MASTERARBEIT | MASTER'S THESIS

Titel | Title

Beyond the Paycheck: A Livability Index-Based Analysis of Salary Differences in the United States

verfasst von | submitted by

Jasmin Schick

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 914
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Internationale Betriebswirtschaft
Betreut von | Supervisor:	Univ.-Prof. Dipl.-Chem. Dr. Markus Georg Reitzig MBR

Abstract

In the context of financial compensation, it is of interest to ascertain the factors that influence salary differences, such as those observed between regions. In addition to the cost of living, the question of the area's livability also plays a role – a non-monetary incentive for which employees could potentially pay a price. The thesis examines the influence of the livability on salaries. The research field considers both economic and social aspects that are of relevance for companies and employees. In order to facilitate the analysis, a Livability Index for the United States is calculated in Python. This index measures the level of livability in counties of the United States based on seven categories, following the model of the American Institute AARP. The influence of the index on salaries at the company-level is analyzed for the period 2015-2019. The results show no significant influence of livability on salary, although influences become apparent when examining the individual categories. These findings suggest that a differentiated consideration of the complex field of livability can contribute valuable insights to research. Thus, the thesis provides new insights into the factors influencing compensation and creates starting points for future investigations.

Geht es um die finanzielle Entlohnung, so stellt sich die Frage nach Einflussfaktoren, die beispielsweise regionale Gehaltsunterschiede hervorrufen. Neben den Lebenshaltungskosten spielt hierbei auch die Lebensqualität eine Rolle – ein nicht-monetärer Anreiz, für den Mitarbeiter möglicherweise einen Preis zahlen könnten. Die Thesis untersucht den Einfluss der Lebensqualität auf das Gehalt in Unternehmen. Das Forschungsfeld berücksichtigt sowohl wirtschaftliche wie auch gesellschaftliche Aspekte, die für Unternehmen und Arbeitnehmer von Relevanz sind. Zur Durchführung der Analyse wird ein Lebensqualitäts-Index für die Vereinigten Staaten in Python berechnet, der die Lebensqualität nach Vorbild des amerikanischen Instituts AARP anhand von sieben Kategorien misst. Anhand dessen wird der Einfluss auf Gehälter auf Unternehmensebene analysiert, wobei die Jahre 2015-2019 untersucht werden. Die Ergebnisse zeigen keinen signifikanten Einfluss der Lebensqualität auf das Gehalt. Bei detaillierter Analyse der einzelnen Kategorien werden allerdings Auswirkungen ersichtlich. Dies deutet darauf hin, dass eine differenzierte Betrachtung des komplexen Felds der Lebensqualität wertvolle Beiträge zur Forschung leisten kann. Die Thesis bietet damit neue Einblicke in die Einflussfaktoren der Vergütung und schafft Ansatzpunkte für zukünftige Untersuchungen.

Acknowledgements

I would like to take this opportunity to thank those who supported and guided me throughout the completion of this master's thesis. I appreciate the time and patience Prof. Dr. Reitzig and Ms. Heiss invested in guiding my work as well as the opportunity to conduct my research within the Strategic Management Subject Area.

My sincere gratitude goes to my supervisor, Prof. Dr. Reitzig, for his valuable feedback and guidance throughout this thesis. His constructive input and expertise have been enriching in shaping my research approach.

I also wish to express my thanks to Ms. Heiss for her continuous support and thoughtful comments. Her suggestions and encouragement helped me to navigate the challenges of this project.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AARP	Formerly the American Association of Retired Persons, today recognized solely by the acronym AARP
ADA	Americans with Disabilities Act
AQI	Air Quality Index
CEO	Chief Executive Officer
FIPS	Federal Information Processing Standards
GDP	Gross Domestic Product
HPSA	Health Professional Shortage Area
IT	Information Technology
PC	Personal Computer
RSEI	Risk-Screening Environmental Indicators
U.S.	United States
ZIP	Zone Improvement Plan

1. Introduction

According to basic economic theory, wages across locations would eventually equalize for similar workers in competitive labor markets (DuMond et al., 1999). However, empirical studies show that regional wage differentials persist, raising questions about the factors influencing these disparities. One aspect is the role of non-monetary incentives in corporate compensation policies. While compensation plans include monetary incentives, such as salaries and bonuses, they also encompass non-monetary benefits like health insurance and workplace amenities.

Quality of life has emerged as a significant non-monetary factor influencing career decisions and compensation strategies (Power, 1980; Myers, 1987). The associated local amenities are seen as a crucial point in wage differentials. Based on the Spatial Equilibrium Theory, the willingness of residents to pay for local amenities is reflected in wages and property prices (Roback, 1982; Rosen, 1986; Shi et al. 2021). Consequently, for companies to remain competitive and attract and retain talent in less attractive locations, they need to offer higher salaries to compensate for the less attractive location (Myers, 1987). The influence of location attractiveness on salary has been demonstrated in various studies (Deng & Gao, 2013; Li et al. 2021; Shi et al., 2021), which underlines its importance in the field of economics.

The aim of the study is to contribute to the topic by examining the impact of livability on salaries in the United States, thus making an important contribution to research into compensation policy and offering valuable insights for academic research and practical business applications. While previous research has focused on geographic levels of cities (Li et al., 2021; Roback, 1982; Shi et al., 2021) or states (Deng & Gao, 2013) and executive pay (Deng & Gao, 2013; Li et al., 2021), this study fills a gap by examining counties in the United States and salaries at company-level in the gaming industry, calculating a differentiated Livability Index that allows for a specific examination of individual categories in the area of livability through the consideration of various metrics. The analysis covers a period of several years, allowing for the examination of the temporal aspect of livability's influence on salaries.

