.

Although the BEA NFP data are by place of work, it is important to remember that the labor pool of many outlying metropolitan counties are substantially shaped by the local economies of the central urban core counties of the metropolitan and/or micropolitan areas, given the substantial shares of workers that commonly commute from any given outlying county to the central county. Denton County has experienced a substantial amount of spillover development from the Dallas-Fort Worth metroplex. Commuters from Denton County primarily travel Interstate 35E to Dallas and Interstate 35W to Forth Worth. Approximately half of Denton County's workforce commutes to various central counties (Table 10), including Dallas, Tarrant, and Collin, suggesting the county functions largely as a bedroom suburb. Lower land costs, an array of entertainment, attractions, and events, in addition to many historic venues (e.g. Campus Theatre, Courthouse on the Square, Hangar 10 Flying Museum) and natural amenities (e.g., Lewisville Lake, Ray Roberts Lake State Park, park trails) have allowed for an identifiable niche in the local economy that has offered a wide range of entrepreneurial opportunities for NFP workers. In this context, it is not surprising that 9 of the top 10 outlying metropolitan counties by percent NFP had at least one-third of their workforce commute to the central county or counties of their local metropolitan area. On average, 42% of the labor force in these top 10 counties commuted to the central county or counties for work compared to an average of just 35% for all 71 outlying counties included in this paper (Table 10).

Table 10. Percentage NFP Top Outlying Counties Ranked by Percent of the Labor Force that Commute to the Central County for Work, 2016

Commuting Flow Strength[1]	Outlying Metropolitan County	% of Workforce Commuting to Central County or Counties
Very Strong >50%	Kaufman County, TX	53
Strong 43-50%	Denton County, TX	50
	Barrow County, GA	47
	Bastrop County, TX	47
	Osceola County, FL	46
	Parker County, TX	46
Medium 35-42%	St. Johns County, FL	40
	Montgomery County, TX	39
	Contra Costa County, CA	36
Weak 27-34%	N/A	0
Very Weak <27%	St. Tammany Parish, LA	26

[1] The outlying county to central county commuting classification was based on an average commute flow of 35% and a standard deviation of 8 for all the outlying counties included in this paper. Each classification is within + or – two standard deviations from the mean.

The uneven distribution of percent NFP employment in Figure 17 suggests that outlying metropolitan counties capable of generating disproportionate shares of NFP workers can be situated in a wide variety of socio-economic contexts. However, a majority of the outlying counties with disproportionate shares of NFP workers (Table 9) could be characterized based on specific economic niches:

- Tourism/Events/Conventions economy (e.g., Osceola County, FL – 29.8% located immediately south-southeast of Orlando)

- Transportation Hub/Industrial/Finance economy (e.g., Parker County, TX – 38.1%, Denton County, TX – 34.3%, and Kaufman County, TX – 30.6% all located on the outskirts of Dallas; and Barrow County, GA – 29.5% located east of Atlanta)

- Medical Research/Energy/Space/Economic/Transportation economy (e.g., Montgomery County, TX – 30.9% located immediately north of Houston)

- Culture/Finance/Economic/Commercial economy (e.g., Bastrop County, TX -33.5% located southeast of Austin; St. Tammany Parish, LA – 31.4% located north of New Orleans across Lake Pontchartrain; St. Johns, FL – 31.3% located south of Jacksonville; and Contra Costa County, CA – 30.4% located east of Oakland)

Many of the outlying metropolitan counties have such unique settings that any explanation of the underlying geography of NFP for all 71 counties included in this analysis is unlikely to be straightforward given the diversity of county settings and varied entrepreneurial ecosystems.

Regression Analysis

Consequently, a stepwise regression analysis was performed to quantitatively assess the potential relationships that might exist between NFP and select socio-economic variables by outlying metropolitan county. Diagnostic tests indicated that the regression models exhibited low multicollinearity among the independent variables and met the assumptions of linearity, normality and homoscedasticity. All models and independent variables were significant at the $p < 0.01$ level.

In the final regression model (i.e., Model 3, Table 11) 63.2% of the variation in the percentage of NFP employment by i=outlying metropolitan county, can be explained by labor pools with a disproportionate share of their workers engaged in *RRL employment, Construction employment, and Finance and Insurance employment*. It seemed that the employment composition of the local labor pool played a more powerful role in shaping the NFP labor market in relative terms than more aggregate socio-economic measures of performance like per capita income, education levels or median household income. Similar results were found by Bignall and Debbage (2020) in their analysis of the geography of NFP employment for the 800 most populated counties in the U.S., where percent construction and percent RRL were found to be key predictors of NFP employment. However, one notable difference was that Bignall and Debbage (2020) found that percent Hispanic and median age were also key predictors, in their analysis of the 800 most populated counties in the U.S., suggesting that ethnicity and the age composition of a county play less of a role in shaping NFP labor pools in outlying metropolitan counties that tend to be more homogenous.

Table 11. Regression Models Indicating Associations Between Socio-Economic Variables and NFP Employment (%) by Outlying Metropolitan County, 2016

Model	Variable	Model R^2	Unstandardized coefficients b	Std. error SE b	Standardized coefficients β	p-value
1	Constant	0.419	13.692	1.678		<.001
	% RRL		2.516	.386	.647	<.001
2	Constant	0.574	8.619	1.823		<.001
	% RRL		2.144	.343	.552	<.001
	% Construction		.962	.210	.405	<.001
3	Constant	0.632	.6.236	1.882		<.002
	% RRL		1.441	.397	.371	<.001
	% Construction		1.165	.208	.490	<.001
	% Finance and insurance		1.080	.359	.302	<.004

