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Using Industry Sector Entropy to Predict Economic Community Disaster Resilience: Real-world Verification from the COVID-19 Pandemic

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Using Industry Sector Entropy to Predict Economic Community Disaster Resilience:

Real-world Verification from the COVID-19 Pandemic

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Abstract

The COVID-19 pandemic has presented an opportunity for disaster science researchers to gain insight into the underlying nature of community resilience through comparing the socioeconomic effects of government action to a common threat across urban population centers of varying economic compositions. For example, the negative effects of the COVID-19 pandemic on employment related to public health mitigation efforts in the leisure and hospitality sector of Las Vegas, NV, during the onset of the pandemic were well publicized. In comparison, other population centers of similar size but with different economic sector composition varied in the degree to which employment were affected, and in their trajectories of economic adaptation and recovery. Local economic development agencies currently use strategies designed to increase regional economic specialization to promote economic growth, however, evidence from disaster science research shows that the promotion of economic specialization over diversification may create vulnerability. This study uses Shannon's Entropy as a calculated measure of diversity in regional economic industry sector composition, to quantify economic resilience through the COVID-19 pandemic in relation to employment. This study is intended to inform regional economic development organizations in building economic disaster resilience through alternative approaches to the use of existing policy tools, and to inform future research into what industry mix is most likely to promote economic disaster resilience, and how different industry sectors interact and connect an urban center to the global economic system.

Keywords: entropy, COVID-19, economic disaster resilience, employment

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Chapter 1: Introduction

Commenting on the often vague and imprecise usage of the term *resilience*, Cutter once lamented that "By not asking the obvious questions of [resilience] to what and for whom, governments or agencies can maintain the status quo and the existing power structure of elites, and perpetuate the disenfranchisement of selected groups and/or communities, as they undertake actions to codify and implement actions ostensibly intended to make them become more resilient" (2016, p. 110). By posing the question "resilience to what?" Cutter posits that, in addition to disaster events and their associated direct and indirect outcomes, population centers are faced with externality-based public policy threats, including government actions where, as Cutter states, "either by design or inadvertent omission, the potential spatial and temporal variability in resilience" can lead to a variety of outcomes (p. 110). In summary, Cutter argues that the current understanding of the term *resilience* lacks adequate consideration for the specific needs of regional population centers as viewed by geographers, who regularly deal in terms of the spatial variance between population centers as well as the interactions in the complex network science of regional economics.

Public policy decisions aimed at enhancing disaster resilience, but in part resulting in perpetuated disenfranchisement and other unintended outcomes, have been acknowledged in the United States throughout the COVID-19 pandemic. Overall, preexisting variability in healthcare access, the average health of the population, and inconsistent state and local mitigation efforts combined to result in the United States hosting the highest number of recorded COVID-19 fatalities in the world (Stiglitz, 2020). Some aspects of the federal response to combat the economic effects of the COVID-19 pandemic have been lauded as successful for certain segments of the US population. It is estimated that during the same time period, up to 150 million children worldwide sank into poverty (UNICEF, 2020), through fiscal stimulus programs including the expansion of the federal Child Tax Credit, an estimated 6 million children in the United States were lifted from poverty, reducing childhood poverty in the US by approximately 40% by July 2021 (Parolin et al., 2021). Ultimately, however, these may have been temporary measures that arguably shifted the vulnerability outward in time without addressing the root causes. Additionally, the near-term inflationary effects of an additional $6 trillion in debt spending directly related to COVID-19 relief, on top of the long-run certainty that further debt spending will inevitably limit the ability of the federal government to respond to future disaster events (CBO, 2018), appear to question the long term viability of these positive economic outcomes.

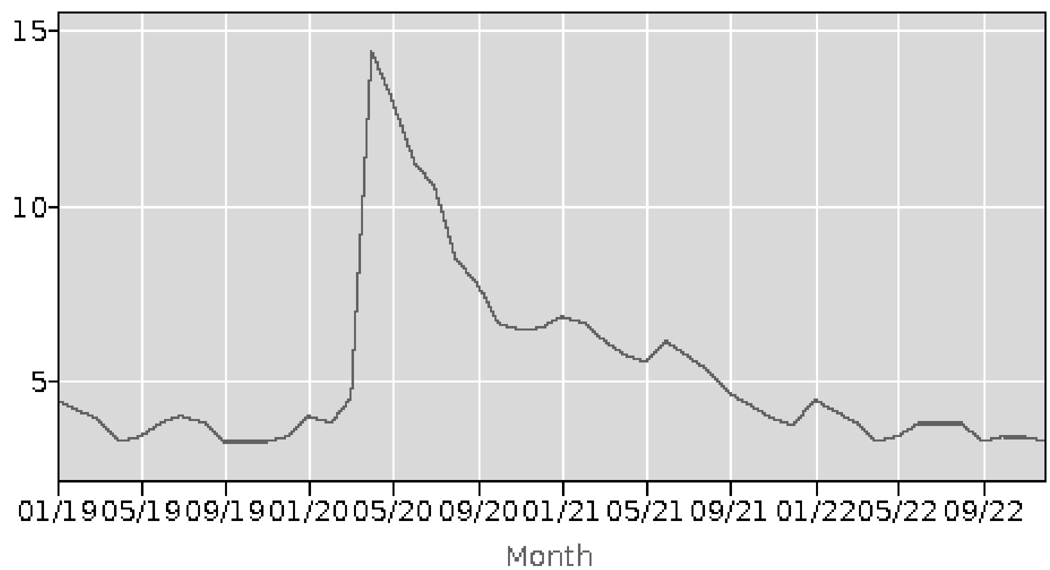
Furthermore, when posed the question of "resilience for whom" as Cutter (2016) has, it is clear that immediate successes in fiscal policy apparent through aggregate statistics often do little to represent the true regional variance in economic conditions for the American worker. At the state and local levels, COVID-19 demonstrated variability in both the effects of the pandemic on vulnerable populations and in the response of governments that, in many cases, had exacerbated these effects. Variances in the curtailing of business and travel, mobility, mask mandates, limitations on gatherings, shot requirements, and even protective measures taken by schools all contributed to the disparate socioeconomic effects of the pandemic across regions governed by politicians with various tolerances for public health risk vs. economic risk. In this way, the COVID-19 pandemic presented an opportunity for disaster researchers interested in topics of population diversity and variability in public policy outcomes to (1) gain insight into the underlying nature of community resilience by comparing the socioeconomic effects of government action to a common threat across population centers of various sizes and compositions, and (2) to comprehensively define and systematically measure specific aspects of community resilience.

Empirical Observation of Uneven Economic Effects of the COVID-19 Pandemic

The onset of the SARS-CoV-2 (COVID-19) pandemic caused the most rapid increase in both the level and the rate of unemployment ever recorded in the history of the United States, but the negative effects on employment were not evenly distributed across all regions or sectors. In total, the national unemployment rate rose from 3.8% in February 2020 to 14.4% in April 2020 (BLS, 2021) as public health officials at the state and local levels imposed measures aimed at reducing the spread of the virus. Starting with the first stay-at-home orders in the United States issued by the State of California on March 19, 2020, indoor commerce deemed non-essential was prohibited in many areas to limit social interaction. Social distancing requirements and other restrictions resulted in an estimated 17 million workers across the United States being temporarily or permanently displaced or otherwise unable to earn wages for varying lengths of time (BLS, 2021) as a direct result of the pandemic. The total number of unemployed workers as a result of permanent displacement peaked in November 2020 at 4.075 million (BLS, 2021). Furthermore, those working part-time for economic reasons, who were still by definition considered employed and therefore not included in unemployment calculations, increased from 4.398 million to 10.899 million (BLS, 2021), indicates a large number of workers remained employed but were likewise negatively affected through having their hours and therefore earnings reduced. In total, the Bureau of Labor Statistics (BLS) estimates that 49.8 million people had their work hours reduced in some way during the month of May 2020 alone (BLS, July 8, 2021). Measures to limit social interaction remained in effect until states slowly increased hospital capacity and adopted a tiered system for implementing mobility restrictions based on the availability of intensive-care hospital beds. The rate of national unemployment, which steadily dropped after peaking in April of 2020, remained above pre-pandemic levels for the subsequent 22 months, when an estimated 3.7% national unemployment rate (not seasonally adjusted) was recorded in December 2021 (Figure 1).

Figure 1

US National U-3 Unemployment Rate, 2019 – 2022



Source: BLS.gov, Current Employment Statistics

Not all industry sectors of the economy in the United States or types of business organizations were equally affected. One study conducted between March 28 and April 4, 2020, found that 43% of small businesses surveyed had already closed due to reduced demand, health concerns, and, to a lesser extent, supply chain disruption. All businesses surveyed from the hospitality, food services, retail, entertainment, and personal service sectors reported reductions in employment by more than 50%, whereas businesses surveyed from the financial and professional services sectors reported far lower levels of disruption and fewer reductions in employed workers (Bartik et al., 2020). Business Employment Dynamics data reported by the

BLS show that 6.2% of total private sector jobs were lost during the first quarter of 2020, and 17.0% of total private sector jobs were lost during the second quarter due to the contraction and closure of business establishments (BLS, 2021). The largest aggregate jobs losses during the second quarter of 2020 were within the service-providing industry sector (-17.825 million, 18.1% of total), including the leisure and hospitality sector (-6.331 million, 46% of total), and the retail trade (-2.538 million, 16.9% of total). The employment data suggest that disproportionately negative effects of the pandemic were felt strongest among low-wage hourly workers, as the service-producing sectors, including leisure and hospitality and retail trade, are calculated to have the lowest average weekly earnings of any private industry sectors in the United States (BLS, 2021).

Regional Economic Specialization and COVID-19

The interdependencies and network structure of the globalized economic system that contributed to the spread of the pandemic from both a global health and economic perspective is, in large part, a product of macroeconomic specialization. Specialization refers to the strategy of gaining economic benefit used by nations or regions by focusing resources on the production of goods and services for which they have a comparative advantage in producing due to the nature of their resources, based on factors such as the cost or availability of natural resources or the size or skill of their labor force. Nations produce and trade goods for which they have a comparative advantage (or lower opportunity cost of production), in exchange for goods that they do not have a comparative advantage in producing. The result is greater levels of consumption of goods and services for all trading partners, compared to a scenario where a country alone must produce all of the goods its citizens consume without trade. This concept, first theorized in the 19th century (Ricardo, 1821) and now supported empirically with economic data (Costinot & Donaldson, 2012), demonstrates the fundamental basis of trade and globalization. Increased consumption through economic specialization has been a proven means of increasing economic output and, by extension, the economic standard of living in *laissez-faire* capitalist societies around the world for the last century.