Moreover, the object of investigation is crucial for both employees and employers. From a company perspective, compensation plans are a key component of talent management, especially in industries that rely on specialized skills, such as the growing gaming industry (Christofferson et al., 2023). When it comes to employees, the associated quality of life also plays a major role in their choice of location (Bollinger et al., 1983; Malecki, 1984). The important role of talent management in the gaming industry, as well as the relevance of local amenities for highly skilled workers, provides a suitable research context. This study not only contributes to insights into salary-setting practices but also lays the groundwork for future research into the dynamic between compensation and livability.

Therefore, the following research question arises:

How does livability influence company-level salaries from 2015 to 2019?

A desirable living environment is addressed by various rankings and the methodology varies in research reports by using metrics or surveys. The AARP, formerly known as American Association of Retired Persons (AARP, 2024-a), has created the AARP Livability Index, which assesses livability in the United States based on seven different categories (AARP, n.d.-a). The research question is examined by calculating a differentiated Livability Index following the AARP model with the categories of Neighborhood, Environment, Engagement, Opportunity, Health, Housing, and Transportation. Utilizing various metrics per category, the Livability Index for the years 2015-2019 is calculated. A fixed effects panel data regression analysis is conducted to test the influence on salaries at the company level.

The thesis begins with an examination of the compensation policies of companies. The initial focus is on the role of monetary incentives and a consideration of the potential influencing factors. Subsequently, the thesis proceeds to elaborate on the concept of non-monetary incentives. In light of the aforementioned considerations, the compensating wage differentials are presented according to the theoretical assumptions posited by Roback (1982) and Rosen (1986). The role of local amenities and quality of life, as well as their relevance, is elucidated. This is followed by a definition of the term livability and its classification in the geographical division of the United States. Based on this foundation, a literature review is then provided on the influence of livability on salaries, from which the hypothesis is derived. Finally, a brief insight into the research context of the gaming industry is presented, where attention is drawn to the relevance of livability and compensation within the sector. Finally, the research model of the study is presented, which is used to answer the research question. The theoretical framework and the literature review are followed by an explanation of the method. The calculation of the Livability Index is described, with the overarching method being discussed first, followed by the individual categories. Thereupon, the variable of the salary at the company level is explained, and subsequently, the control variables are described. The methodology section concludes with an explanation of the fixed effects model for analyzing the panel data. The results are presented next, beginning with an overview of the Livability Index and the data. Thereafter, the regression analysis results are presented, starting with the Livability Index before taking a closer look at the individual categories. In the following, the results are discussed, placing them first in the context of the findings from previous research. Subsequently, managerial implications are presented. The limitations are then outlined, along with indications for future research. The thesis finishes with a conclusion drawing final remarks on the findings.

2. Theoretical Framework and Literature Review

The following chapter presents the theoretical background and research findings on the influence of livability on salary. For this purpose, the compensation policy is examined, which incorporates both monetary and non-monetary incentives. Initially, the monetary incentive of the salary paid is addressed, along with the factors that may influence it. Subsequently, non-monetary incentives are outlined, including the role of quality of life. Ultimately, the balance between monetary and non-monetary incentives in the compensation policy and the role of local amenities are presented. These findings establish a foundation for the investigation of the non-monetary factor of livability in relation to the monetary factor of salary. Based on the literature review regarding this aspect of research, a hypothesis is formulated to address the research question of how livability affects salary. Following an overview of the research context within the gaming industry, the research model is presented.

2.1 The Role of Incentives in Compensation

When it comes to the choice of compensation for employees, monetary and non-monetary incentives are considered. Incentives are crucial factors that stimulate employees' motives and thus motivate them (Holtbrügge, 2010). Monetary incentives take the form of financial rewards, which can include bonuses or profit sharing in addition to salary (Faust, 2021) and are influenced by various factors.

One factor that has been extensively researched is the cost of living, as workers need higher wages to be able to work and live in a work location with higher prices for goods and services (Winters, 2009). Costs of living play a crucial role in the remuneration system (Henderson, 2000) and serve as a factor for regional differences in nominal wages (Gerking & Weirick, 1983; Kim et al., 2009; Winters, 2009). The adaptation of companies does not necessarily have to be linear here, as not all consumption is characterized by local cost differences due to possibilities like online shopping (Sturman et al., 2017). However, a positive relationship has been found between cost of living and wage (Black et al., 2009; DuMond et al.; 1999; Gerking et al.; 1983, Kim et al., 2009; McHenry & McInerney, 2014; Winters, 2009).

Moreover, research findings indicate that company size is an influential factor in determining pay, with larger companies paying their employees higher wages (Brown & Medoff, 1989; Gibson & Stillman, 2009; Oi, 1983).

One potential explanation for this is the necessity for large companies to provide compensation to their employees due to the obligation to comply with administrative regulations (Oi & Idson, 1999). A further potential reason may be that larger companies are more expedient in their adoption of new technologies requiring a skilled and productive workforce (Oi & Idson, 1999). Not only company size but also company performance has gained importance in compensation research, with CEO compensation being a common area of examination (Tosi et al., 2000; Yang et al., 2020; Ye et al., 2023). Bronars and Famulari (2001) show a relationship between wages and company performance for employees in the United States. A 1 % increase in a company's annual stock return leads to a pay increase of approximately 0.25 % to 0.30 % for employees with at least three years of service, indicating a direct relationship between performance and wages.

However, companies' compensation policies are not only based on monetary incentives but also on non-monetary incentives. Non-monetary incentives include non-wage amenities such as the design of the office and working conditions, employee benefits such as health and life insurance, fringe benefits such as housing, and even minor ones such as free coffee (Crifo & Diaye, 2011). In addition, factors such as power, prestige or public visibility are also non-monetary benefits (Jensen & Murphy, 1990). From a geographical standpoint, another non-monetary factor is the living environment, which is associated with the quality of life (Deng & Gao, 2013). Non-monetary incentives are more symbolic of the well-being of employees than salaries, which are liquid (Crifo & Diaye, 2011). Economists recognize the importance of non-monetary incentives, which are essential to total compensation for many jobs. Mathios (1989) asserts that neglecting non-monetary incentives can disturb the understanding of compensation policies. They are considered strong incentives that are suitable for increasing employee performance.