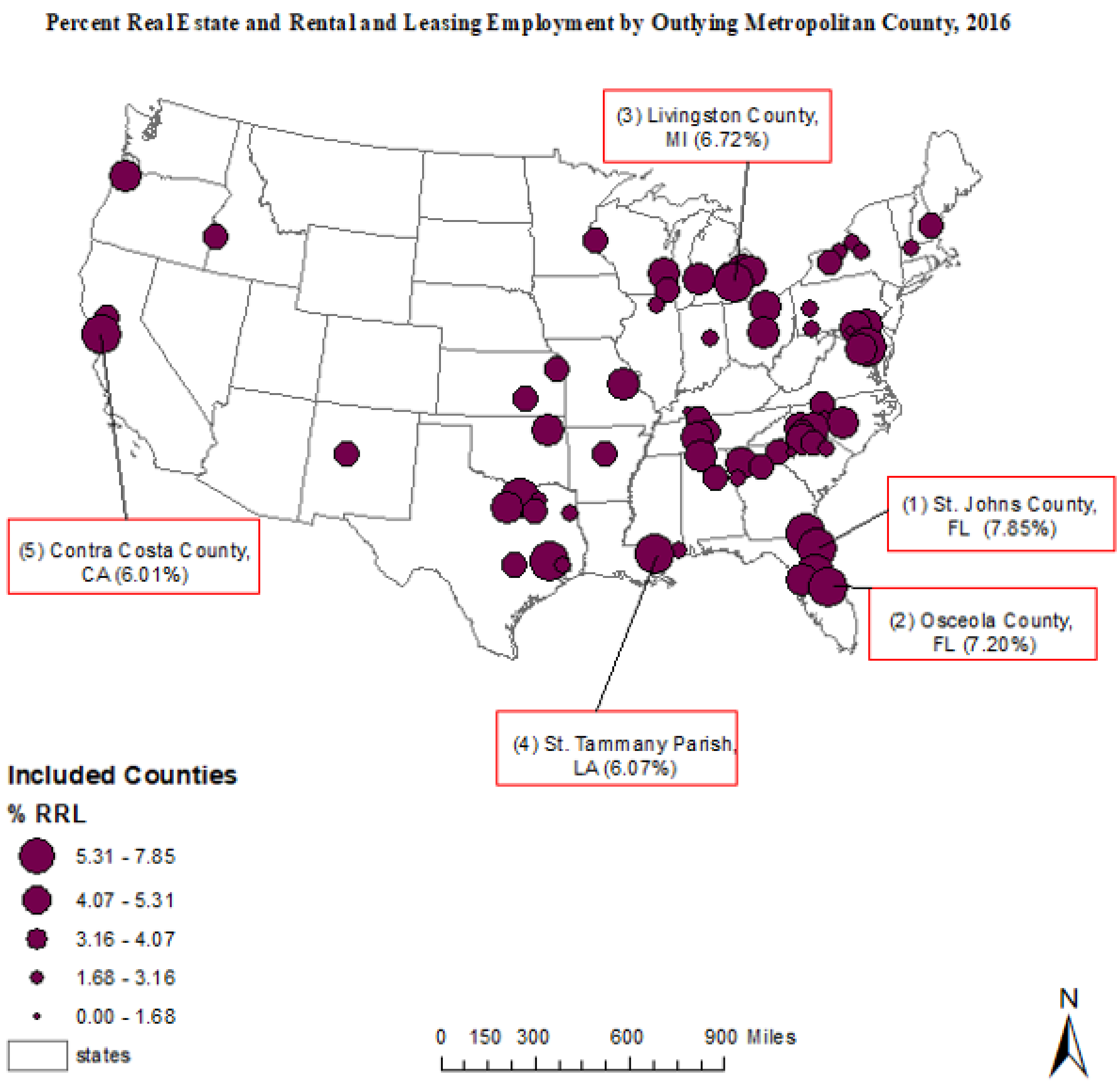
Note: The regression analysis included n=61 counties due to a small number of missing values for some counties.

Percent Real Estate and Rental and Leasing Employment

The first predictor variable to enter the regression model was percent *RRL*. In model 3 (Table 11) the variable's b coefficient suggested a 1% increase in the percentage of RRL employment is expected to result in a 1.44% increase in NFP employment. The counties with the highest percent RRL included St. Johns County, FL (7.85%), Osceola County, FL (7.02%), Livingston County, MI (6.72%), St. Tammany Parish, LA (6.07%), and Contra Costa County, CA (6.01%) (Figure 18). By contrast, the average percent RRL employment for all counties was just 4.0% (Table 7). It should also be noted that four of the top five counties for percent RRL employment featured prominently in Table 9, which also listed the top ten outlying counties by percent NFP, the only exception was Livingston County, MI. Additionally, many of the most highly concentrated RRL labor pools were located in Florida (Figure 18) including; St. Johns County (7.85%), Osceola County (7.02%), Lake County (5.74%), and Nassau County (4.31%).

Much like Bignall and Debbage (2020), these results suggest that percent RRL may be a proxy for access to a particular type of capital tied to vibrant land markets, particularly in outlying metropolitan counties with more urban and tourist-related economies like St. John's County which is located south of the city of Jacksonville and stretches from Ponte Vedra Beach in the north to St. Augustine – the county seat – to Flagler Estates in the south. St. Augustine is the largest city in St. Johns County, the Nation's oldest city, and a well-known tourist destination, boasting "beautiful natural amenities, a highly educated workforce, and progressive government with a commitment to economic development" (Economic Development (st-johns.fl.us)). In an analysis based on the Florida Economic Analysis Project of long-term RRL employment growth trends, St. Johns County experienced a 6.73% growth rate from 2010-2019 compared to a state average of just 4.63%. Beyond just tourism and the RRL sector, St. John's County has been actively engaged in nurturing entrepreneurial activity. The St. Johns County Chamber of Commerce Economic Development Council has recently stated that a goal of their economic development program is to foster entrepreneurship and innovation.