But despite the widely accepted benefits attributed to economic specialization and free trade including increases in median wages, populist criticisms of free trade and specialization that center around the displacement of workers abound (Golub, 1998). Specialization and the globalization of trade have also undoubtedly motivated countries to manipulate the value of their currency in relation to trading partners, resist the organization of labor, and ignore environmental considerations- all decisions that can increase the vulnerability of the individual to maintain a macroeconomic comparative advantage. The possibility that economic specialization could inherently lead to the creation of economic vulnerability to disaster events at the regional level is an area that has not been explored in the academic literature.

For example, field observation during the COVID-19 pandemic showed us that spatial variance contributed to the negative economic effects of the pandemic, which were felt disproportionately across metropolitan areas of the United States. In total, urban areas accounted for 90% of all COVID-19 cases (UN, 2020). Of the 50 largest metropolitan areas by population, the associated rise in unemployment varied considerably as different metropolitan areas have different economic compositions related to their competitive advantages resulting in variable sector sizes. While the City of Las Vegas, NV, with an estimated 2020 population of 662,368, and Oklahoma City, OK, with an estimated 2020 population of 662,314, cover roughly the same size of geography boundaries, the onset of COVID-19 had very different effects on the respective labor markets of each area. In Las Vegas, the unemployment rate grew from 3.6% in

February to 29.6% in April 2020 (BLS, 2020), and mobility had reportedly decreased by 59% by April 2020 (IHME, 2020). Meanwhile, in Oklahoma City, the unemployment rate increased from 2.9% in February to 13.7% in April of 2020 (BLS, 2020), and mobility had decreased by only 34% by April 2020 (IHME, 2020). Given the degree to which the COVID-19 pandemic affected both airline travel and the service industry, this variability in effects on employment is not surprising. Las Vegas is known as an international tourist destination. One can assume that this variance is reflected in the size of each city's Leisure and Hospitality sector, which made up 27.8% of the Las Vegas total nonfarm work force and 11.16% of the Oklahoma City total nonfarm work force, respectively (BLS, 2021).

As the concepts of vulnerability and resilience are disaster specific, the travel and social gathering restrictions put into place during the initial outbreak of COVID-19 would have varying effects on each sector. While healthcare-related economic output likely rose due to the nature of the pandemic in all areas, most adopted suppression measures would directly impact the leisure and hospitality sector. One would then expect a regional economy constructed more heavily upon the leisure and hospitality sector, such as Las Vegas, to be more affected than an economy with a sizable portion built on healthcare, or secured by the stability of the public sector such as a state capital like Oklahoma City, OK.

However, a simple comparison of the proportion of an area's economy built on the Leisure and Hospitality sector or public sector employment alone would not explain the substantial increase in unemployment in other urban areas such as Detroit, MI between February 2020 (7.6%) and April 2020 (37.5%), which a completely different industry composition centered more heavily around manufacturing and trade (26.92% vs, Las Vegas, NV, and Oklahoma City, OK, with 15.26% and 18.68% percentage of employment in manufacturing and trade sectors, respectively) (BLS, 2021). The Detroit Metropolitan Statistical Area (MSA) also had a sizeable proportion of its nonfarm employment in the Government and Education and Healthcare sectors (25.35%) at the onset of the pandemic. Since anecdotal evidence has shown that disasters will affect different sectors to different degrees, it is therefore logical to speculate that regional economic development strategically designed to either more uniformly distribute industry composition towards a more equal distribution by sector, or towards an optimal and determinable industry mix based on the disaster events that a region is most likely to face, could cause a region to be less impacted economically by a disaster event and to recover more quickly.

Diversification and Specialization in Regional Economic Community Resilience

Economic resilience has been conceptualized at both the macroeconomic and microeconomic levels as the ability of an individual, entity, or geographic region to both withstand or absorb the initial impact of a disaster event and to restore function after a period of post-disaster recovery (CARRI, 2013). Likewise, the economic impact of a disaster event has typically been measured in dollars, while economic recovery is commonly measured in units of time (Chang & Rose, 2012). Regional economic diversity is typically seen as an organic function of serving local demand, while economic specialization is either a necessity based on limitations in resource availability in smaller economies, or a strategic choice that allows a larger urbanized region to partake in foreign markets through the global economic system (Kemeny and Storper, 2014). In studying the use of regional specialization strategies throughout the European Union mandated in 2014 in an effort to support economic growth and innovation, Dzemydaite found that neither the use of specialization or diversification is consistently better at promoting economic development, and that regional economic structure and industry composition must be considered (Dzemydaite, 2021). Studies have occasionally shown a positive effect of economic diversification on regional economic resilience (Li et al., 2019) and on technological innovation (Zheng et al., 2022)

If macroeconomic level resilience is in part conceptualized as the ability for a region to regain function after a disturbance, there are many factors that determine the functionality of an economic region within the larger global economic system. The EPIC framework, used in the academic study of operations research and supply chain management to identify regions suitable for global trade based on having characteristics that foster economic growth, evaluates the fitness of regional economies based on four categories: economics, politics, infrastructure, and competency or regional strategic advantage (IHS Markit, 2020). By extension, these same categories of characteristics would also be relevant factors in returning a regional economy to functionality as a part of the global economic system after the harmful effects of a disaster event or crisis. For example, economic factors including the availability of capital were a major constraint that slowed economic recovery in the aftermath of the 2009 global financial crises (Acharya et al., 2011). Other economic factors such as currency inflation or devaluation, or stagnant wages, could have a similar effect on economy recovery, just as political unrest could result in uncertainty that leads to lower levels of capital investment spending in the short term (Aisen & Veiga, 2013), and infrastructure damaged by a major earthquake could slow the return of economic activity to a region.

However, to date, regardless of criticisms of free trade and the subsequent possible unexamined creation of disaster vulnerability, regional economic development policy in the United States is widely designed to support and propagate specialization over diversification. Businesses often look to relocate to an area where a skilled labor pool relevant to their industry already exists and regional economic development agencies leverage their existing concentration of skilled labor in an attempt to grow employment, economic output, and therefore tax revenues. These policies have also been shown to result in the gentrification of areas by forcing out long-time residents of urban centers to accommodate business interests and wealthier transplants (Lees et al., 2008). The potential for adoption of industry sector diversification strategies in regional economics as a strategy to support resilience rather than economic growth, given the benefits of diversity on ecological systems and the well-established practice of diversification in financial investment portfolios as an accepted practice to manage risk (Samuelson, 1967), may provide a path towards better understanding and attaining economic disaster resilience.

Purpose

Maslow's Hierarchy of Needs (Maslow, 1943) has been used as a foundational construct in human psychology to model a hierarchical and ordered structure of human motivation. The theory is presented as a pyramid of needs, with each tier representing a category of requirements necessary for well-being. Physiological needs, comprised of basic requirements for human survival such as food, water, and shelter, as well as security needs, must be met before higher order psychological or emotional needs such as interpersonal relationships, recognition, and self-esteem can be addressed (Maslow, 1943).

Meeting the needs of individuals and communities in the aftermath of a disaster events is the domain of both the study and the practice of emergency management. Disasters not only endanger physical well-being, but take away the resources and relationship necessary for individuals to meet their own needs and the needs of their families, relevant to all tier of Maslow’s hierarchy. Emergency management therefore involves addressing a complex array of psychological and interconnected social dimensions, and requires a thorough and comprehensive understanding of the specific needs of disaster survivors to enact meaningful interventions in all phases of the disaster cycle.

During the disaster response phase, individuals often face immediate physiological needs, including access to water, food, shelter, or medical treatment (Norris et al., 2002). Providing for the basic physiological needs of individuals with disaster response efforts in the immediate aftermath of a disaster event is critical to ensure the survival and welfare of affected individuals, and prerequisite to addressing their psychological and emotional needs. Once immediate physiological needs are addresses, individuals may begin to process the trauma and loss associated with a wide variety of disaster event related mental health challenges, including depression and post-traumatic stress disorder that may arise during the recovery phase of the disaster cycle (Norris et al., 2002).

Unlike aggregate measures of economic output, employment is the primary means by which individuals acquire income necessary for securing the physiological needs of adults and their dependents. In the United States, employment also plays a critical role in an individual's access to healthcare, as the primary source of health insurance. Gainful employment has also been shown to carry a social component that facilitates the meeting of higher level psychological and emotion needs detailed in Maslow's hierarchy, and has been positively associated with feelings of satisfaction and quality of life (Kahneman & Deaton, 2010). Employment provides the environment for individuals to connect with each other as a member of a community, as well as an environment for personal growth and achievement (Bakker, et al., 2009). Employment has also been linked to generally lower levels of anxiety and stress, as well as improvements in mental wellness (Waddell & Burton, 2006).

For these reasons, total employment by region was used in this study as the primary measure of economic disaster impact and recovery. This is an appropriate choice to evaluate regional economic resilience specifically from a perspective of emergency management, as it is more closely tied to the lived experience of the individual through the response and recovery phases of the disaster cycle than other measure of economic activity such as economic output commonly used in the fields of regional economics or finance.

Cutter notes that “Determining the root causes of vulnerability as a prologue to understanding and enhancing resilience is one of the key failings in the literature to date” (Cutter 2016, p. 111). When determining the root causes of regional economic vulnerability, it is reasonable to assume that both a deconstruction of regional economic composition by industry sector to quantify levels of economic specialization and diversification that have occurred both through economic policy as well as organically, in addition to analysis that considers the specific role and function of regional economies in the global complex economic system, are necessary to shed light on the construction of economic resilience. These processes could help to identify the components of economic resilience and determine how economic resilience at the regional level can best be anticipated and measured. With this in mind, the following research is an initial step towards better informing economic development agencies with regard to the construction of regional economic disaster resilience, and their role through the use of existing economic development policy tools.

Chapter 2: Literature Review

The following review of academic literature begins with various definitions and uses of the term *resilience*, including perspectives on resilience from the social sciences fields of economics and disaster science that represent a *static* understanding of resilience. The usage of the term resilience in the field of ecology, representing a dynamic and adaptive understanding of resilience, are then discussed in detail. Finally, the concept of economic specialization as a deterrent to the use of diversification to manage risk in the fields of finance and economics are discussed, and theories for measuring system heterogeneity are reviewed with application to regional economic resilience. A discussion of how these topics inform the creation of a new adaptive economic model capable of quantifying regional economic resilience through heterogeneity ends the chapter.

Definitions of Resilience

Definitions of the term *resilience* in academic literature vary primarily by academic field, with usage and scope having evolved to reflect aspects such as the static or dynamic nature of the object being studied. Traditionally, the term resilience, from the Latin root *resalire* meaning "to spring back," has referred to the ability of an object or system to withstand exposure to stress and to return to a former pre-exposure state (Plodinec, 2009, p.1). However, social science applications have more recently evolved to move past a static understanding of resilience and to include the capacity of social constructs in complex systems (Meadows, 2008).