2.2 Compensating Wage Differentials and the Relevance of Quality of Life

The theory of equalizing differences (Rosen, 1986) is based on Adams Smith's work on political economy "The Wealth of Nations" (1776), and describes the relevance of compensating wage differences, including monetary and non-monetary incentives.

The theory is a central concept in labor economics and contributes to understanding the behavior of workers and employers in the labor market. In 1967, Fuchs found that wages in the South were lower than elsewhere in the United States. In subsequent years, these differences were broken down by components such as different costs of living (Hoch, 1974), as previously mentioned as an influencing factor on wages. Rosen names in addition to working conditions, work-time scheduling, and the composition of pay packages, also interregional differences in climate, crime, pollution, and crowding as reasons for wage differences. Rosen emphasizes in her theory that there must be a balance between locational amenities and prices: "If workers earn the same money and have the same costs of living in a better environment compared to a poorer one, no one would choose to live in the less amenable place." (Rosen, 1986, p. 673*)* This statement emphasizes the importance of considering location-specific characteristics.

In this context, housing markets and regional productivity can also play an important role, as mentioned in the Spatial Equilibrium Theory (Roback, 1982). As the work builds on the hedonic wage model of Rosen (1979), the model is also referred to as the Rosen-Roback Model (Shi et al., 2021). In this framework, labor mobility across different locations results in a spatial equilibrium where individuals and firms have no further incentive to relocate, as the key factors of wage, rent, and local amenities reach a state of balance. The theory highlights the significant role of the factors in determining locational choices. For firms operating in less attractive regions, the ability to offer higher wages becomes crucial to attracting workers, a factor that can be offset by lower rents or productivity advantages at those locations to maintain overall cost efficiency. Simultaneously, for workers, wages and housing costs must adjust to ensure the utility is equalized across different regions. Otherwise, there would be an incentive for them to migrate. By considering both the firm's cost structure and the workers' utility, an equilibrium emerges that defines wage levels. This model underscores the critical influence of local amenities on wages, while also acknowledging that costs of living, represented in this model by rents, also play an essential part.

The theoretical assumptions underscore the critical role of local amenities in relation to salary as a factor in the compensation policy. Local amenities are important determinants of quality of life (Shi et al., 2021). Quality of life is considered an important component of economic development and plays a major role in shaping local labor costs (Myers, 1987). In 1980, Power drew attention to the need for monetary compensation, through which workers should be willing to accept a lower level of local amenities. Disamenity compensation is necessary, whereby locations with a lower quality of life must offer a higher wage to attract employees with the same quality as locations with a higher quality of life (Myers, 1987). Furthermore, the quality of life positively influences migration (Porell, 1982), meaning that company locations with a good quality of life can attract skilled employees with a lower wage level than in less favorable places. This factor can be particularly crucial when specialized labor is required, as it often necessitates relocation. If the supply of skilled workers at a location is insufficient, companies attempt to recruit skilled employees from other locations. In addition to training opportunities and housing factors, incentives such as amenability or air quality are promoted (Feldman, 1985).

However, quality of life plays an important role not only in recruitment but also in retention. A negative development of the quality of life can also lead to skilled workers turning away from the location (Myers, 1987). Therefore, maintaining a favorable quality of life is important for stimulating future economic development. This underscores the relevance of the topic for companies in terms of shaping their compensation policies and the resulting labor costs, as well as for attracting and retaining employees. However, the topic is highly relevant not only from the company’s perspective but also from the employees’ point of view. The quality of life can play a relevant role in career decisions (Power, 1980; Myers, 1987). Quality of life is, therefore, an important factor for maintaining economic development in the present and in the future, shaping the compensation policy appropriately, and consequently attracting and retaining employees (Myers, 1987). Given the role of quality of life in economic development, compensation policy, and talent management, it is evident that an investigation into the overarching concept of livability in the context of compensation is a valuable research area. The following section will undertake a more detailed examination of the definition of livability and its geographical distinction.

2.3 Definition and Geographic Distinction of Livability

Livability is a complex term with no unique definition. The exact definition can vary depending on the context, culture, or organization. A livable environment can be understood as a place "where the built structure promotes quality of life by supporting the basic needs of its residents" (Khorrami et al., 2021, p. 398). As outlined, quality of life is at the center of the concept. The terms are differentiated in that quality of life focuses on the perception of people in the community, whereas livability refers to the structural aspects of the environment (Ghasemi et al., 2018; VanZerr et al., 2011). Therefore, quality of life is more related to the subjective well-being of residents (Bérenger & Verdier-Chouchane, 2007). In contrast, livability refers to objective conditions intended to ensure residents' well-being by fulfilling social, economic, physical, and environmental needs (Ghasemi et al., 2018). In this sense, livability can be understood as a fundamental basis for a high quality of life. The AARP measures it annually using the AARP Livability Index. The AARP (2023-2024) defines livable communities in the Policy Book as follows:

> A livable community is one that is safe and secure. [...] Livable communities: enhance personal independence, allow residents to remain in their homes and communities as they age, and provide opportunities for residents of all ages, ability levels, and backgrounds to engage fully in civic, economic, and social life. [...] These include mixed-use zoning, safe and varied transportation options, and diversity of housing types. Livable communities also have public spaces that benefit everyone. In addition, they provide access to essential businesses and services, such as grocery stores, high-speed internet, and healthcare options. (Chapter 13, Introduction)

AARP is the largest non-profit and non-partisan organization in the United States that aims to empower individuals aged 50 and older to make their own lifestyle choices as they age (AARP, 2024-b). The AARP Livability Index is a web-based tool published by the AARP Public Policy Institute that measures the livability in a community on a scale of 0 to 100, with higher scores indicating a higher livability. The score is measured using 40 metrics and 21 policies that are divided into seven categories: Housing, Neighborhood, Transportation, Environment, Health, Engagement, and Opportunity (AARP, n.d.-a). These were selected through an evaluation process with a technical advisory committee and other policy and research experts to determine the metrics, policies, and data sources that best measure critical aspects of livability. In addition, survey research was used with adults aged 18 and older, and more than 4,500 people aged 50 and older, to understand what characteristics make a community livable for various groups. It aims to cover how a community meets residents' current and future needs, regardless of age, income, physical ability, or ethnicity (AARP, 2015).