Figure 18. Real Estate and Rental and Leasing Employment (%) by Outlying Metropolitan County, 2016



Percent Construction Employment

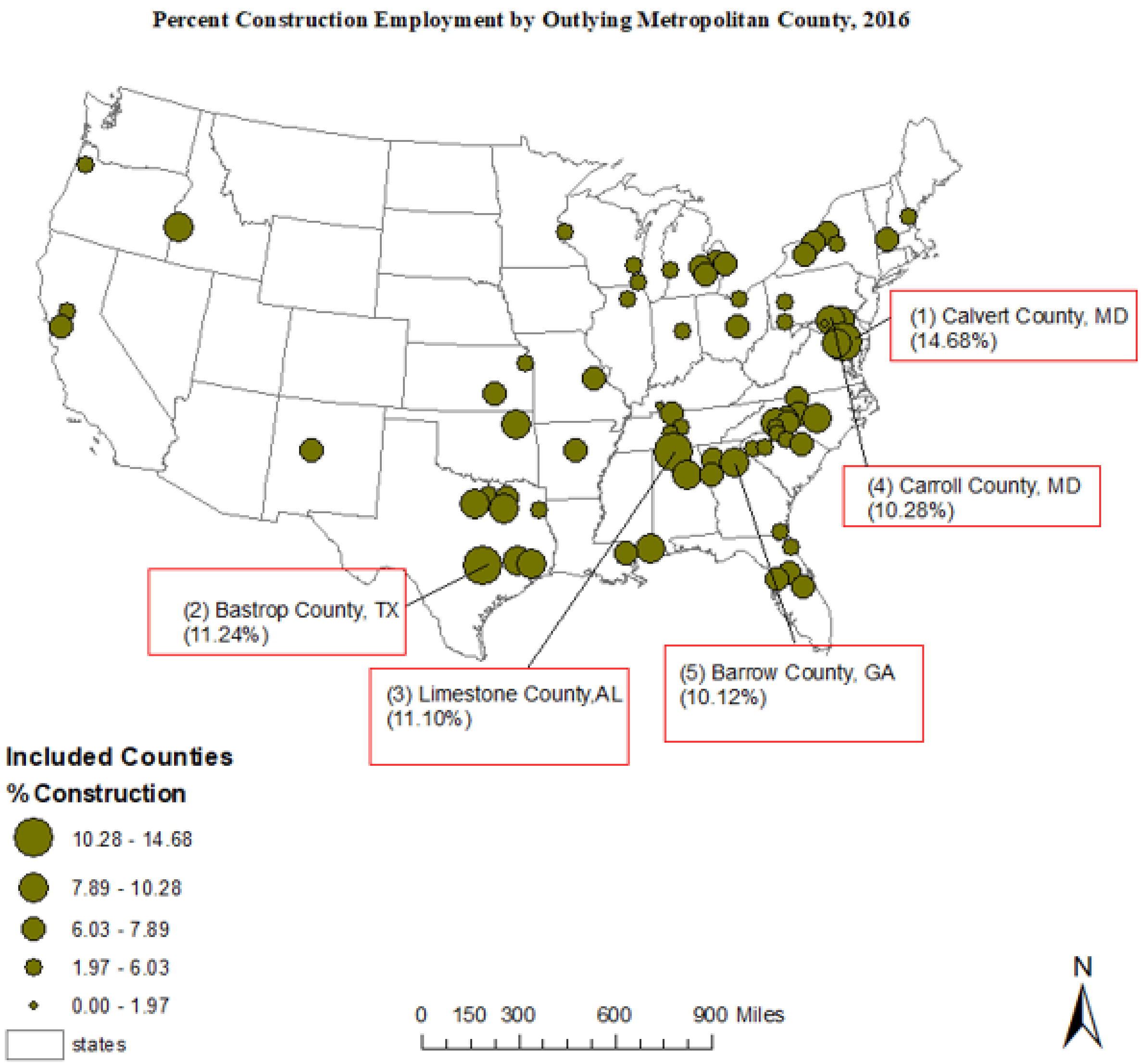
The regression analysis not only identified RRL as a key predictor in shaping the geography of NFP by outlying county but also highlighted the important role that construction jobs can play in shaping the spatial distribution of NFP workers. The unstandardized regression coefficient suggests that if the percent of construction workers increased by 1%, then the share of

NFP employment would increase by 1.17%. The counties with the highest percent of their labor pools in construction employment included Calvert County, MD (14.7%), Bastrop County, TX (11.24%), Limestone County, AL (11.1%), Carroll County, MD (10.28%), and Barrow County, GA (10.1%) (Figure 19), compared to an average for all 71 outlying counties of just 6.8%. Two of these counties featured in the top ten NFP labor pools listed in Table 9 including Bastrop County and Barrow County.

Goetz and Rupasingha (2009) have found that "many construction workers are self-employed, and this trend seems to be increasing over time" (p. 435). Bignall and Debbage (2020) also found that percent construction employment was a key predictor of percent NFP in their analysis of the 800 most populated counties in the U.S. In this context, it is not surprising that percent *construction* plays such a pivotal role in shaping NFP labor pools in outlying metropolitan counties given the much higher population growth rate for this subset of counties (i.e.,1.4% vs 0.6% for the 800 counties included in the Bignall and Debbage (2020) analysis) (Table 8).

Although Calvert County, MD (14.7%) ranked highest in percent construction, it is second ranked Bastrop County, TX (11.2%) that ranked highest among the top 10 for percent NFP employment (i.e., 33.5%) (Table 9). Bastrop County is located within a short drive to downtown Austin and the Austin-Bergstrom International Airport. It is not surprising that Bastrop ranks high in construction since companies like Ascension Seton Medical and JAMCo Construction have recently moved to Bastrop County. This may be in response to the "abundance of commercial land and affordable shovel ready sites" in addition to lower taxes and other financial incentives highlighted by the Economic Council as reasons for moving to Bastrop (Bastrop EDC). In a similar vein, , Barrow County, GA which was ranked fifth in construction employment (i.e., 10.12%) also ranked highly in percent NFP employment (i.e., 38.2%) (Table 9). Barrow County Economic Development highlights transportation as a major incentive for businesses to move to Barrow County. Located between Atlanta and Athens, GA, access to major airports, research universities, and major highway systems (e.g., Interstate 85 and, Georgia Highway 316) are promoted as assets to any company looking to move into the county. New businesses desiring the construction of new buildings or complexes, may also be lured by the county's affirmation of "plenty of developable land" (Barrow County Georgia Economic & Community Development (choosebarrow.com)). The availability of land and lower land costs in addition to its proximity to the larger Atlanta market may have helped foster the growth of construction and NFP employment in Barrow County.