In researching the origin of the term *resilience*, the earliest scientific usage is documented in 1818 from the material sciences (McAslan, 2010), where Tredgold used the term resilience in reporting the results of testing comparing the strength and elasticity of samples of timber for possible use in shipbuilding (Tredgold, 1818). In 1856, Mallet defined *resilience* as "the power of elastic recovery" and developed the measure *modulus of resilience* to quantify the resilience of materials used in the manufacturing of field artillery (Mallet, 1856). Mallet soon after employed this measure in the fields of engineering with applications in disaster science, in studying the resilience of construction materials when observing and comparing structures that were damaged during the 1857 Basilicata earthquake (Mallet, 1862). Material science definitions of resilience generally deal with a static physical state, and the principles of elasticity in an object's ability to withstand a force and maintain form (Gordon, 1978).

Economic Disaster Resilience

Applications from the social sciences such as economics have thus far relied primarily on a similar *static* understanding and modeling of resilience. Rose explicitly makes the distinction between *static* and *dynamic* economic resilience, defining *static* economic resilience in terms of ability to maintain function through a shock (Rose, 2009) rather than demonstrating evolution through adaptation. Overall, academic literature specific to the topic of community resilience, including economic resilience related to disaster science, is limited primarily to the ability of a community to absorb a shock and subsequently bounce back from it (CARRI, 2013). Attempts have been made to both refine the definition of economic resilience and to identify its component parts through deconstructing various aspects of the disaster cycle, using traditional economic models from the point of view of both demand and supply.

While economic systems are inherently dynamic in nature, the use of traditional neoclassical economic models with rigid and unrealistic assumptions such as market states of equilibrium are often interpreted as *static* in nature, given a certain level of supply and demand, rather than as a fluid and complex organic system through time (Arthur, 2021). For example, instruments such as the Computable General Equilibrium (CGE) modeling attempt to explain regional economic impacts at the macroeconomic and microeconomic level, based on the concept of economic equilibrium resulting from market forces on supply equals demand (Rose, 2007).

Additionally, from this static modeling perspective, Park et al. (2011) defines economic resilience at the supply-side operational level as the “ability to dampen the maximum potential economic output loss” through recapturing production that was interrupted during a disaster event, and offering a theoretical framework for supplier production rescheduling. The COVID-19 experience has shown that pandemics have the ability to cause considerable disruptions in global trade on the supply side, related to both supply chain issues and the inability to accurately forecast consumer demand for products with long production lead times. The interconnected nature of the global economy has shown that the ability to recapture and reschedule lost production is likely a function of several factors in a complex network outside the control of any one supplier.

Sensier et al. (2015), in defining resilience again from the aggregate supply side but using Gross Domestic Product and the business cycle, offers methodology to measure resilience in an economy’s ability to once again expand after a shock. The business cycle refers to the oscillating pattern commonly found when graphing GDP in dollars through time, where periods of economic growth are represented by and increase in GDP, and periods of recession are shown as decreasing GDP.

Resilience and Heterogeneity

After the aforementioned early uses, academic uses of the term *resilience* in the 19th century remained relegated primarily to the material sciences for the following century, until widely adopted in the study of ecological systems. Holling contrasts the concept of *stability* in ecological systems, which he defines as “the ability of a system to return to an equilibrium state after a temporary disturbance” with *resilience*, which he defines as “a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations and…variables” (Holling, 1973, p. 15). Holling gives examples of an observed inverse relationship between stability and resilience, even assigning a causal relationship, and concluding that instability can contribute to the creation of highly resilient ecological systems over time. The definition of resilience in the field of ecology has evolved dramatically since these early uses, as reflected by Scheffer, in defining the resilience of a forest ecosystem as an ability to “re-organize under change to maintain similar functioning and structure” (2009). This definition, which emphasizes system function and allows for adaptation, recognizes the fluidity and ever-evolving dynamics of natural systems by showing flexibility in relation to the question of “resilience for whom?”

Studies from the field of ecology have examined the benefits of biodiversity in combating the effects of both natural and man-made changes to environmental conditions and ecosystems since the 1950s (Odum, 1953). Early studies observed a positive relationship between species diversity and stability in ecosystems (Elton, 1958), presumably because there is a greater likelihood that during system disruption some species will succeed while others fail, an idea commonly referred to as the *insurance hypothesis* (Yachi & Loreau, 1999). However, early application of statistical methods to better define the relationship between stability and species diversity found a destabilizing effect of diversity when the strength of the relationships between species and their interactions (e.g., predator vs. prey) were randomly assigned (May, 1973), indicating a complex relationship between the stability and diversity that is dependent on species interaction (McCann, 2000). Hooper et al. (2005) found that there is a high level of confidence that ecosystems with combinations of species that are complementary in their use of resources can increase productivity. Additionally, a diverse array of species that vary in their response to environmental disruption can work to stabilize an ecosystem. Ives and Carpenter, in reviewing empirical studies on the relationship between ecological stability and species diversity, noted that systems can vary in the number of stable states that they can assume, and the relationship between diversity in species and system stability is complex, and can differ depending on the definition of the terms and nature of the disruption within the same ecosystem (Ives & Carpenter, 2007).

Diversification Strategies in Finance and Economics

Diversification in financial investment portfolios has long been an accepted and proven practice in the management of non-compensated risk exposure (Samuelson, 1967). In a study of the performance of 60,000 investment portfolios in the United States between 1991 to 1996, heavily diversified portfolios outperformed portfolios with low levels of diversification by 2.04% annually (Goetzmann & Kumar, 2008). Meanwhile, in terms of economic sector heterogeneity, it has been observed that developing countries have largely specialized economies, concentrated by factors such as available natural resources. These countries then diversify as per capita income grows, perhaps through a causal relationship (Imbs & Wacziarg, 2003). Aggregate data then shows a “re-specialization” effect noted in national economies with the highest levels of per capita income, possibly indicating the emergence or “development of highly diversified clusters of economic activity” (Bahar, 2016, p.9). Ciuriak (2015) adds that specialization and diversification likely work together, speculating that specialization “by individual economic agents will happen naturally in an environment characterized by great diversity at the economy level” (2015, p.10). The academic literature to date, however, does not discuss risk exposure associated with this re-specialization effect that would be relevant to the study of economic resilience.

More recent studies, however, have shown evidence of benefits of regional economic sector diversity related to economic resilience and environmental considerations. In a study of unemployment rates in counties in Ohio between 1977 and 2011, Brown & Greenbaum concluded that employment in counties with diverse industrial compositions were more stable and less reactive to external shocks than counties with more specialized economies (2017). Likewise, Zhang et al. (2021) found that urban economic resilience can be improved through diversification during the impact phase of a crisis, but industrial specialization can improve urban economic resilience during the recovery phase. It has also been observed that regions with industries that are technologically related and use the same workforce skill sets are more resilience to external economic shocks (Cainelli, Ganau, & Modica, 2017). Additionally, Pei et al. (2021) noted a positive relationship between specialized industrial agglomeration and pollution levels, as well as a relationship between industry diversification and environmental protections.

Measures of Heterogeneity

Measures and indices of species diversity in ecological systems are helpful in comparing different regions when evaluating the impact of environmental conditions. Researchers in the fields of ecology and environmental science use several different methods of calculating diversity, with no common agreement upon which measure is most useful in a given situation (Morris et al., 2014). Two fundamental concepts that are represented in the construct of diversity are *richness* and *evenness*. Whittaker defines species *richness* as simply the number of species present in a sample (1972). *Evenness* is defined as equality in the abundance of species within a population (Pyron, 2010). Quantitative measures of diversity designed to incorporate both *richness* and *evenness* into a single measure were developed in the late 1940s. Simpson's Index can be described as the probability that two independent and random selections chosen from within a population will be the same species (Simpson, 1949). However, this measure has been found to be limited in usefulness when applied to a population dominated by a small number of species (DeJong, 1975). One of the most frequently used measures, adapted from Shannon's Mathematical Theory of Communication (Shannon & Weaver, 1949) and known as Shannon's Diversity or Shannon's Entropy can be interpreted as the level of uncertainty that a random individual selection from a population will belong to a specific species or group (DeJong, 1975).

As specialization has been a widely accepted practice to promote growth in the field of regional economic development in the United States, the most frequently used measure related to employment diversity is the Location Quotient (LQ), which compares the concentration of an industry in a regional economy to the concentration in the entire United States, allowing the user to identify areas of the nation with a concentration of workers in a particular industry (Nissan & Carter, 2002). Few studies have approached the topic of quantitatively measuring true economic sector diversity. Nissan and Carter used a standardized version of Shannon's Entropy to rank state level employment diversity by industry sector at the three-digit NAICS code level (2002). However, measuring diversity at the state level could limit the usefulness of findings, as aggregate state employment totals do not necessarily represent an interconnected regional economic system.

Research Objectives

As the resilience of a population center cannot be known until after the realization of a disaster event, the aforementioned literature shows the utility of metrics specifically designed to quantitatively measure resilience, which is useful in estimating the future economic resilience of geographic regions. While economic resilience refers to only one aspect of disaster recovery, it can be assumed to have a moderating effect on other aspects of social resilience, and is perhaps the easiest attribute to attain quantitative time series data, as economic data is gathered at the local level by the United States Bureau of Labor Statistics and the United States Bureau of Economic Analysis. Several aspects, including adaptation and dynamic economic resilience, are understudied in the academic literature, and many attempts to measure economic resilience are limited to supply-side aggregate economic output measures, rather than focusing on the perspective of the worker.

Some of the earliest adoptions of the term resilience are applicable to disaster science in that they deal with the ability for the unit of analysis, such as a regional economy as in this study, to return to its former state. However, the use of static measures of resilience to describe the return to a previous state or economic equilibrium do not account for the adaptive and dynamic nature of social systems, and is not entirely appropriate in that it does not account for the lived experience of the individual through the disaster events. This is also true of choosing an aggregate measure, such as a regional economy, as the unit of analysis. When measures from other fields are directly applied to human society, assumptions made such as in measuring the resilience of non-anthropomorphized animal or vegetation ecosystems, are also inappropriate. For example, stating that a city such as New Orleans, LA, in the recovery phase after Hurricane Katrina has returned to its previous level of economic output, or gross domestic product (GDP), or employment, when calculated based on an aggregate number of people able to find any work, and using the city rather than the original residents as the unit of analysis, is insufficient in measuring recovery, in the same way that economic development policy that promotes the process of gentrification injures rather than serves an existing residential population. Economic output measurements such as GDP tend to obscure the human experience.