The AARP Livability Index can be retrieved for any community in the United States. Communities are “a group of people living in the same locality and under the same government, or a political subdivision of a state or other authority that has zoning and building code jurisdiction over a particular area” (Federal Emergency Management Agency, 2020). Depending on the availability of data and appropriateness, the measurement is performed at neighborhood, metro-area, county, or state level. Neighborhood-level is defined as the census block, block group, census tract, or high school district (AARP, n.d.-a). A census block is the smallest geographic unit of the U.S. Census Bureau, bounded by streets or other physical features, which combines into block groups within census tracts. Metropolitan Statistical Areas are regions with an urban core of 50,000+ people, including central and nearby counties with strong social and economic links (U.S. Census Bureau, 2022). As the Livability Index in this thesis is conducted at the county level, in accordance with the scope of the study and data availability, counties are defined in greater detail in the following section.

The United States consists of 50 states and the District of Columbia, and 3,141 counties[1] and county equivalents[1] (U.S. Census Bureau, n.d.). The U.S. Census Bureau (2022) describes counties as "the primary legal divisions of most states" (Geography Program Glossary). Exceptions are Louisiana, which is divided into parishes, and Alaska, which is divided into boroughs. Other exceptions are the states of Maryland, Missouri, and Nevada, where only one city, and Virginia, where several cities are not subject to any county organization. The District of Columbia has no

[1]The number varies slightly depending on the definition of administrative regions and classification criteria.

primary administrative divisions. States, counties, and county equivalents are identified using the Federal Information Processing Standards (FIPS) coding system, which was developed by the National Institute of Standards and Technology and the U.S. Department of Commerce and is maintained by the U.S. Geological Survey (U.S. Census Bureau, 2022). States are assigned a unique two-digit numeric code, and counties are assigned a three-digit numeric code. Combining the two results in a unique five-digit number that identifies the county in that state. The standardized administrative units of counties provide an opportunity for systematic data collection.

2.4 Literature Review on the Impact of Livability on Pay

Numerous studies have examined the influence of livability as a non-monetary incentive on pay. Thus, a distinction must be made about the objects of investigation. This differentiation is relevant to clearly explain the factors of this study in terms of geographic categorization and salary observation.

Based on the Spatial Equilibrium Theory (Roback, 1982), Shi et al. (2021) investigated the willingness of residents to pay for urban amenities in Chinese cities based on wages or housing prices. They analyzed the quality of life based on factors such as climate, cultural facilities, education, and parks. It should be noted that the authors do not directly include the subjective impressions of residents, but still speak of quality of life. However, the authors analyze their ranking in relation to subjective well-being, which establishes a connection to the subjective component. The results show that residents are willing to pay a price for local amenities, both in terms of housing costs and lower monthly income. According to the authors, a positive wage coefficient for amenities indicates that amenities increase productivity for the company, which means that higher wages can be achieved.

Li et al. (2021) investigate the influence of urban livability on CEO compensation. Urban livability indicators encompass the four aspects of economic affluence, environment, public and social security, and convenience of life in Chinese cities. The top 30 cities with the highest urban livability index in 2016 were then analyzed, and executive pay was calculated based on the three highest salaries of companies in these cities. The results show that at the mean value of the samples, each unit increase in urban livability will reduce executive pay by 30.8 %. Despite the high economic relevance of China, it is important to bear in mind the differences to Western developed countries, which are emphasized by the authors. Due to rapid urbanization over the last forty years, urban livability in China is generally relatively low due to issues such as pollution and traffic congestion (Li et al., 2021).

Deng and Gao (2013) analyzed the United States and found in their panel data analysis from 1993-2008 that companies in less livable locations pay higher compensation to their executives than in more livable locations. At the U.S. state level, they looked at the Livability Rankings published by Morgan Quitno (as cited in Deng & Gao, 2013), which measure livability based on factors such as crime rates, cost of living, unemployment, education systems, household income, weather, and infrastructure. In contrast to a Livability Index, as examined in this study, a ranking is considered. The total compensation of executives was analyzed, which is significantly influenced by livability. According to the study, companies in the ten least livable states pay 12 % higher remuneration to executives than companies in the ten most livable states. In the analysis, both industry and year fixed effects were taken into account, but this did not show any major change in the results. Even when excluding the state of California, where many IT companies and headquarters are located, the results remain unchanged. In exploring the relationship between livability and salary, firm size and performance have also been recognized as significant factors (Deng & Gao, 2013).

Studies have already examined variations in salaries across different geographical classifications. While some researchers have focused on executive pay (Deng & Gao, 2013; Li et al., 2021), this study aims to determine the average salary to draw broader conclusions about companies. Additionally, there are various methods for measuring and categorizing livability geographically. Most research has focused on livability at city (Li et al., 2021; Roback, 1982; Shi et al. 2021) or state level (Deng & Gao, 2013), but this study categorizes it according to counties. Similar to Deng & Gao's (2013) academic approach, panel data is considered, enabling a differentiated analysis of the research question of whether livability influences salary.

These findings lead to the following hypothesis:

H1: The higher the Livability Score of a county, the lower the mean salary will be at this company location.

2.5 Economic Growth and Workforce Dynamics in the Gaming Industry

The research question is investigated within the context of the gaming industry in the United States. The following section explains the relevance in the context of the study based on the economic growth and workforce dynamics of the industry, before presenting the research model and the subsequent method.