Figure 19. Construction Employment (%) by Outlying Metropolitan County, 2016



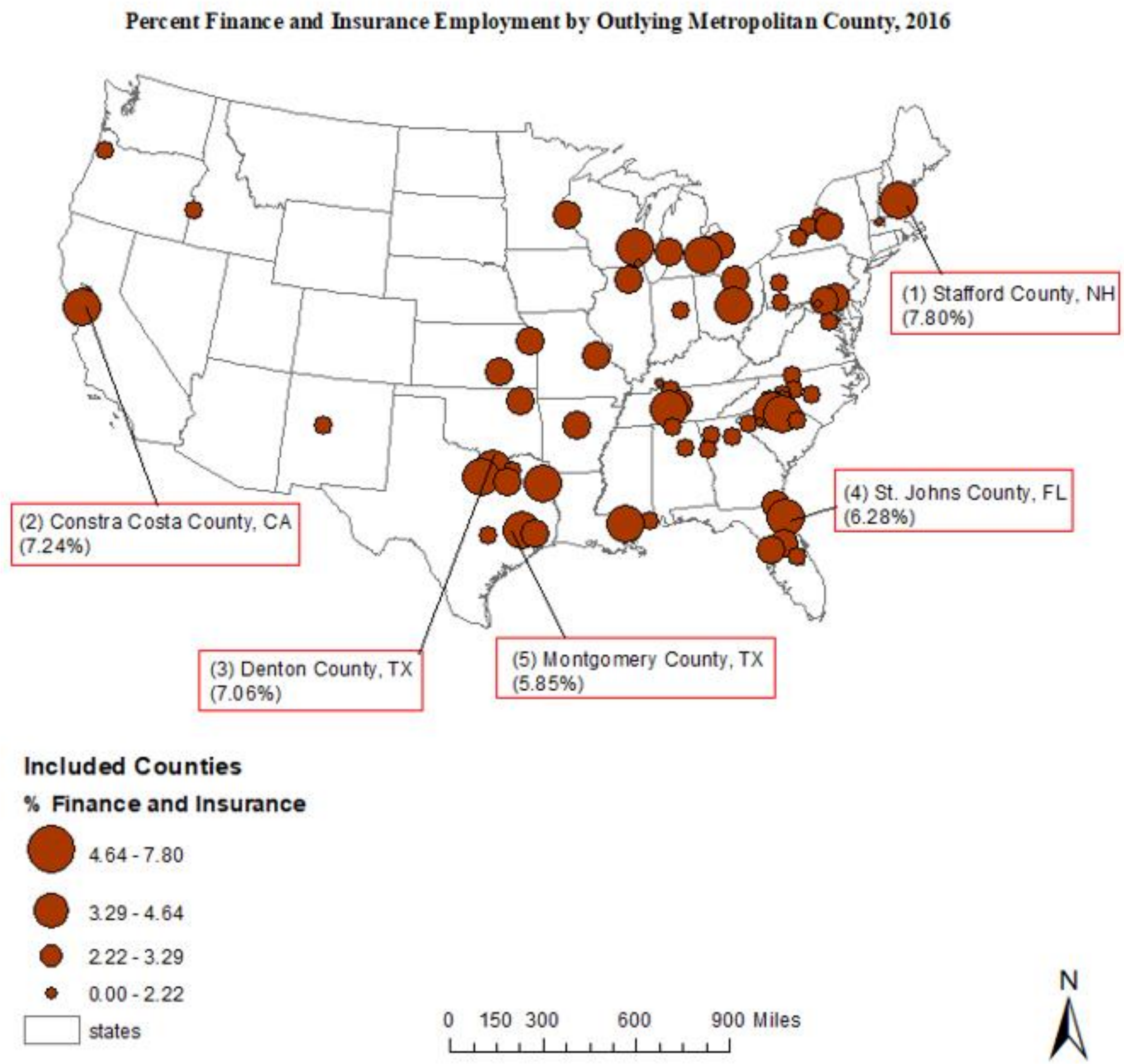
Percent Finance and Insurance Employment

The stepwise regression analysis also identified percent *Finance and Insurance* employment to be a significant predictor of percent NFP employment by outlying metropolitan county. The unstandardized regression coefficient indicated that a 1% increase in finance and insurance employment, will lead to an increase of 1.08% in NFP employment. The outlying metropolitan counties with the highest share of finance and insurance workers included Stafford

County, NH (7.8%), Contra Costa County, CA (7.1%), St. John's County, FL (6.3%), and Montgomery County, TX (5.8%) (Figure 20) compared to an average of just 3.6% for all 71 counties included in this analysis (Table 7). Three of these counties also featured prominently in the percent NFP top ten (Table 9) including Contra Costa, Denton, and St. John's County. Both Contra Costa and Denton are also very large NFP labor markets in absolute terms (i.e., 129,839 and 168,896 NFP workers, respectively), in part, because they serve as major bedroom suburbs for San Francisco-Oakland and Dallas, respectively.

Contra Costa County, CA is part of the Northern California Mega Region and the county includes 19 cities and unincorporated communities all concerned about local economic development. The Contra Costa County Office of Economic Development emphasizes the county's role as a "break-in-bulk point" where access to multiple modes of transportation (e.g., rail, deep-water ports, freeways) are close by and serve as assets and enticements to new businesses, large and small. In unincorporated Contra Costa County, FIRE was the third largest employer by industry, with over 500 employers. (Largest Employers | Contra Costa County, CA Official Website). Overall, it is possible that percent *finance and insurance* employment is acting as a proxy for access to loan capital and other financial services that are crucial when first developing non-farm proprietorships. Rupasingha and Goetz (2013) have argued that access to capital via banks can enhance the growth of self-employment rates while Debbage and Bowen (2018) found similar effects in their analysis of metropolitan areas.

Figure 20. Finance and Insurance (%) by Outlying Metropolitan County, 2016



Conclusion

NFP employment continues to be an important emerging research area in the field of entrepreneurship. Since Goetz (2003) asserted the significant absolute and relative growth of nonfarm proprietors, their economic and entrepreneurial contributions have been positively noteworthy to local economies, but further study of the geography of entrepreneurship via NFP employment, requires more spatially disaggregated analysis. The current article is one step toward better understanding entrepreneurship in communities located in the suburban ring around the more centrally located urbanized cores of metropolitan areas.

Building on the work of Bignall and Debbage (2020), this paper described and explained the spatial distribution of outlying metropolitan counties based on the percent shares of NFP employment in 2016. The results of this study support the idea that the geography of entrepreneurship is unevenly distributed. Most outlying metropolitan counties found to rank highest in NFP employment were also found to have strong or very strong commuting links with the central core counties and were situated in a variety of milieus.