At the most fundamental level, a regional economy can be defined as a collection of workers organized by occupation according to skill set and the sector or type of economic output by which service ultimately contributes. While workers are somewhat free to choose their own skill set and minimum required wage, the demand for output determines the size of each sector, as well as the labor market for each occupation, in terms of the quantity of workers demanded and the price paid for labor. If the economy of a location can in fact be modeled as a complex system, and structural change related to a disaster event is measured in terms of sector size or economic output, adaptation would be reflected in the change in economic composition, which would more closely represent the impact of the disaster event on the worker, whom economic activity is ultimately intended to serve. Adam Smith's infamous invisible hand, while too often incorrectly viewed as creating an ideal market equilibrium, acts as a driving force behind economic adaptation related to labor market supply and demand, providing measurable attributes from which the state of economic activity can be deduced (Smith, 2012). As composition is commonly measured using heterogeneity in the field of ecology, change in economic composition reflective of the impact of an event such as the COVID-19 pandemic and the resulting adaptation can possibly be measured in terms of change in entropy. However, this study assumes that one must first determine the general nature of the relationship between the total regional employment *impact* and total employment *recovery time* with *heterogeneity.* Given these assumptions, the following sequence of research objectives will be explored in this study to determine if more diverse regional economies would be less impacted in the form of reduced levels of employment in the direct aftermath of a disaster event, and show faster total employment recovery from the employment shock:

RO1: Adopt a model to measure regional economic heterogeneity.

RO2: Determine if the measure of heterogeneity obtained in RO1 can be used to estimate the initial economic impact of a disaster event related to employment, as well as regional economic resilience as defined as the time required for regional employment to recover.

RO3: Verify the accuracy of the predictive models created in RO2 by applying it to a subset of the data.

In addition to the intrinsic value of the research related to the study of regional economic disaster resilience, these objectives are designed to serve as a foundation to inform future research that will explain the nature of relationships between industry sectors within a specific regional economy and between regional economies arranged spatially as nodes in a larger complex dynamic economic system.

Chapter 3: Method

Measuring Instruments

Related to RO1 and RO2, this study uses employment as defined and measured by the United States Bureau of Labor Statistics to both describe regional economic composition and as an economic indicator to determine if heterogeneity can be used as a measure to predict regional economic impact and resilience. First, Shannon's Entropy is used as an index to quantify the heterogeneity of the economic composition of an MSA, in a similar manner to uses of Shannon's Entropy in the academic literature from the field of ecology, as well as uses in calculating state level industry diversity (Nissan & Carter, 2002):

$$E_s = \frac{-\sum p_i \log p_i}{\log(s)} \tag{1}$$

In other words, if a single worker is randomly selected from a given MSA, there is a relatively higher probability that the selected worker will be from the industry sector with the most workers. Since this result has a relatively higher probability, there would be a relatively low level of "surprise" if a worker with the highest probability was selected, whereas the random selection of a worker from a smaller industry sector would be more surprising. Surprise has an inverse relationship to probability and is calculated as the log of the inverse of the probability, $\log\left(\frac{1}{p(x)}\right)$. The average surprise per selection, or the expected value of the surprise for each selection, known as *Entropy*, is the summation of the probability of the selection times the surprise for each selection:

$$E_s = \sum \log\left(\frac{1}{p(x)}\right) p(x) \tag{2}$$

This formula is commonly rewritten as the Shannon's Entropy formula:

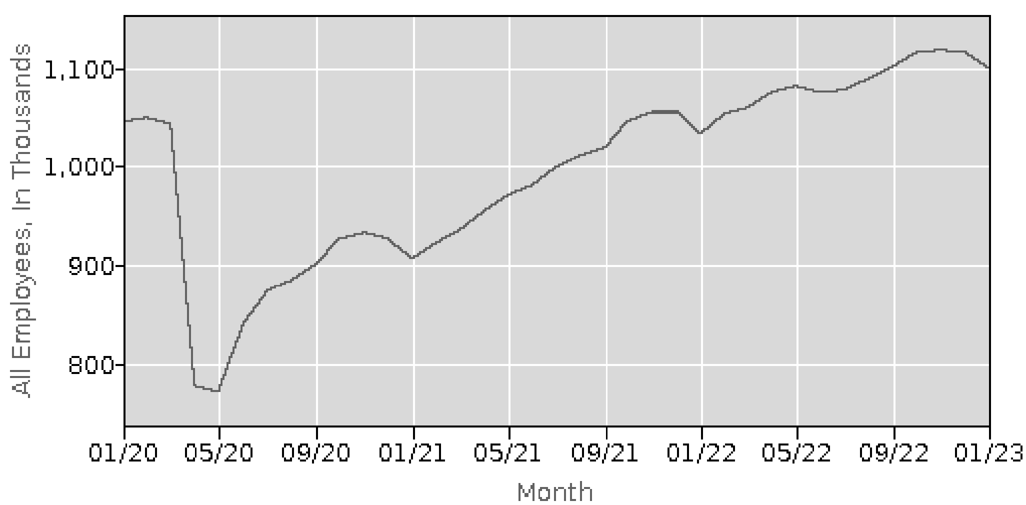
$$E_s = -\sum_{i=1}^{S} p_i \log p_i \tag{3}$$

Where *S* is the total number of species (i.e. industries, for the purposes of this study), and p_i is the fraction of the ecosystem represented by single species *i*. In this study, the entropy measure will be standardized by dividing by the maximum value *log(s)* per the method used by Campiglio and Caruso (2007) to calculate relative entropy per the above equation.

As the ability to withstand or absorb an initial shock, and then to return to a former pre-exposure state (CARRI, 2013), are common attributes in the definitions of community resilience in the academic literature, this study will use the initial impact of the pandemic on employment as well as the recovery time of employment in months as measures of community resilience. The loss in employment as a ratio to the expected April 2020 employment total, as well as employment recovery time in months to the expected April 2020 employment level, measured using February 2020 as a baseline, are calculated at the MSA level.

Figure 2

Las Vegas MSA Total Nonfarm Employment, 2020 – 2023 (not seasonally adjusted, thousands)



Source: BLS.gov, Current Employment Statistics

For example, the impact of the COVID-19 pandemic caused an initial reduction in employment from 1,049,900 to 778,400 workers in the Las Vegas, NV Metropolitan Statistical Area, as measured from February to April of 2020 (a reduction of 271,500 workers, or -25.86%)

(BLS.gov, 2023). As employment between the months of February and April changed by an average of +1.33% in the Las Vegas MSA over the previous 20 years (from 1999 to 2019), the calculated expected April 2020 employment without a pandemic was an expected employment value of 1,063,864.

$$Employment\ Impact = \frac{Apr\ 2020\ MSA\ Employment}{Feb\ 2020\ Employment \times Avg\ \Delta} \tag{4}$$

In this case, the calculated impact factor of the COVID-19 pandemic on employment for the Las Vegas MSA was 0.7317. In other words, employment in April 2020 was 73.17% of expected employment. Regarding nonfarm employment recovery time, total employment in the Las Vegas MSA exceeded 1,063,864 for the first time since the pandemic during the month of April 2022. Therefore, the recuperation of employment in the Las Vegas MSA took a total of 24 months. This measure of economic resilience will be calculated for each MSA included in the study.

Data Collection

This study uses a combination of publicly available federal data calculated by the United States Census Bureau and Current Employment Statistics (CES) calculated and published by the United States Bureau of Labor Statistics (BLS). First, the largest 60 metropolitan areas in the United States (Figure 1) as of the 2020 outbreak of the COVID-19 pandemic were identified to create a model to validate and test the use of *entropy*. The largest 60 metropolitan areas accounted for an estimated 192,969,864 residents, or 67.45% of the U.S. metropolitan area population of 286,104,556 during the first quarter of 2020, as estimated by the U.S. Census Bureau (2021). This figure is an estimated 58.22% of the entire U.S. population, estimated at 331,449,520 for April 1, 2020 (U.S. Census, 2021). These estimates were downloaded from the U.S. Census Annual Metropolitan and Micropolitan Statistical Area Resident Population Estimates by Selected Age Groups and Sex for the United States: April 1, 2020, to July 1, 2021

(CBSA-EST2021-AGESEX) dataset and the Monthly Population Estimates for the United States: April 1, 2020 to December 1, 2023 (NA-EST2022-POP) dataset. See Appendix A for a complete list of the 60 MSAs included in this study. Given the relationship between specialization and diversity as explained in the aforementioned academic literature, it is theorized that diversification is a characteristic of developed regional economies past a certain threshold, and would not consistently be a characteristic of smaller regional economies. Therefore, economic heterogeneity would not likely be a meaningful measure in regions with smaller residential populations, such as rural areas.

The BLS Current Employment Statistics (CES) program are used by federal and state officials as well as the private sector to evaluate current macroeconomic conditions for demand forecasting purposes and to measure the regional economic growth of an industry (BLS, 2022). The program uses a survey of business payroll records collected by states to estimate employment totals and earnings for metropolitan areas. Primarily, rate of change in employment from the previous month, based on data collected from a sample of employers, is calculated, and then applied to the estimated total regional employment to arrive at a new current month employment total. Monthly employment totals from the CES survey are defined as the number of individuals who earned wages during the pay period which included the 12th day of that month. The BLS uses the U.S. Office of Management and Budget definition of Metropolitan Statistical Area, describing an area of interconnected economic activity that includes one or more urban centers with at least 50,000 residents (BLS, 2022).

BLS Current Employment Statistics by month are available to be retrieved for the U.S. BLS data tools at https://www.bls.gov/data/. In this study, employment is downloaded for February 2020 as a pre-pandemic baseline before COVID-19 mitigation measures in the form of lockdowns began to take place across the United States. Employment totals for April 2020 are then downloaded to show the immediate effects of the pandemic on employment, allowing for slight variation in the exact time local COVID-19 precautions were enacted to limit mobility.

Total employment data by industry Super Sector for each MSA, starting with February 2022 are then retrieved to demonstrate and measure the trajectory of employment recovery, compared to expected pre-pandemic levels. Each Super Sector includes all occupations within that Super Sector. For example, an accountant who works for a hospital is included in the Education and Health Services Super Sector employment total, whereas an accountant who works for an oil company would be included in the Mining and Logging Super Sector employment total. Table 2 shows a sample of the data for the aforementioned Las Vegas MSA. Limitations of using the employment estimates calculated in the CES, such as the inclusion of part-time workers and the underemployed, defined as individuals working part-time for economic reasons but would prefer to be working full-time, or individuals working in a role that does fully utilize their skill set or capabilities for economic reasons, cause the full effect of the pandemic on employment to be obscured by the data. While also calculated at the regional level, percentages of unemployment and total unemployed workers were not used in the study because the methodology used in calculating unemployment does not account for groups such as *discouraged workers*, defined as individuals no longer actively seeking employment although they want to work.