According to a report by Schudey et al. (2023), gaming ranks second behind television in the media sector with a global turnover of 184.4 trillion dollars in 2022. Sales of over 210 trillion dollars are expected by 2025. In terms of the U.S. market, the gaming industry generated 101.4 trillion in total economic impact in 2023, contributing 65.7 trillion dollars to the United States GDP (Grueber & Yetter, 2024). Games include mobile devices, PCs, and consoles as instruments. Due to technological advances, the industry requires games publishers and developers to adapt their corporate strategy (Schudey et al., 2023). Publishers are investing more resources in the development of games to create the opportunity for extended game life cycles and to satisfy the demand for immersive, high-quality games. Game lifecycles can be extended through new content and in-game purchases, rather than through the constant development of new games.

The game industry provided 104,080 direct jobs in the United States in 2023 (Grueber & Yetter, 2024). More than 42 % of the workforce is employed in California, and around 72 % of the industry's workforce in California, Washington, Texas, New York, and Florida. It is common for companies in competitive industries to be geographically concentrated (Porter, 1990). In the agglomeration of high-tech companies, the quality of life provided by local amenities is an important aspect of the location preferences of skilled workers (Bollinger et al., 1983; Malecki, 1984). Remote working is also a factor in the industry's labor market, with 17 % of industry employment represented by remote workers (Grueber & Yettter, 2024). The average compensation in 2023 is $168,600 (Grueber & Yettter, 2024).

Christofferson et al. (2023) emphasize the challenges for gaming companies in continuing to attract talent for game development to remain competitive due to the growth of the industry. The authors state that is no longer enough to rely on employees' passion for games. Talent strategies are needed that attract and retain employees through salary, career opportunities and non-monetary incentives such as work-life balance. The study by Christofferson et al. (2023) shows that the majority of employees are hired from the industry (80 %) and remain in the industry even when finding a new job (85 %). However, the attrition rate of 10 % is higher than that of the broader technology industry at 6 % in 2022. This highlights the importance of retaining talent through an appropriate compensation policy. To respond to the high attrition rates and the growth of the industry, it is of great importance for gaming companies to be attractive to talent within the industry, but also from other industries. Both the compensation policy and the work-life balance are mentioned by the authors as key areas for investment. These recent findings reflect the continued importance and dynamism of the industry. By answering the research question, this work can provide valuable insights into the design of the compensation policy of gaming companies, which is of great importance for future talent management. Livability as a non-monetary factor also plays an important role in the work-life balance by enhancing leisure opportunities outside the workplace.

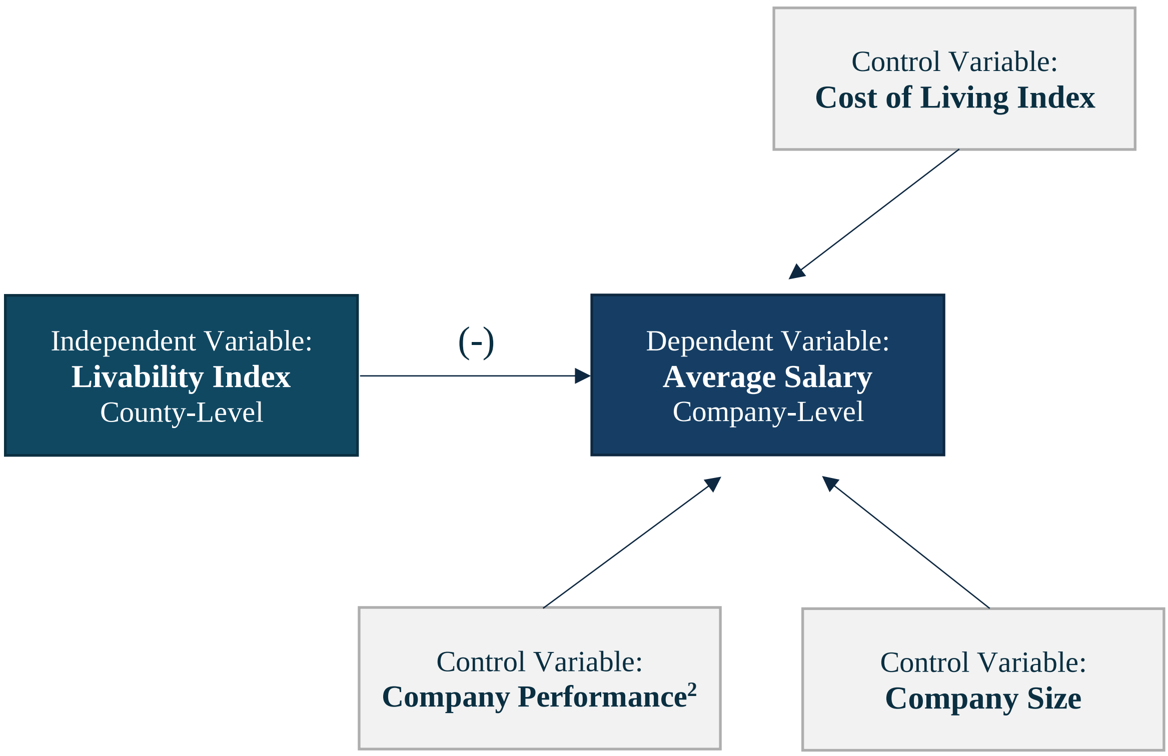
2.6 Research Model of Livability's Influence on Salaries

The preceding chapters have demonstrated that compensation is constituted of both monetary and non-monetary incentives (Holtbrügge, 2010). Monetary incentives are defined as financial rewards (Faust, 2021), whereas non-monetary incentives include factors such as the living environment, which is non-liquid (Crifo & Diaye, 2011). As postulated by Roback (1982) and Rosen (1986), wage disparities can compensate for discrepancies in local amenities. This emphasizes the interconnection between the non-monetary aspect of livability, which encompasses the local amenities, and the monetary element of wage.