The results of a stepwise regression suggest that the geography of NFP employment by outlying metropolitan county may best be explained by the composition of the local labor pool in relative terms. The combination of percent RRL, percent Construction, and percent Finance and Insurance employment seemed to best explain NFP employment by outlying metropolitan county. Larger lot sizes, lower land values, multiple modes of transportation access, and local economic incentives, all within proximity to central-city resources, may be driving up the share of proprietorship workers in these outlying areas.

With respect to future post-COVID research agendas, it would seem that additional research concerning the relationship between NFP workers situated in the suburbs and whether or not they return to work in central counties/cities or continue the "work-from-home" trend is an arena worthy of attention. This is an important issue for future research as the "worker to job site relationship" can considerably impact the socio-economic and demographic makeup of local entrepreneurial ecosystems. Since the intrametropolitan relationship provides benefits for both the outlying metropolitan counties and the central urbanized core counties (Oh, 2008), policymakers should pay close attention to possible changes in commuter flows.

This paper has also highlighted the continued importance of entrepreneurship/self-employment to local economies. Planners, stakeholders, and local government officials of outlying metropolitan counties should be aware of the benefits and challenges associated with intrametropolitan relationships. Many outlying counties' labor pools are shaped by the local economies of the central counties (i.e., metropolitan or micropolitan counties) and may encourage or discourage local NFP/self-employment. I concur with Kline et al. (2020) that, "entrepreneurs are often some of the most significant change agents in development,…" (p. 15) and as such, supportive services, programs, and access to capital, for entrepreneurs or the self-employed, may all aid in providing a balance in outflow and inflow of workers and revenues in outlying metropolitan counties. Also, a better understanding of the economic interconnectedness of outlying counties and central counties should make for better and more effective future planning and development.

I am aware that this research does not speak directly to the specific types of jobs local workers are engaged in, such as types of construction workers (e.g., brick mason, concrete finisher, glazier, crane operator, construction inspector, civil engineer, surveyor), but instead to the broader categories. Future studies will have to investigate the role of specific industries in determining which specific local NFP jobs are most likely to influence local economic growth and how successful those jobs are in terms of years in business.

CHAPTER V: CONCLUSION

U.S. non-farm proprietorship (NFP) employment is an important research area in the field of entrepreneurship and an increasingly important determinant of entrepreneurial economic development, that has seen significant employment increases since the 1980s. Faster growing local economies have been found to be associated with higher rates of entrepreneurial activities, while NFPs and self-employment have generated new economic development opportunities, having positive effects on the economic well-being of local communities (Rupasingha and Goetz, 2013; Acs and Armington, 2004). NFP employment gains are a valuable means to local job formation and economic growth, and although economic development research continues to attract academics and policymakers, in the past, less attention has been paid to NFP employment, particularly regarding its uneven distribution across U.S. counties. Here, I demonstrate that areas of higher/lower NFP employment shares are not random but rather express distinct geographical patterns.

A better understanding of the spatial distribution of non-farm proprietorship (NFP) employment for various county typologies (i.e., most populated U.S. counties, micropolitan counties, and outlying metropolitan counties) can help create awareness of how NFP might contribute to local entrepreneurial opportunities. Each paper in this three-article dissertation explores the links between NFP employment and the specific and broader based socio-economic and demographic milieu that lie outside the traditional entrepreneurial ecosystem, for various county typologies.

Data for all three papers in this dissertation were collected from the U.S. Census American Community Survey, Bureau of Economic Analysis (BEA), and the Office of Management and Budget (OMB) for counties in the contiguous U.S. in 2016. Throughout this dissertation, the IRS definition of NFPs is used to refer to those businesses that are unincorporated, sole proprietorships (i.e., self-employed) or partnerships, and in business for profit. The socio-economic and demographic independent variables by county identified in previous literature. Each research paper's dataset was subject to a stepwise regression analysis and the results were used to identify those socio-economic variables most likely to help explain the geography of NFP employment. The first paper of this dissertation focused on the 800 most populated counties in the U.S. while the second paper analyzed NFP patterns for 107 micropolitan counties and the final paper concentrated on the geography of NFP employment. Table 12 summarizes the essential findings of these three papers.

Overall, these three papers highlighted the uneven distribution of NFP-/self-employment (Figures 2, 12, and 17) for all three county typologies. The top ten counties based on percent NFP for each county typology are uncommon in that there are few counties featuring in more than one top ten ranking (exceptions include Nevada County, CA and Parker County, TX). Although the top-ranking counties also included counties with smaller populations, such counties were more likely to be located within proximity of larger metropolitan areas and seemed to benefit from the "spillover effect" linked to being adjacent to larger more urbanized areas, seeming to confirm that job growth in one county is positively affected by job growth in a neighboring county (Shrestha et al., 2007).

Table 12. Top Ten Counties Ranked by NFP Employment (%) and the Key Predictors

Most Populated U.S. Counties		Micropolitan Counties		Outlying Metro Counties	
Counties	%NFP	Counties	%NFP	Counties	%NFP
Wagoner County, OK	44.4	Nevada County, CA	39.0	Parker County, TX	38.2
Nevada County, CA	39.0	Henderson County, TX	35.2	Denton County, TX	34.4
Randall County, TX	38.4	Litchfield County, CT	32.6	Bastrop County, TX	33.5
Parker County, TX	38.2	Island County, WA	30.9	St. Tammany Parish, LA	31.4
Rockwall County, TX	37.8	Carteret County, NC	29.7	St. Johns County, FL	31.3
Fort Bend County, TX	37.1	Flathead County, MT	29.4	Montgomery County, TX	31.0
Marin County, CA	36.8	Mendocino County, CA	29.3	Kaufman County, TX	30.6
Cherokee County, GA	36.7	Monroe County, FL	27.7	Contra Costa County, CA	30.4
Newton County, GA	36.4	Gallatin County, MT	27.6	Osceola County, FL	29.8
Paulding County, GA	36.1	Lake County, CA	26.6	Barrow County, GA	29.5
Averages					
Top Ten	38.1	Top Ten	30.8	Top Ten	32.0
N=800	21.2	N=107	20.2	N=71	24.2
Predictor Variables		Predictor Variables		Predictor Variables	
% RRL		% Construction		% RRL	
% Construction		% RRL		% Construction	
% Hispanic		% 65+		% Finance and Insurance	
Median Age					
$R^2 = 0.60$ ($p<0.01$)		$R^2 = 0.68$ ($p<0.01$)		$R^2 = 0.63$ ($p<0.01$)	

By contrast, the top ten micropolitan counties based on percent NFP predominantly located in geographically desirable amenity-rich (e.g., mountains, coastal) locations and were conceptualized in terms of their relationship and distance to more urbanized counties. Finally, the highest ranked outlying metropolitan counties, included counties with larger populations such as Contra Costa, CA (30.4%) and counties with strong commuting connections (e.g., Kaufman County, TX (30.6%) to nearby central metropolitan counties.