Table 1

BLS Employment by MSA, Largest 60 MSAs, February 2020

Rank	MSA	Feb 2020 Employment	Rank	MSA	Feb 2020 Employment
1	NY	9,932,300	31	KC	1,094,700
2	LA	6,303,500	32	COL	1,111,400
3	CHI	4,699,100	33	IND	1,087,200

Rank	MSA	Feb 2020 Employment	Rank	MSA	Feb 2020 Employment
4	DFW	3,836,300	34	CLE	1,066,800
5	HOU	3,191,800	35	SJ	1,158,800
6	WAS	3,352,200	36	NAS	1,057,900
7	PHI	2,978,400	37	VIR	793,700
8	MIA	2,769,000	38	PRO	593,900
9	ATL	2,883,500	39	JAC	731,600
10	BOS	1,917,500	40	MIL	865,900
11	PHX	2,233,400	41	OKC	660,200
12	SF	2,507,700	42	RAL	654,200
13	RIV	1,587,900	43	MEM	652,900
14	DET	2,026,100	44	RIC	686,100
15	SEA	2,103,500	45	LOU	671,300
16	MIN	1,973,400	46	NO	590,300
17	SAD	1,515,100	47	SLC	759,100
18	TAM	1,408,500	48	HAR	584,700
19	DEN	1,539,700	49	BUF	558,200
20	BAL	1,411,600	50	BIR	548,700
21	STL	1,401,600	51	ROC	533,400
22	ORL	1,347,600	52	GRP	567,700
23	CHA	1,259,500	53	TUC	397,500
24	SAA	1,082,600	54	HON	478,900
25	POR	1,232,500	55	TUL	458,700
26	SAC	1,032,300	56	FRE	367,800
27	PIT	1,176,800	57	WOR	289,300
28	AUS	1,144,800	58	OMH	502,800
29	LAV	1,049,900	59	BRP	397,300
30	CIN	1,111,500	60	GRE	431,000

Source: BLS.gov, Current Employment Statistics (CES)

Table 2

Total U.S. Employment by Super Sector, February 2020 (thousands, not seasonally adjusted)

NAICS Super Sector	Employment
Total Nonfarm	**150,967.0**
Total Goods Producing	**20,680.0**
Total Service Producing	**130,287.0**
Mining and Logging	675.0

NAICS Super Sector	Employment
Construction	7,278.0
Manufacturing	12,727.0
Wholesale Trade	5,858.7
Retail Trade	15,292.2
Transportation and Warehousing	5,745.9
Utilities	545.0
Information	2,894.0
Financial Activities	8,820.0
Professional and Business Services	21,195.0
Private Education and Health Services	24,668.0
Leisure and Hospitality	16,292.0
Other Services	5,882.0
Government	23,094.0

Source: BLS.gov, Current Employment Statistics (CES)

Analysis Method

In reference to the stated research objectives RO2 and RO3, the following data analysis methods will be employed:

1: To test for correlation between both initial employment impact and employment recovery time in months with heterogeneity as measured using Shannon's Entropy, this study uses correlation analysis. Pearson's correlation coefficients are calculated to determine the nature of the correlations and the statistical significance.

2. This study then uses multiple linear regression modeling, using Shannon's Entropy and an independent variable, to estimate facets of regional economic resilience in terms of initial impact on employment and employment recovery time for each MSA. Dependent on the results of the multiple linear regression modeling, it may be necessary to further create a multi-level model, as variable interactions and moderators such as MSA population size could exist that could affect the ability of the models to estimate employment impact and recuperation time.

3. Validation analysis is then performed to determine the accuracy and goodness of fit of the models. Of the 60 largest metropolitan areas chosen, 80% of the MSAs (48 MSA in total) will be randomly selected and used to develop and train the regression models. These models will then be tested against the remaining 20% of the data (12 MSAs) to make a prediction of both the initial impact of the pandemic on employment and the number of months required to return total employment to estimated pre-pandemic levels, to ultimately determine the usefulness of Shannon's Entropy in quantifying economic disaster resilience. Predicted employment impact will be evaluated through the calculation of prediction intervals. Given the cyclical nature of employment, the accuracy of the model in predicting *recovery time* will be analyzed by classifying results by the future business cycle in which they fall, and then using a confusion matrix to calculate precision, recall, and F1 score.

The above explanation of the methodology used in this study was submitted to the Jacksonville State University Institutional Review Board for consideration as exempt from 45 CFR 46 based on the exclusive use of secondary aggregate employment data that is publicly available from the U.S. Bureau of Labor Statistics. Approval of this requested exemption, received from JSU on August 1, 2023, has been attached as Appendix B.

Chapter 4: Results

As explained in Chapter 2, the overall purpose of this study is to test the value of including regional industrial sector employment heterogeneity, measured using Shannon's Entropy, in modeling to predict two important measures of economic disaster resilience: employment impact measured as the reduction of total regional employment and months required to return to estimated employment levels for April 2020 if the pandemic had not occurred. In this study, the regional economic structure for the 60 largest MSAs in the United States are evaluated, and measures of Shannon's Entropy were calculated based on the distribution of total nonfarm employment by industry sector as of February 2020 using the method detailed above. The summations of probabilities were then divided by the calculated maximum Shannon's Entropy value for each MSA to arrive at standardized entropy measures as shown in Table 3. Also reported in Table 3 are measured of economic impact and recovery, namely employment *Impact %* calculated above in equation (4), and *recovery time*, or the months until employment recovery was obtained (whether it was actual employment reported by the U.S. Bureau of Labor Statistics or forecasted at the time that this study was conducted).

Table 3

Shannon's Entropy, Employment Impact %, and Employment Recovery Time (month) - Largest 60 MSAs

MSA	Entropy Feb 2020 (E_S)	Impact %	Recovery Time (m)	MSA	Entropy Feb 2020 (E_S)	Impact %	Recovery Time (m)
NY	0.91823	19.086	33	KC	0.93684	11.382	29
LA	0.93840	16.713	32	COL	0.92926	13.443	20
CHI	0.93625	12.930	31	IND	0.94232	12.380	19
DFW	0.95189	11.117	18	CLE	0.91704	14.108	50*
HOU	0.94105	11.257	25	SJ	0.90155	13.203	31
WAS	0.86527	11.652	40*	NAS	0.94387	13.527	19
PHI	0.91330	16.146	30	VIR	0.90604	11.705	44*
MIA	0.93380	16.280	24	PRO	0.90997	19.970	38*

MSA	Entropy Feb 2020 (E_S)	Impact %	Recovery Time (m)	MSA	Entropy Feb 2020 (E_S)	Impact %	Recovery Time (m)
ATL	0.94679	13.504	19	JAC	0.94023	11.263	18
BOS	0.88935	16.334	38*	MIL	0.92280	12.842	51*
PHX	0.93456	11.279	19	OKC	0.91567	10.785	29
SF	0.92846	15.811	38*	RAL	0.92703	11.969	14
RIV	0.92124	13.867	19	MEM	0.93363	9.312	26
DET	0.92059	25.581	43*	RIC	0.92105	10.786	28
SEA	0.95255	11.467	28	LOU	0.94774	14.688	29
MIN	0.92892	14.052	39*	NO	0.92445	18.397	57*
SAD	0.91008	16.454	25	SLC	0.94666	8.655	15
TAM	0.92400	12.190	19	HAR	0.91412	14.554	54*
DEN	0.94514	12.106	20	BUF	0.91820	20.656	44*
BAL	0.90678	12.617	45*	BIR	0.94954	10.680	20
STL	0.93155	11.936	31	ROC	0.88208	16.685	49*
ORL	0.90815	15.346	21	GRP	0.90989	21.437	31
CHA	0.94760	11.854	19	TUC	0.89802	11.547	32
SAA	0.92426	12.128	20	HON	0.90419	20.484	56*
POR	0.94131	13.493	31	TUL	0.93588	9.723	42*
SAC	0.88744	13.087	19	FRE	0.90019	11.528	20
PIT	0.92009	17.658	49*	WOR	0.89779	15.658	31
AUS	0.92670	11.985	15	OMH	0.94124	9.368	43*
LAV	0.87343	25.860	25	BRP	0.91820	17.543	27
CIN	0.93769	14.062	28	GRE	0.92011	13.503	19