This topic represents an examination of the compensation structure, which plays an important role in the talent management of companies and is of great relevance in the context of the gaming industry. The thesis examines the research question of how livability influences salary by analyzing gaming companies in the years 2015-2019. It is hypothesized that higher livability has a negative effect on salary. Other factors that may influence salary include the cost of living, company size and performance, which are also considered in the analysis. The following research model is assumed:

Figure 1

Research Model



[2]The performance of the company is assessed based on two variables, which are described in the method chapter.

3. Method

The following chapter explains the method used to analyze the research question. First, the data for the variables are discussed. Subsequently, the fixed effects panel regression is examined, which is used to test the hypotheses. The data files and Python scripts for calculating the Livability Index and analyzing the research model are accessible via the GitHub repository Livability-Index-Analysis (Schick, 2024).

3.1 Description of Variables

This section explains how the Livability Index was calculated. Additionally, the data for the variables mean salary, cost of living, company size, and performance are presented.

3.1.1 The Livability Index

The creation of the Livability Index was based on the AARP Livability Index and used its categories, metrics, and data sources depending on availability. However, the exact structure was adapted to the purpose of the research. This Livability Index was created for the years 2015-2019, with the respective data sets for the year being used for each year. The years were chosen because the AARP Livability Index was first published in 2015, and these years provide the best data availability. Additionally, they represent the period before COVID-19 was declared a global concern in January 2020, which affected the quality of life through sociodemographic, health, and financial factors (Nshimirimana et al., 2023) and could potentially distort the data. In the case of non-availability of a year, the nearest year was used as a reference, depending on availability, or the missing values were estimated by linear interpolation. Linear interpolation is a mathematical method for estimating values within the range of two known values (Huang, 2021), assuming a linear change within the values. This technique makes it possible to fill gaps in the data series and thus ensure a consistent and continuous time series.

The counties of the United States were chosen as the basis for calculating the Livability Scores, as the best data availability was at this geographical level and the unique identification by the respective FIPS code enables a smooth linkage. If metrics were available for further geographical categorization, they were assigned to the respective counties or states. For data that was only available at the state level, the state average was used for the counties of the respective state. Likewise, missing values were supplemented by the average of the respective state, and if this was not available, by the national average, following the AARP method (AARP, n.d.-b). Before the metrics are presented, it should be emphasized that the AARP serves as a reference, and this Livability Index is therefore not an exact reflection of the AARP Livability Index. Depending on data availability, missing data sources are omitted, supplemented by alternatives, or calculations are carried out differently. Furthermore, the focus is exclusively on the metrics of the AARP that reflect current livability. The AARP supplements the consideration of future livability with policies (AARP, n.d.-a).

A total of 32 metrics were considered in the categories Housing, Health, Environment, Engagement, Neighborhood, Opportunity, and Transportation. These are based on 113 data sets from over 20 different sources for the years 2015 - 2019. A formula was created in Python 3.9.10 for each metric, which reads the associated data records, processes them, and makes them linkable. The libraries Pandas, OS, and NumPy were used for all categories. Pandas and OS were used to read the data sets, while NumPy was used to calculate the percentile ranking. As the data is available in different units, it was made comparable using the percentile ranking method. Here, each data point was assigned a percentile value that indicates how it relates to all other data points in the same data set. A method was chosen that calculates the average of the possible ranks that these values could occupy for identical values (the pandas development team, n.d.). This ensures that identical values receive the same middle rank, which guarantees a fair and balanced distribution of the ranks. Such an approach prevents distortions in the ranking that could arise if values occur multiple times. It enables standardized scaling and, thus, comparability of the data, regardless of their original units. If lower values are considered more favorable for livability, the ranking was inverted to give higher ranks to the lower values. The data were linked using the

FIPS codes. Each of the seven categories received its own score between 0 and 100 based on its metrics.

The overall Livability Score was then calculated from the average of the Category Scores. The mean of each variable was calculated to compare it with the respective mean of the AARP. Although this Livability Index is not an exact replication of the AARP Livability Index, it was still considered a model, which is why a robustness check was carried out to guarantee the validity of the index. The robustness check measures the correlation between the Livability Index of this thesis and the AARP Livability Index. For this purpose, the scores of the counties analyzed were retrieved from the AARP website (AARP, n.d.-a). However, the scores are only available for the year 2023. The individual categories with their associated metrics of the calculated Livability Index are presented below (see Appendix Table A1 for a detailed list of variables, geographical information and sources).

Health

The Health category is calculated on the basis of six metrics. On the one hand, current smoking and obesity among adults are considered, which are collected by the Centers for Disease Control and Prevention (2017, 2018, 2019). A further metric looks at access to exercise opportunities through the percentage of the population with adequate access to locations for physical activity (University of Wisconsin Population Health Institute, 2018–2022). In addition, the satisfaction of hospital patients is considered. This metric is taken from the Hospital Consumer Assessment Healthcare Providers and Systems Patient Survey, looking at the percentage of patients who give the hospital of their stay a rating of 9 or 10 on a scale up to 10 (Centers for Medicare & Medicaid Services, 2015–2019). Furthermore, Health Professional Shortage Areas identified by the Health Resources & Services Administration (n.d.) are considered, for which the HPSA score (0-25) is used to indicate the severity of the shortage of primary care. Moreover, the Preventable Hospitalization Rate is considered based on the rate of hospital stays for ambulatory-care-sensitive conditions per 100,000 Medicare enrollees (University of Wisconsin Population Health Institute, 2018–2022).