R-squared values for all three county types were statistically significant and positive with each having over 60% of the variation in NFP employment being explained by the predictor variables which were all significant at the 1% level (Table 11). The general picture that emerged from these analyses was that for each county typology (i.e., most populated U.S. counties, micropolitan counties, outlying metropolitan counties), disproportionately large labor pools of real estate and rental and leasing (RRL) and construction workers best explained why some counties had disproportionate numbers of NFP jobs (Table 11), although other predictor variables also entered each of the three final regression models for each county type (i.e., (1) % Hispanic and median age, (2) % age 65+, (3) Finance and Insurance). Although the geography of NFP employment is not straightforward, the shares of employment in RRL and Construction seemed to be of great consequence in predicting the share of NFP employment as growth of these industries is positively linked with areas with higher geographical amenities.

Policymakers and stakeholders involved in planning and development of local economies can benefit from the findings of this research in a powerful way – a better understanding of entrepreneurship and those factors that support and encourage job generation – while also being able to distinguish those locales most likely to provide entrepreneurial opportunities. Cultivating labor pools by providing economic support services while tailoring those services toward specific types of entrepreneurship may help local NFP employment continue as an important generator of new jobs, in locations with attributes specific to the locale. However, this dissertation study does not address the specific types of NFP jobs that would be most beneficial.

"Under the broad umbrella of NFP, many different forms of self-employment exist…" (Debbage and Bowen, 2018, p. 155). Further research is encouraged to examine the role of specific industries in determining which NFP jobs are most likely to influence local NFP employment growth. Future studies will also need to explore NFP employment within specific counties to better understand the micro-geography of NFP at a more site specific level.

REFERENCES

Ács, Z., & Armington, C. (2004), "Employment growth and entrepreneurial activity in cities", *Regional Studies*, 38(8), 911-927. https://doi:10.1080/0034340042000280938

Ács, Z.J., Autio, E. & Szerb, L. (2014), "National systems of entrepreneurship: Measurement issues and policy implications", Research Policy, Vol. 43 No. 3, pp. 476-494.

Anggadwita, G., Luturlean, B. S., Ramadani, V. & Ratten, V., (2017), "Socio-cultural environments and emerging economy entrepreneurship: Women entrepreneurs in Indonesia", *Journal of Entrepreneurship in Emerging Economies*, 9(1), 85-96. https://doi:10.1108/JEEE-03-2016-0011

Aparicio, S., Turro, A., & Noguera, M. (2020). Entrepreneurship and intrapreneurship in social, sustainable, and economic development: Opportunities and challenges for future research. *Sustainability*, 12(8958), 1-11. https://doi.org/10.3390/su12218958.

Audretsch, D.B. & Belitski, M. (2017), "Entrepreneurial ecosystems in cities: establishing the framework conditions", *The Journal of Technology Transfer*, Vol. 42 No. 5, pp. 1030-1051.

Backman, M., & Loof, H. (2015), "The geography of innovation and entrepreneurship", *The Annals of Regional Science* 55, (1-6). https://doi:10.1007/s00168-015-0713-x

Baycan-Levent, T., & Nijkamp, P. (2009), "Characteristics of migrant entrepreneurship in Europe", *Entrepreneurship & Regional Development*, 21(4), 375-397. https://doi:10.1080/08985620903020060

Beladi, H., & Kar, S. (2015), “Skilled and unskilled immigrants and entrepreneurship in a developed country”, *Review of Development Economics*, 19(3), 666-682. https://doi:10.1111/rode.12155

Bignall, N. M. & Debbage, K. G. (2020). Self-employment by US county: key predictors. *Journal of Enterprising Communities: People and Places in the Global Economy*, 14(4), 583-602. https://doi:10.1108/JEC-05-2020-0087

Bradford, W.D. & Mijid, N. (2016), *State of the Field: Distilling the Universe of Entrepreneurship Research – Race,* Kauffman Foundation, Kansas City.

Breitenecker, R. J. & Harms, R. (2010), “Dealing with spatial heterogeneity in entrepreneurship research”, *Organizational Research Methods*, 13(1), 176-191. https://doi:10.117711094428109338871

Brown, D. L., Cromartie, J. B., & Kulcsar, L. J. (2004). Micropolitan areas and the measurement of American urbanization. *Research and Policy Review*, 23, 399-418.

Carree, M., Congregado, E., Golpe, A. & van Stel, A. (2015). Self-employment and job generation in metropolitan areas, 1969-2009. *Entrepreneurship and Regional Development*, 27(3-4), 181-201. https://doi:10.1080/08985626.2015.1025860

Center for an Urban Future (2019), *Brooklyn's growing innovation economy*, available at: file:///C:/Users/bmnik/Documents/A-PhD%20Research%202019-2020/Article%20One%20-%20No2%20Writings%20October%202019/Brooklyns_Growing_Innovation_Economy_6-12.pdf

Chi, G., & Marcouiller, D. (2013). Natural amenities and their effects on migration along the urban-rural continuum. *Annals of Regional Science*, 50, 861-883. https://doi.org/10.1007/s00168-012-0524-2.

Cortes, B. S., Davidsson, M., & McKinnis, M. (2015). Growth and volatility of micropolitan statistical areas in the U.S. *International Journal of Business and Finance Research*, 9 (4), 89-102.