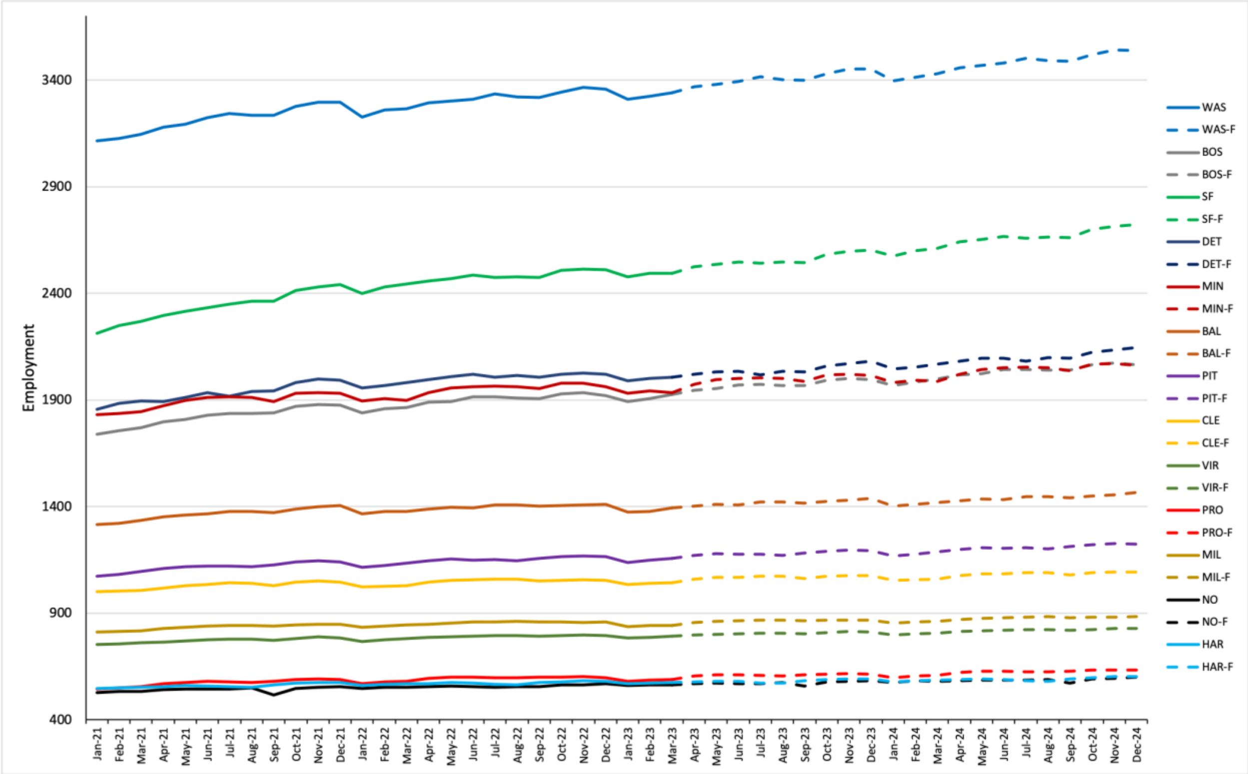
forecasted Recovery Time in months

Treatment of Missing Data

Of the 60 largest metropolitan statistical areas in the United States selected for this study, 18 MSAs had not returned to predicted non-pandemic April 2020 levels of total nonfarm employment as of March 2023, the most recent available revised data published by the Bureau of Labor Statistics at the time that this study was conducted. Total nonfarm employment was therefore forecasted for these metropolitan areas using the FORECAST.ETS algorithm in Microsoft Excel, trained using total nonfarm employment by MSA data from January 2021 through March 2023. This method was chosen rather than using a linear regression model to account for normal seasonal employment fluctuations present in employment data. The FORECAST.ETS algorithm uses a simple additive exponential smoothing forecasting technique, accounting for error, trend, and seasonality. Figure 3 shows total nonfarm employment for the 18 MSAs forecasted through December 2024, with published employment represented by solid lines and forecasted employment continued as dashed lines. The month in which total nonfarm employment was forecasted to first exceed expected April 2020 non-pandemic employment for each MSA were noted as the predicted month regional employment would be considered recuperated, and the total months required to reach this point for each MSA were summed.

Figure 3

Forecasted Employment by MSA- March 2023 through December 2023 (thousand)



Testing of Research Objectives

In relation to RO1 and RO2, correlations between the variables used in this study were calculated first as illustrated in Table 4. Notably, Shannon's Entropy is significantly negatively correlated to both *Impact %* (-0.409, $p < 0.05$) and *recovery time* (-0.342, $p < 0.05$), indicating that as industry sector diversity as measured by Shannon's Entropy increased, the initial impact of the pandemic on nonfarm employment as well as the number of month necessary for total nonfarm employment to return to a total equal to or exceeding the calculated expected employment for April 2020 both decreased. Shannon's Entropy was also significantly negatively correlated with the percentage of total nonfarm employment made up by Government sector employment (-0.363, $p < 0.05$), indicating that as industry sector diversity as measured by Shannon's Entropy increased, the percentage of government sector employment decreased. Shannon's Entropy was not significantly correlated to the percentage of total nonfarm employment made up by the goods-producing or service-producing sectors at $p < 0.05$.

Table 4

Correlation Matrix

	Feb 2020 Emp	Entropy	Impact %	Recovery Time (m)	% Goods	% Services	% Gov
Feb 2020 Emp	1						
Entropy	0.117	1					
Impact %	0.131	**-0.409**	1				
Recovery Time (m)	-0.057	**-0.342**	**0.371**	1			
% Goods	**-0.261**	0.250	-0.022	0.040	1		
% Services	**0.369**	0.119	**0.264**	-0.043	**-0.533**	1	
% Gov	-0.171	**-0.363**	**-0.274**	0.011	**-0.328**	**-0.625**	1

p < 0.05

Feb 2020 Employment was significantly positively correlated (0.369, $p < 0.05$) with the percentage of nonfarm employment that was comprised by the service sector (i.e. *% Services*, which includes the Wholesale Trade, Retail Trade, Transportation and Utilities, Information, Financial Activities, Professional and Business Services, Education and Health Services, Leisure and Hospitality, and Other Services sectors), and similarly was significantly negatively correlated (-0.261, $p < 0.05$) with the percentage of nonfarm employment that was dedicated to goods-producing industries (i.e. *% Goods,* which includes the Mining, Logging, and Construction and Manufacturing sectors).

The percentage of total nonfarm employment that was lost between February and April 2020 (i.e. *Impact %)* was positively correlated (0.371, $p < 0.05$) with the other measure of economic disaster resilience in this study, the total months required to return to the level of expected employment for April 2020 – *Recovery Time*. *Impact %* was also significantly positively correlated (0.264, $p < 0.05$) with the percentage of nonfarm employment made up by the service industry sectors (*% Services*). However, *Impact %* was significantly negatively correlated (-0.274, $p < 0.05$) with the percentage of nonfarm employment made up by Government employment (*% Gov*). However, *Recovery Time* was not significantly correlated to any of the included categories of employment.

Based on the above determination of significant correlations, *Feb 2020 Employment* and *% Gov* variables were chosen for inclusion with *Entropy* in multiple linear regression models to predict *Impact %* and *Recovery Time* relevant to RO2. In building the models, 48 of the 60 MSAs included in this study were randomly selected for model training as discussed above in the methodology section. *Feb 2020 Employment* was chosen based on the aforementioned literature theorizing the natural evolution of metropolitan area development with regard to industry specialization and diversification. *Feb 2020 Employment* was also not found to be significantly correlated with the calculated Shannon's Entropy, avoiding possible multicollinearity issues. As government sector employment is widely accepted to be less volatile and responsive to changes in economic conditions, *% Gov* was included in the models as an assumed relevant contributor to the economic disaster resilience of a region not significantly correlated to *Feb 2020 Employment*.

Table 5 shows the results of multiple linear regression modeling for the dependent variable *Impact %*. The coefficient of determination was calculated as 0.434, with a standard deviation of the residuals calculated as 0.0296. The model has an F-statistic of 11.262 at a significance level of $p < .001$. *Entropy* ($t = -4.632$, $p < 0.001$) and *% Gov* ($t = -4.376$, $p < 0.001$) were both determined to be statistically significant predictors, with *February 2020 Employment* ($t = 1.084$, $p = 0.284$) not significantly contributing.

Table 5

Multiple Linear Regression Model – Impact %

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.659[a]	.434	.396	.029603028934309

a. Predictors: (Constant), % GOV, Feb 2020 Emp, Entropy Feb 2020

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.030	3	.010	11.262	<.001[b]
	Residual	.039	44	.001		
	Total	.068	47			

a. Dependent Variable: Impact %

b. Predictors: (Constant), % GOV, Feb 2020 Emp, Entropy Feb 2020

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.197	.216		5.549	<.001
	Feb 2020 Emp	2.767E-6	.000	.124	1.084	.284
	Entropy Feb 2020	-1.052	.227	-.546	-4.632	<.001
	% GOV	-.637	.146	-.519	-4.376	<.001

a. Dependent Variable: Impact %

Table 6 shows the results of multiple linear regression modeling for dependent variable *Recovery Time*. The coefficient of determination was calculated as 0.168, with a standard deviation of the residuals calculated as 10.558. The model has an F-statistics of 2.964 at a significance level of $p < .042$. *Entropy* ($t = -2.980$, $p = 0.005$) was determined to be a statistically significant predictor, with *Feb 2020 Employment* ($t = 0.021$, $p = 0.983$) and *% Gov* ($t = -.885$, $p = 0.381$) not significantly contributing.

Table 6

Multiple Linear Regression Model – Recovery Time (months)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.410[a]	.168	.111	10.558

a. Predictors: (Constant), % GOV, Feb 2020 Emp, Entropy Feb 2020

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	991.098	3	330.366	2.964	.042[b]
	Residual	4904.569	44	111.467		
	Total	5895.667	47			

a. Dependent Variable: Months

b. Predictors: (Constant), % GOV, Feb 2020 Emp, Entropy Feb 2020

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	258.970	76.916		3.367	.002
	Feb 2020 Emp	1.930E-5	.001	.003	.021	.983
	Entropy Feb 2020	-241.377	81.008	-.426	-2.980	.005
	% GOV	-45.952	51.929	-.127	-.885	.381

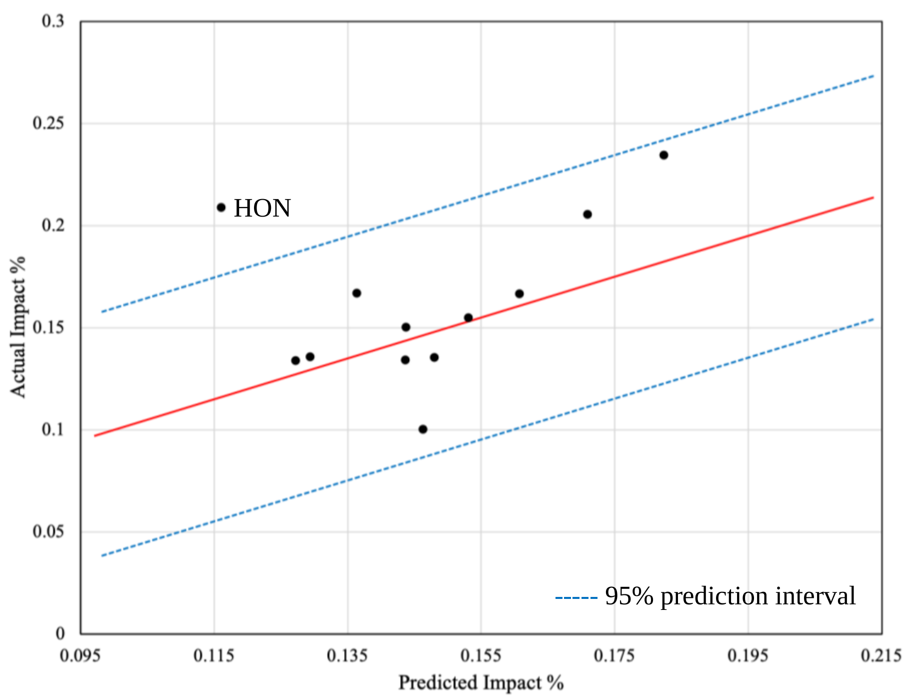
a. Dependent Variable: Months

Model Evaluation

Relevant to RO3, the predictive power of the multiple linear regression model for dependent variable *Impact %* was assessed by calculating the 95% prediction interval for the training data illustrated in Figure 4. The multiple linear regression model is shown in red, with positive and negative prediction interval bounds plotted in blue. The set of 12 randomly selected validation data MSAs are then plotted to evaluate if the model is able to predict *Impact %* within the calculated interval of plus or minus 5.966% with 95% accuracy. Of the 12 MSAs in the validation set, 11 fell within the prediction interval of the model, with only the Urban Honolulu, Hawaii MSA actual *Impact %* of 20.88% exceeding the upper bound of the 95% prediction interval for the predicted *Impact %* of 11.61%.