Neighborhood

Neighborhood is also measured by six metrics. Firstly, the combination of violent and property crimes per 10,000 people is considered (U.S. Department of Justice, & Federal Bureau of Investigation, 2014, 2016). A further metric considered is the percentage of vacant housing units (U.S. Census Bureau, 2015-2019b). Additionally, access to parks is taken into account based on the percentage of residents within Half-Mile Walk of Park, where an allocation of counties to the respective cities was necessary (Trust for Public Land, 2015, 2016, 2017, 2019). The number of libraries in relation to the population is also considered (Institute of Museum and Library Services, 2015–2019). Another metric considered is access to grocery stores, which is determined by the share of the tract population that is beyond half a mile from a supermarket (Economic Research Service, 2015, 2019). Access to farmers markets is measured by the number of farmers markets (U.S. Department of Agriculture Agricultural Marketing Service, & Michigan State University, n.d.). The ZIP codes of the farmers markets were assigned to the respective FIPS codes by an additional data set (Ofer, 2017).

Opportunity

Opportunity is determined by four metrics. For one, income inequality is measured using the Gini coefficient, where 0 stands for perfect equality of income among households and 1 for perfect inequality (U.S. Census Bureau, 2015–2019c). In addition, age diversity is measured using the local (U.S. Census Bureau, 2015–2019d) and national age distribution (U.S. Census Bureau, 2015-2019e) by calculating the Pearson correlation coefficient with the SciPy library. The Pearson correlation coefficient is a statistical measure that assesses the strength and direction of the relationship between two variables (The SciPy community, n.d.). In this analysis, it analyzes the percentage shares of different age groups, children, working-aged residents, as well as experienced and retired residents within a county with the corresponding national shares. A Pearson value of +1 indicates a perfect positive correlation, which means that the municipality has an age distribution that exactly matches the national distribution. A value of 0 indicates no linear correlation, while a value of -1 indicates a perfect negative correlation. In addition, the high school graduation rate is considered using the U.S. Department of Education's (2016-2020) adjusted cohort graduation rate for the respective year. Furthermore, the jobs per worker are calculated by dividing the number of jobs by the number of people employed (U.S. Census Bureau, 2015–2019a).

Engagement

Engagement is measured using five metrics. The first is social associations based on the number of member associations per 10,000 population (University of Wisconsin Population Health Institute, 2018–2022). Secondly, a Social Involvement Index modeled by the AARP (n.d.-a) was calculated, which reflects the "extent to which residents belong to groups, organizations or associations, see or hear from friends and family, do favors for neighbors or do something positive for their community" (Methods and sources: Livability Index). Here, the value 1 of the index reflects the average. Data from the Current Population Survey was used for the calculation (U.S. Census Bureau, 2019). In addition, art and entertainment institutions are analyzed based on museums, aquariums, and zoos (Institute of Museum and Library Services, 2014). Furthermore, voter turnout is analyzed based on the results of presidential elections (MIT Election Data and Science Lab, 2021). The election results were set in relation to the population over the age of 18 using a further dataset. The voting rate was restricted to between 30 % and 85 %, following the approach of the AARP (AARP, n.d.-a), to avoid outliers by using two data sets. As the presidential election only takes place in 2016 and 2020, the interpolation method was used to obtain the data for the years 2015, 2017, 2018 and 2019. The proximity of the years to the known data points was considered between the years, with neighboring years or closer data being weighted more heavily to achieve more realistic estimates. Broadband cost and speed are used as a further metric based on the percentage of residents who have access to three or more wireline internet service providers, and two or more providers that offer advertised download speeds of 25 megabits per second and upload speeds of 3 megabits per second (Federal Communications Commission, 2016-2019).

Housing

Housing is measured using four metrics. Firstly, the number of multi-family housing units is measured in relation to the number of residents (U.S. Census Bureau, 2015-2019b). Multi-family housing here refers to attached housing units, meaning all housing units that are not detached single-family homes. This includes apartment blocks, terraced houses, and semi-detached houses. Another indicator is the subsidized housing units, which state the number of housing units subsidized by the U.S. Department of Housing and Urban Development (2015-2019a). Both the multi-family housing units and the subsidized housing units were placed in relation to the population by using a further data set (U.S. Census Bureau, 2015–2019f). In addition, the Housing Costs (U.S. Census Bureau, 2015-2019b) are considered, which include the median monthly owner costs, with and without mortgage, and the monthly rental costs. The values were capped at 4000, following the approach of the AARP (AARP, n.d.-a). The Housing Cost Burden is also calculated, which is measured based on costs in relation to average income. An additional dataset was used, which depicts the income of the population (U.S. Department of Housing and Urban Development, 2015–2019b). For the purposes of this study, housing costs and the housing cost burden were excluded from the calculation of the index. The reason for excluding these factors is that these variables include utility costs, which are also included in the cost of living variable. Furthermore, including housing costs at the county level could lead to distortions due to the geographical level of the other data.

Transportation

Four metrics measure Transportation. On the one hand, the number of fatal car crashes per county in a year is considered (National Highway Traffic Safety Administration, 2015–2019). The crashes were set in relation to the population using a further data set (U.S. Census Bureau, 2015–2019f). In addition, the average speed limits per state are considered (Insurance Institute for Highway Safety, 2024). Furthermore, the number of ADA-accessible (Americans with Disabilities Act-accessible) stations and vehicles to all transit stations and vehicles is considered (Federal Transit Administration, 2015-2019a, 2015-2019b). ADA-accessible means that the accessibility meets the requirements of the Americans with Disabilities Act (ADA) and is therefore barrier-free. The variables are assigned to the National Transit Database Identification Number, which were matched to the states using an additional data set (U.S. Department of Transportation, 2022). The fourth metric is the Household Transportation Costs, which are taken from the Location Affordability Index of the Department of Housing and Urban Development and the U.S. Department of Transportation (n.d.). The average of eight household profiles, which vary by household income, size, and number of commuters, is calculated.