Cowell, M., Lyon-Hill, S. & Tate, S. (2018), "It takes all kinds: understanding diverse entrepreneurial ecosystems", *Journal of Enterprising Communities: People, and Places in the Global Economy*, 12(2), 178-198. https://doi:10.1108/JEC-08-2017-0064

Curran, W. (2010), "In defense of old industrial spaces: Manufacturing, creativity and innovation in Williamsburg, Brooklyn", *International Journal of Urban and Regional Research*, 34(4), 871-885. https://doi:101111/j.1468-2427.2010.00915x

Debbage, K., & Bowen, S. (2018), "Non-farm proprietorship employment by US metropolitan area", *Journal of Enterprising Communities: People and Places in the Global Economy*, 12(2), 139-157. https://doi:10.1108/JEC.07.2017.0043

Drucker, P. F. (1985). Purposeful Innovation and the Seven Sources for Innovative Opportunity. *Innovation and Entrepreneurship*. Harper.

Dvorkin, E. (2019), *Brooklyn's innovation economy* (United States Department of States). New York City: Foreign Press Centers, available at: https://www.state.gov/brookyns-innovation-economy.

Faggian, A., Partridge, M. & Malecki, E. (2017). Creating an environment for economic growth: Creativity, Entrepreneurship or Human Capital? *International Journal of Urban and Regional Research* 41(6), 997-1009.

Gardner, T. K., & Marlay, M. (2013). Wither the jobs: Identifying concentrations of employment in metropolitan areas. *Urban Geography*, 34(6), 795-814. https://doi.org/10.1080/02723638.2013.790692.

Goetz, S. J. (2003). Proprietor employment-dependent counties., (RDP No. 17). Retrieved from Pennsylvania State University, Northeast Regional Center for Rural Development website: http://www.cas.nercrd.psu.edu

Federal Reserve Bank of Minneapolis. (2011), Hispanic entrepreneurship grows, but barriers persist. available at: https://www.minneapolisfed.org/article/2011/hispanic-entrepreneurship-grows-but-barriers-persist

Feld, B. (2012), *Startup Communities: Building an Entrepreneurial Ecosystem in Your City*, New York, John Wiley and Sons.

Fisher, M. & Lewin, P. A. (2018), "Push and pull factors and Hispanic self-employment in the USA", *Small Business Economics*, 51, 1055-1070. https://doi:10.111007/s11187-018-9987-6

Florida, R., Adler, P. & Mellander, C. (2017), "The city as innovation machine", *Regional Studies*, Vol. 51 No. 1, pp. 86-96.

Fritsch, M., & Wyrwich, M. (2016), "The persistence of regional entrepreneurship: Are all types of self- employment equally important?", In Elizabeth A. Mack and Haifeng Qian (Eds.), *Geographies of Entrepreneurship* (pp. 48-67). London and New York: Routledge Taylor & Francis Group.

Goetz, S.J., & Rupasingha, A. (2009), "Determinants of growth in non-farm proprietor densities in the US, 1990-2000", *Small Business Economics,* 32, 425-438. https://doi:10.1007/s11187-007-9079-5

Harvey, A.M. (2008), "Personal satisfaction and economic improvement: Working-class Black women's entrepreneurship in the hair industry", *Journal of Black Studies*, 38(6), 900-915.

Helmer, G. (2008). Micropolitan Statistical Areas: A few highlights. *Monthly Labor Review*, 40-42.

Henderson, J., & Weiler, S. (2010), "Entrepreneurs and job growth: Probing the boundaries of time and space", *Economic Development Quarterly*, 24(1), 23-32. https://doi:10.1177/0891242409350917

Hipple, S. F. (2010, September). Self-employment in the United States. *Monthly Labor Review*, 17-32. https://www.bls.gov/opub/mlr/2010/09/art2full.pdf

Internal Revenue Service. (2020), Tax information for businesses, available at: https://www.irs.gov/businesses, (accessed 9 March 2020).

Kanas, A., van Tubergen, F., & van der Lippe, T. (2009), "Immigrant self-employment: Testing hypotheses about the role of origin- and host-country human capital and bonding and bridging social capital", *Works and Occupations*, 36(3), 181-208. https://doi:10.1177/0730888409340128

Karoly, L. A., & Zissimopoulos, J. (2004, July). Self-employment among older U.S. workers. *Monthly Labor Review*, 24-47. https://www.bls.gov/opub/mlr/2004/07art3full.pdf

Kline, C., Duffy, L., & Clark, D. (2020). Fostering tourism and entrepreneurship in fringe communities: Unpacking stakeholder perceptions towards entrepreneurial climate. *Tourism and Hospitality Research*, 20, 3-17.

Kosmopoulou, G., Buttry, N., Johnson, J. & Kallsnick. (2007). Suburbanization and the rank-size rule. Applied Economics Letters, 14, 1-4. https://doi.org/10.1080/13504850500425675.

Liguori, E., Winkler, C., Hechavarria, K. & J. Lange (2018) "Guest Editorial: Interdisciplinary Perspectives on Entrepreneurial Ecosystems", *Journal of Enterprising Communities, 12(2), 86-91*.

Lin, X. (2010), "The diaspora solution to innovation capacity development: Immigrant entrepreneurs in the contemporary world", *Thunderbird International Business Review*, 52(2), 123-136. https://doi:10.1002/tie.20319

Liu, C. Y., Painter, G., & Wang, Q. (2014). Lessons for U.S. metro areas: Characteristics and clustering of high-tech immigrant entrepreneurs. Ewing Marion Kauffman Foundation.

Liu, S., Qian, H., & Hayes, K. E. (2020). Entrepreneurship in small cities: Evidence from U.S. micropolitan areas. *Economic Development Quarterly*, 1, 1-19.

Lofstrom, M. (2017), "Immigrant entrepreneurship: Trends and contributions", *Cato Journal*, 37(3), 503-522.

Mack, E. (2016), The geography of entrepreneurship. In Elizabeth A. Mack and Haifeng Qian (Eds.), *Geographies of Entrepreneurship* (pp. 1-12). Routledge Taylor & Francis Group, London and New York.