Figure 4

Validation Data Plotted against MLR Impact % - 95% Prediction Interval Results



Likewise, the accuracy of predictions of *recovery time* validation data by the multiple regression model were calculated using the F1 Score method, commonly found in classification model evaluation in the field of machine learning and data sciences. For the 80% of MSAs randomly selected for model training (48 MSAs), a 5x5 confusion matrix (Table 7) was created to evaluate the ability of the multiple regression model to classify within which business cycle total MSA employment would likely return to estimated non-pandemic April 2020 levels, due to the non-linear, cyclical nature of employment data. For example, Class 1 represents a return to non-pandemic levels during the current business cycle (during months 1 through 12). Net True Positives when the correct class was predicted (20 MSAs), Net False Positives (28 MSAs) when a specific class was predicted but the actual return to non-pandemic level employment occurred in a different business cycle, as well as Net False Negatives (equal to Net False Positives, 28 MSAs) where totals were calculated to arrive at a final micro-F1 score for accuracy calculated as 41.67%.

Table 7

Confusion Matrix and Accuracy by Class – Training Data (48 MSAs)

		Predicted				
	Class	1	2	3	4	5
Actual	1	0	0	0	0	0
	2	0	3	14	0	0
	3	0	0	15	2	0
	4	0	0	7	2	0
	5	0	0	4	1	0

Class	**Recall %**	**Precision %**	**F1-Score %**	**Specificity**
1	N/A	NA	NA	1.000
2	0.176	1.000	0.300	0.689
3	0.882	0.375	0.526	0.750
4	0.222	0.400	0.286	0.837
5	0.000	NA	NA	0.896

For the 20% of MSAs randomly selected for validation of the model (12 MSAs), another 5x5 confusion matrix (Table 8) was created to once again evaluate the ability of the multiple regression model to classify within which business cycle total MSA nonfarm employment would likely return to estimated non-pandemic April 2020 levels. Net True Positives (3 MSAs), Net False Positives (9 MSAs), and Net False Negatives (equal to Net False Positives, 9 MSAs) where totals were calculated to arrive at a final micro-F1 score for accuracy of 25.0%.

Table 8

Confusion Matrix and Accuracy by Class – Validation Data (12 MSAs)

		Predicted				
	Class	1	2	3	4	5
Actual	1	0	0	0	0	0
	2	0	0	4		
	3	0	1	3		
	4	0		2	0	
	5	0		2	0	0

Class	**Recall %**	**Precision %**	**F1-Score %**	**Specificity**
1	NA	NA	NA	1.000
2	0.000	0.000	NA	0.636
3	0.750	0.273	0.400	0.000
4	0.000	NA	NA	0.833
5	0.000	NA	NA	0.833

Chapter 5: Discussion

Correlation analysis performed in this study successfully demonstrates that industry sector heterogeneity as measured by Shannon's Entropy is significantly negatively correlated with both *Impact* % on employment and the length of time required as measured by *recovery time* during the COVID-19 pandemic. As heterogeneity in the sample data increased, both the percentage of employment lost between February 2020 and April 2020 (*Impact %)* and the number of months required to return to the expected level of employment for April 2020 without a pandemic (*recovery time*) decreased, indicating that greater industry sector heterogeneity is notably associated with greater employment resilience and faster employment *recovery time* after a pandemic. This result was expected, given the success of diversification strategies in fields such as finance that are well documented in the literature. Just as Shannon's Entropy used in this study is a measure of general diversity, and it is possible that more specific diversification strategies adopted from the field of finance could be utilized, treating regional industry sector employment as a portfolio to build economic resilience.

The significant positive correlation between employment *Impact %* and *recovery time* was intuitive and supported the internal validity of this study. Given that the first wave of the COVID-19 pandemic was an acute public health crisis, findings showing that the economic impact on employment were positively associated with large concentrations of employment in service-related industries (*Service %)* is also reasonable. Employment *Impact %* having a significant correlation with the percentage of employment attributed to the government sector (*Gov %*) is also intuitive and supports the widely accepted assumption that government entities may have greater access to credit and are less dependent on profit to ensure the continuity of operations and employment for their workers through a disaster event, in comparison to the private sector. However, overall MSA employment structural attributes, as measured by the percentage of employment in the public sector (*Gov %*), percentage of employment in the production of goods (*% Goods*), and percentage of employment in service-oriented industries (*% Services*), were shown to have no significant correlations with employment *recovery time*. These results may hide the presence of underlying complexity related to the economic interactions and relationship between specific service and goods-producing industry sectors. Since this study only drills down to identify specific industries service or goods producing industries in the calculation of Shannon's Entropy, and tests for correlation with only aggregated industries categories (goods-producing, service-oriented, and government sectors), the likely possibility that specific industries are particularly impactful in economic resilience was not investigated.

Total nonfarm employment had no correlation with the two measures of economic resilience considered in this study. However, as urban center population growth shows a u-shaped curve relationship with diversity in industry mix, it is reasonable to assume that this result reflects the choice to include only the 60 largest MSAs in the United States, varying in February 2020 employment from 9,932,300 to 431,000 workers. A stratified sample of urban centers that included all phases of specification and diversification in urban development may show a correlation with calculated entropy functioning as a mediator for mid-sized urban centers. The introduction of smaller population centers would likely show a smaller proportion of total nonfarm employment contributed by the service industry due to the smaller potential customer base, which could also have unknown effects on interactions affecting economic resilience during a pandemic. In this study, as total nonfarm employment increased, the percentage of employment in service-oriented industries (*% Service*) also increased, and the percentage of employment in goods-producing industries (*% Goods*) decreased.

The multiple linear regression analysis illustrated in Table 5 showed that the independent variables accounted for 43.4% of the variance in dependent variable *Impact %*, with *Shannon's Entropy* and *% Gov* significantly contributing to the model. A comparison of the Standardized Beta coefficients demonstrates that heterogeneity measured by *Shannon's Entropy* had a similar if not slightly stronger effect on *Impact %* (*Entropy Feb 2020*, $\beta = -0.546$) and employment than the percentage of total nonfarm employment attributed to the public sector *(% Gov*, $\beta = -0.519$). Given the widely accepted stable nature of public sector employment through macroeconomic disruption, this result supports the use of Shannon's Entropy in explaining the uneven economic impact of disaster events across geographic regions, and warrants further study into the effects of regional economic composition on economic disaster resilience.

Validation of the model using the 95% prediction interval illustrated in Figure 4 suggests that the model was accurate in predicting *Impact %* to within the calculated interval of plus or minus 5.966% when tested against a randomly selected subset of the data. More testing is needed, however, including the use of a larger subset sample size and the introduction of additional variables to build a robust model to predict the impact of disaster events on employment with greater accuracy.

The multiple linear regression analysis illustrated in Table 6 showed that the independent variables accounted for 16.8% of the variance in the dependent variable *Recovery Time (months)*, with only *Shannon's Entropy* significantly contributing to the model ($t = -2.980$, $p = 0.005$), and a standardized $\beta = -0.426$. Since regular seasonal fluctuations in employment, particularly due to the effects of seasonal weather on goods and service-producing industries and academic schedules, can obscure the impact of disaster events when comparing total nonfarm employment from different months, it is useful to categorize the recovery in employment by business cycle (i.e., number of business cycles until employment was recuperated to expected non-pandemic April 2020 levels). Classifying the results of the model by business cycle allowed for the comparison of actual to predicted *recovery time* values using a confusion matrix. Table 7 evaluates the predictive power of the model for the training data, where the overall prediction accuracy was 41.67%.

However, a full evaluation of the predictive power of the model requires analysis of additional metrics. For example, the vast majority of the MSAs in the training data (83.3%) were predicted by the model to return to estimated April 2020 non-pandemic employment levels during the third business cycle (between 25 and 36 months after the onset of the pandemic). While the model accurately identified 15 of the 17 total MSA to recover within the third business ($recall_3$ = 88.23%), these predictions lacked precision, incorrectly predicting an additional 25 MSAs to recover within the third business cycle ($precision_3$ = 0.375%). A more comprehensive metric to validate the model, the F1-Score, found by calculating the harmonic mean of the precision % and recall % for each class, is therefore presented in Table 7, such that the performance of future iterations of this model can be evaluated in comparison to this one. Similar results were found when evaluating the quality of predictions generated by applying this model to the subset of validation data, resulting in an overall prediction accuracy of 25.0%. However, 11 of 12 MSAs were predicted to recover once again in the third business cycle, with a calculated $precision_3$ = 27.3%.

Chapter 6: Conclusion

Although employment is not the only economic indicator that can help researchers better understand the effects of disaster events on a regional economy, the intentional choice to focus on both disaster impact and recovery in terms of employment in this study allows the unit of analysis to be the geographic region, while at the same time acknowledging that the region at its essence is a collection of workers with unique skills sets rather than an engine of economic output. This choice addresses both aspects of Cutter's concerns regarding the improper usage of the term *resilience* in disaster research- "resilience for whom" ultimately being the worker, and "resilience to what" encompassing not only the public health mitigation efforts of COVID-19 pandemic but the role of the economic composition of a region which is shaped by pro-growth economic development and policy tools in the United States that propagate specialization. The results of this study suggest that in some cases specialization can have the ability to construct disaster vulnerability by offering confirmation that heterogeneity indeed has a significant negative correlation with impact on employment and recovery time. The following section examines the limitations of this study and offers recommendations for further research based on the key findings related to industry sector heterogeneity and disaster resilience.

Implications of this Research

Federal, state, and local government agencies in the United States regularly utilize a diverse set of policy tools to support regional economic development. Often, these take the form of tax abatements, either on the collection of real property tax (including land and improvements) or business personal property tax (based on the value of equipment, supplies, and inventory) for a specified period of time, to encourage business investment and the relocation of jobs to within a specified geographic area. As the collection of these taxes is considered speculative based on the relocation of a business or corporation, state and local governments view the abated tax revenue to be of zero cost consideration. In exchange for these tax abatements, businesses and corporations are often required to meet and maintain specified minimum criteria such as employment totals, with specific wage requirements. All of the 60 metropolitan areas included in this study have various policy mechanisms available to recruit or retain employment through offering businesses and corporations grants and tax incentives. Justification for these economic development agreements consists of primarily economic cost-benefit analysis using estimated benefits in tax revenues (including forecasted sales tax for increased economic activity brought about by new workers, forecasted property taxes collected from increases in property values, and forecasted income taxes collected from employees where applicable). It is estimated that over the past four decades, urban areas in the United States have foregone hundreds of billions in tax revenues through these agreements (Pew, 2021).