Markeson, F. & Deller, S. (2012). Growth of rural US non-farm proprietors with a focus on amenities. *Review of Urban A Regional Development Studies (RURDS)*, 24 (3), 83-105. https://doi:10.1111.rurd.12000

Marshall, J. (2002). Florida's downtowns: The key to smart growth, urban revitalization, and green space preservation. *Fordham Urban Law Journal*, 29(4), 1509-1528.

Messina, J. (2018), Starting Later: Realizing the promise of older entrepreneurs in New York City. Center for an Urban Future (CUF), available at: https://nycfuture.org/pdf/CUF-StartingLater_final_9-11_.pdf

Motoyama, Y., Henderson, C., Gladen, P., Fetsch, E., & Davis, S. (2017). *A New Frontier: Entrepreneurship ecosystems in Bozeman and Missoula, Montana*. Montana High Tech Business Alliance. https://mhtbamedia.s3-us-west.amazonaws.com/2017/04/Enterpreneruship-Ecosystems_Montana-Report.pdf

Mulligan, G. F. & Vias, A. C. (2006). Growth and change in the U.S. micropolitan areas. *Annals of Regional Science*, 40, 203-228. https://doi:10.1007/s00168-005-0034-6

Office of the New York State of Deputy Comptroller (2018), *New York City Employment Trends*. (Report 10-2018), available at: https://www.osc.state.ny.us/osdc/rpt10-2018.pdf#search=%20february%202018%20new%20york%20city%20employment%20trends

Oh, J. (2008). The quest to understand self-employment in American metropolitan areas. *Urban Studies Journal*, 45(9), 1769-1790. https://doi.10.1177/0042098008093378.

Orozco, M., Oyer, P., & Porras, I.I. (2017), *State of Latino Entrepreneurship*, Stanford Graduate School Business, Stanford.

Ramadani, V., Dana, L., Sadiku-Dushi, N., Ratten, V. & Welsh, D.H.B., (2017), “Decision-making challenges of women entrepreneurship in family business succession process”, *Journal of Enterprising Culture”,* 25(4), 411-439. https://doi:10.1142/S0218495817500157

Ratten, V., Ramadani, V., Dana, L., Hoy, F., & Ferreira J., (2017), “Family entrepreneurship and internationalization strategies”, *Review of International Business and Strategy*, 27(2), 150-160. https://doi:10.1108/RIBS-01-2017-0007

Rupasingha, A., & Goetz, S. J., (2013), “Self-employment and local economic performance: Evidence from US counties”, *Papers in Regional Science*, 92(1),141-162. https://doi:10.1111/j.1435-5957.2011.00396.x

Rural County Representatives of California Economic Development Department in partnership with Golden State Finance Authority. (2018). *Center for Economic Development: Nevada County economic & demographic profile, 2018*. https://www.mynevadacounty.com/DocumentCenter/View/25418/2018-Nevada-Economic-and-Demographic-Profile

Scott, T. (2020, October 28). The road to Montana. *Flathead Beacon*. https://flatheadbeacon.com/2020/10/28/moving-to-montana/

Shrestha, S.S., Goetz, S.J., & Rupasingha, A. (2007), “Proprietorship formations and U.S. job growth”, *The Review of Regional Studies*, 37(2), 146-168.

Spell, L. (2019). Micropolitan statistical areas: A lens on small-town America. Retrieved from U.S. Census Bureau website: https://www.census.gov/library/stories/2019/07/micropolitan-statistical-areas-small-town-america.html

Spigel, B. (2017), “The relational organization of entrepreneurial ecosystems”, Entrepreneurship Theory and Practice, 41(1), 49-72. https://doi:10.1111/etap.12167

Spiral Internet. (2014, October 30). *What will Nevada County look like in 2025 with a Gigabit 100% fiber optic Internet network in place?* [Conference session]. Spiral Gigabit Launch Conference, Nevada City, CA, United States. http://www.mendocinobroadband.org/wp-content/uploads/2025NevadaCountyCalifornia-GigabitVision-March2016-Spiral.pdf

Stam, E. (2009), *Entrepreneurship, Evolution and Geography*. (Papers on Economics and Evolution No. 0907), Max-Planck-Inst, für Ökonomik, Jena. Utrecht University, Urban and Regional Research Centre, available at: http://hdl.handle.net/10419/32668

Statista.com. (2017), Most Active Industrial Construction Markets in the United States in Q1 2016 by Select City, available at: https://www.statista.com/statistics/618302/us-industrial-construction-market-by-major-city/

Tsvetkova, A., Partridge, M. & Betz, M. (2017). Entrepreneurial and employment responses to economic conditions across the rural-urban continuum. *The Annals of the American Academy*, 672, 83-102.

U.S. Bureau of Economic Analysis. (2020). Total full-time and part-time employment by industry (CAEMP25), 2019 and 2007 [Data sets]. https://www.bea.gov/

U.S. Bureau of Economic Analysis. (2019). Total full-time and part-time employment by industry (CAEMP25), 2017 [Data set]. https://www.bea.gov/

U.S. Bureau of Economic Analysis. (2019). Total full-time and part-time employment by industry (CAEMP25), 2016 [Data set]. https://www.bea.gov/

U.S. Bureau of Economic Analysis. (2020). Total full-time and part-time employment by industry (CAEMP25), 2009 and 2018 [Data sets]. https://www.bea.gov/

U.S. Bureau of Economic Analysis. (2019a). Total full-time and part-time employment by industry (CAEMP25), 2015 [Data set]. https://www.bea.gov/

U.S. Bureau of Economic Analysis. (2019b). Total full-time and part-time employment by industry (CAEMP25), 2016 [Data set]. https://www.bea.gov/

U.S. Census Bureau. (2020). Micropolitan American July 23, 2019. https://www.census.gov/library/visualizations/2019/demo/micropolitan-america.html

U.S. Census Bureau. (2019). Regional data: American community survey 2016 1-year estimates [Data set]. https://data.census.gov

Valdez, Z. (2014), "Latino entrepreneurship on the rise, but is that always a good thing?", available at: https://zulemavaldez.wordpress.com/2014/09/17/latino-entrepreneurship-is-on-the-rise-but-is-that-always-a-good-thing/

Vias, A. C., Mulligan, G. F., & Molin, A. (2002). Economic structure and socioeconomic change in America's micropolitan, 1970-1997. *The Social Science Journal*, 39, 399-41.