However, incentives alone are usually not enough to attract employers, and the existence of a skilled work force relevant to the particular operations of the business is necessary and prerequisite to relocations. In this way, regional economic development organizations build specialization and economic homogeneity by using incentives to attract employers to areas that already have a concentration of workers in that industry, at the risk of possibly creating vulnerability by actively clustering industry sectors. The results of this study suggest that the same policy tools could be redirected and used in regional economic development to intentionally increase heterogeneity and therefore build increase resilience, if focus was instead placed on building a diverse industry sector portfolio through the relocation of workers and firms from varying sectors.

Meanwhile, challenges facing the field of emergency management in the United States, such as the increasing frequency and intensity of disaster events related to climate change, aging infrastructure, and the growing national debt, will make the financing of future disaster response and recovery operations by the federal government unsustainable (CBO, 2018). The convergence of increasing costs and a decreasing capacity of the federal government to finance the cost of disasters will place an enormous financial burden on state and local governments, and likely will result in a renewed focus on regional disaster mitigation and resilience initiatives. This study, therefore, contributes to the toolkits of state and local governments to create sustainable and resilient communities using existing policy tools. As entropy has been shown by this study to be significantly negatively correlated with both disaster impact and recovery time, the use of economic development policy tools to leverage greater specialization for an urban area should be questioned, and the use of these policy tools to strategically diversify a regional economy in the name of economic disaster resilience should be considered.

Study Limitations & Recommendations for Further Research

As this study specifically examines economic resilience with regards to the impact of the COVID-19 pandemic on employment, there may be limits to which this study is generalizable to other disaster events. The COVID-19 pandemic has presented a valuable research opportunity for economists to compare the effects of urban center characteristics from a wide variety of regional economies that were impacted by the same event (the first wave of the COVID-19 pandemic) at roughly the same time. However, it can be assumed that a pandemic is unique in that certain service-related industries having direct contact with the public would be impacted to a greater degree than total nonfarm employment in other industries. For example, the effects of public health mitigation efforts such as shelter-in-place orders and the closure of businesses engaged in commerce deemed non-essential were well documented during the COVID-19 pandemic. The characteristics of other types of disaster events (e.g., hurricanes and earthquakes) and their second and third-order effects on urban infrastructure would likely impact employment in different industry sectors to a greater degree with regard to impact and recovery time. Although the modeling methodology used here introducing Shannon's Entropy as a measure of industry sector heterogeneity would likely still be correlated to employment resilience and therefore extremely relevant, the degree by which industry sector diversification would affect overall economic resilience during other disaster events is unknown. Further research is needed both in terms of analysis of a wider array of disaster events with different characteristics, as well as the introduction of urban centers in other countries with different public health mitigation protocols and strategies, to assess the external validity of the models presented here and the usefulness of an economic heterogeneity measure.

It should be noted that while Shannon's Entropy as a component in modeling economic disaster resilience is more likely to be of value in large metropolitan areas that have undergone re-specialization as discussed in the literature review, rather than in smaller population centers where the expected industry mix may start out very specialized and then go through a natural process of diversification as they grow, this theory should be verified to better understand the precise role of economic heterogeneity in disaster resilience.

Additional limitations include other facets of economic resilience and impact beyond employment that were outside the scope of this study. Given the well-documented disproportional effects of disaster events on vulnerable populations, other metrics of the economic health of a region related to income inequality, housing, healthcare costs, inflation, the availability of capital, and externalities associated with unemployment also should be evaluated to comprehensively examine economic impact and resilience. Further research using data publicly available through the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis would help to reveal the relationship between industry heterogeneity and provide a more comprehensive view of economic resilience beyond the scope of this study.

This study is also limited in that it relies upon common definitions of disaster resilience from other fields applied to economics, and does not address the concept of economic adaptation or allow for an urban center to organically grow back differently. A disaster event may forever change the economic structure of a region, and measuring economic recovery as a return to a previous pre-disaster state is likely to be logically flawed. Total nonfarm employment surpassing an expected employment level viewed as recovery in this study may be the result of a structural change in a regional economy, where a new equilibrium between supply and demand in the labor market has formed. It should be expected that employment in different industry sectors will recover at different speeds, and the use of aggregate employment totals could be misleading as a measure of actual recovery. Individual industry sectors that did not recover to the projected non-pandemic employment levels were not captured in this study due to the use of aggregate totals. The use of total nonfarm employment before and after a disaster event where the unit of analysis is a geographic region is likewise problematic as it may not necessarily represent the same individuals, or account for demographic changes in population such as those seen in New Orleans in the aftermath of Hurricane Katerina. Further research examining each industry sector separately would likely result in a clearer account of regional economic recovery to measure economic adaptation.

Certain industry sectors that share required worker skill sets, such as the oil field production and construction sectors, may have interactions that guide economic adaptation and affect the nature of economic disaster resilience. For example, displaced construction workers in the United States are able to find work in the oil and gas exploration industry during periods of recession in the construction industry due to a shared set of skills. Interactions between industry sectors such as these can be modeled using techniques common in the evaluation of complex dynamic systems to predict economic adaptation.

The spatial nature of regional employment data and the distance between urban sectors and their unique industries sector concentrations could additionally play a role in interactions in a complex dynamic system. It is possible that the appropriate unit of analysis to correctly identify an economic region is larger than the MSA level used here. Future studies should evaluate the definition of a regional economy, as the increasingly digital nature of employment post-COVID-19 pandemic has reduced the need for employees to reside in a specific location. It is also likely that certain industries such as the transportation and warehousing sector, for example, play specific roles in connecting urban centers to the larger global economic system, and the presence of large concentrations of specific industries that function to support other sectors could have an effect on both economic impact and economic recovery time in the aftermath of disaster events.

Finally, the accessibility of comprehensive economic data that provides a clear picture of the economic impact of disaster events creates several limitations. The measure of nonfarm employment used in this study by definition does not account for those, for example, who are underemployed either in hours or compensation. A more comprehensive measure of economic impact should also account for those either forced to work only part-time for economic reasons or those working in lower-paying positions than their skills and training could attain under better economic conditions. Measures such as total wages earned by industry sector, used in combination with employment, could provide an alternative measure of economic activity that better represents the negative economic effects experienced by all workers. To produce actionable information that informs economic policy, further study would need to examine all mechanisms behind total nonfarm employment, and how disaster events may also affect the labor force participation rate. For example, if there was a reduction in the availability of childcare that pushed parents of small children out of the workforce, changes in aggregate employment totals alone would not adequately represent economic impact. Further study of these known limitations mentioned above is necessary to better understand the potential benefits of using entropy in predictive disaster resilience modeling, and its implications for the modeling of adaptive economic resilience.

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Appendix A

Metropolitan Statistical Areas with Abbreviations

Abbr.	MSA	Abbr.	MSA
NY	New York-Newark-Jersey City, NY-NJ-PA	KC	Kansas City, MO-KS
LA	Los Angeles-Long Beach-Anaheim, CA	COL	Columbus, OH
CHI	Chicago-Naperville-Elgin, IL-IN-WI	IND	Indianapolis-Carmel-Anderson, IN
DFW	Dallas-Fort Worth-Arlington, TX	CLE	Cleveland-Elyria, OH
HOU	Houston-The Woodlands-Sugar Land, TX	SJ	San Jose-Sunnyvale-Santa Clara, CA
WAS	Washington-Arlington-Alexandria, DC-VA-MD-WV	NAS	Nashville-Davidson--Murfreesboro--Franklin, TN
PHI	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	VIR	Virginia Beach-Norfolk-Newport News, VA-NC
MIA	Miami-Fort Lauderdale-West Palm Beach, FL	PRO	Providence-Warwick, RI-MA NECTA
ATL	Atlanta-Sandy Springs-Roswell, GA	JAC	Jacksonville, FL
BOS	Boston-Cambridge-Newton, MA NECTA Division	MIL	Milwaukee-Waukesha-West Allis, WI
PHX	Phoenix-Mesa-Scottsdale, AZ	OKC	Oklahoma City, OK
SF	San Francisco-Oakland-Hayward, CA	RAL	Raleigh, NC
RIV	Riverside-San Bernardino-Ontario, CA	MEM	Memphis, TN-MS-AR
DET	Detroit-Warren-Dearborn, MI	RIC	Richmond, VA
SEA	Seattle-Tacoma-Bellevue, WA	LOU	Louisville/Jefferson County, KY-IN
MIN	Minneapolis-St. Paul-Bloomington, MN-WI	NO	New Orleans-Metairie, LA
SAD	San Diego-Carlsbad, CA	SLC	Salt Lake City, UT
TAM	Tampa-St. Petersburg-Clearwater, FL	HAR	Hartford-West Hartford-East Hartford, CT NECTA
DEN	Denver-Aurora-Lakewood, CO	BUF	Buffalo-Cheektowaga-Niagara Falls, NY
BAL	Baltimore-Columbia-Towson, MD	BIR	Birmingham-Hoover, AL
STL	St. Louis, MO-IL	ROC	Rochester, NY
ORL	Orlando-Kissimmee-Sanford, FL	GRP	Grand Rapids-Wyoming, MI

Abbr.	MSA	Abbr.	MSA
CHA	Charlotte-Concord-Gastonia, NC-SC	TUC	Tucson, AZ
SAA	San Antonio-New Braunfels, TX	HON	Urban Honolulu, HI
POR	Portland-Vancouver-Hillsboro, OR-WA	TUL	Tulsa, OK
SAC	Sacramento--Roseville--Arden-Arcade, CA	FRE	Fresno, CA
PIT	Pittsburgh, PA	WOR	Worcester, MA-CT NECTA
AUS	Austin-Round Rock, TX	OMH	Omaha-Council Bluffs, NE-IA
LAV	Las Vegas-Henderson-Paradise, NV	BRP	Bridgeport-Stamford-Norwalk, CT NECTA
CIN	Cincinnati, OH-KY-IN	GRE	Greenville-Anderson-Mauldin, SC

Source: BLS.gov, Current Employment Statistics

Appendix B

Institutional Review Board for the Protection of Human Subjects in Research
203 Angle Hall
700 Pelham Road North
Jacksonville, AL 36265-1602

August 1, 2023

Thomas Brindle
Jacksonville State University
Jacksonville, AL 36265

Dear Thomas:

Your protocol for the project titled "Using Industry Sector Entropy to Measure Economic Community Disaster Resilience: Real-world Verification from the COVID-19 Pandemic" protocol number 08012023-01 has been approved by the JSU Institutional Review Board for the Protection of Human Subjects in Research (IRB).

If your research deviates from that listed in the protocol, please notify me immediately. One year from the date of this approval letter, please send me a progress report of your research project.

Best wishes for a successful research project.

Sincerely,

Staci Stone
Human Protections Administrator, Institutional Review Board

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