Environment

The Environment category is measured using three metrics. First, air quality is determined using the median air quality index (AQI) published by the U.S. Environmental Protection Agency (2015-2019) per county. In addition, the Drinking Water Quality was calculated based on the number of violations of drinking water per state (U.S. Environmental Protection Agency, n.d-a). In addition, the Local Industrial Pollution was measured using the Risk-Screening Environmental Indicators (RSEI) score. The U.S. Environmental Protection Agency (n.d.-b) produces a RSEI model that measures relative health-related risks by considering the size, distribution, potential exposure and toxicity of chemical releases.

3.1.2 Salary at Company-Level

The salary data was provided by Ms. Heiss and consists of H-1B salary data. The H-1B visa allows companies to hire non-immigrant employees with specialized knowledge (U.S. Department of Labor, n.d.). The data set contains gaming companies with information on their corporate locations and the salaries of employees at various career levels and positions. The date related to the analyzed year 2015-2019 is the date when the employee started working for the company at the respective salary. For the analysis, the mean salary was determined from the salary information for each company location, and the corresponding county was assigned. In order to obtain an overview of the geographical distribution, the five states with the highest number of companies and the number of considered counties in these states were observed.

3.1.3 Control Variables

Cost of Living

The costs of living are based on the Numbeo Cost of Living Index. Numbeo is the world's largest data collection of information on cities and countries, provided by many contributors (Numbeo, n.d.-a). The relative prices of groceries, restaurants, transportation, and utilities such as water, electricity, and gas are included in the Cost of Living Index. The Index is based on New York City, with a baseline index of 100% (Numbeo, n.d.-b). Places whose costs of living are higher than in New York City therefore achieve a value above 100. The index for the years 2015-2019 for cities in the United States was used for the analysis (Numbeo, 2015-2019). Each city was assigned to the respective county.

Company Performance and Size

The company performance data was provided by Ms. Heiss and is evaluated through two indicators. The first variable is the number of games published within the respective year, while the second variable is the average MobyScore of each year. This score is determined by MobyGames, a video game database that specializes in information on electronic games (MobyGames, n.d.). The MobyScore reflects the rating of a game on a scale of 1 to 10. The company size data was also provided by Ms Heiss and shows the number of employees of the companies for the years 2015-2019, based on the number of employees on LinkedIn for each year. The companies of the two datasets were matched to the salary data using the FuzzyWuzzy library in Python. In this process, the similarity of strings is measured, and a similarity score is calculated (Lam, 2023). For the process of this merge, a similarity of 100, the maximum, was defined to create an exact assignment. The data set was adjusted by companies for which no clear assignment was possible.

3.2 Panel Data Regression Analysis

A final dataset with all scores, salary data, costs of living, company size, and performance was created based on the counties of the United States. Python was used for sorting to ensure that every year from 2015-2019 is available for every company location. Since the mean salary is determined, all variables that only include one salary value as a reference are removed so that the mean is shown rather than only one salary value.

In order to test the influence of the Livability Index on the salary, a panel data regression analysis is carried out using the software Stata 17.0. Panel data is available when both cross-sectional and time series data are available and is very common in economic research (Greene, 2012). In this case, the data is available over several time periods, the years 2015-2019, as well as for different individuals, the companies at their different locations by counties. Panel data enable a comprehensive analysis, accounting for heterogeneity across units such as companies or counties, and dynamic effects that are not apparent in cross-sectional analysis (Greene, 2012). A distinction can be made between unbalanced and balanced panel data sets (Greene, 2012). In a balanced panel, each individual in the panel is observed the same number of times, whereas in an unbalanced panel, the individuals are observed different numbers of times. By dropping salary values with one observation, the number of observations per year varies, resulting in an unbalanced panel in this analysis.

In the analysis of the panel data, the individuals i are defined by the respective company at their locations. This creates a separate panel ID for each combination of company and location. The time t is defined by the years 2015-2019. Care was taken to ensure robust and accurate estimation of the results. The standard errors were calculated by clustering according to the panel ID to control for dependencies within the groups, making the estimates robust against heteroscedasticity and autocorrelation (Hoechle, 2007). Year dummy variables were introduced to control for time effects.

A distinction can be made between a fixed effects and a random effects model. In this study, a fixed effects regression model was used, which is explained in more detail in the following. In a fixed effects model, within-group variations are captured (Tilburg Science Hub, n.d.), whereby time-invariant, individual-specific effects that are not observable can be controlled (Williams, 2018). By considering the individual-specific effects (α_i), heterogeneities across the entities can be captured (Hanck et al., 2024). In the random effects model, the unobserved effects are seen as uncorrelated or independent of the variables in the model (Allison, 2009). Whether the implementation of a fixed effects model or a random effects model is appropriate can usually be determined using a Hausman test (Kalita, 2013; Wooldridge, 2002). However, it was not possible to perform the Hausman test in Stata with clustering. An alternative test of whether a fixed effects model or a random effects model is appropriate can be performed by the Sargan-Hansen statistic, which conducts a test of overidentifying restrictions, whereby the orthogonality conditions are tested (Schaffer & Stillman, 2010). If the test is significant, the null hypothesis that the overidentifying restrictions are valid is restricted, indicating that the random effects model is not appropriate. This test can be performed with clustering. Stata performed the test with the years 2015-2018, as it was not possible to run the test with the omitted variable of 2019.

Since the company and the location are defined as the panel ID, they form the individuals that are considered in the panel regression. The variables used as regressors include the Livability Index and the Cost of Living Index, which vary by location, as well as company performance and company size, which vary by company. The fixed model allows for individual-specific effects to be correlated with the regressors (Kalita, 2013). By controlling for these time-invariant effects, the analysis can focus on the variation within the combination of company and location over time to estimate the influences of the regressors. By adjusting for unobserved unit- and time-specific effects, a two-way fixed effects regression is employed (Imai & Kim, 2020).

Based on these considerations, the following regression equation results:

$$Salary_{it} = \beta_1 * livabilityscore_{it} + \beta_2 * costoflivingindex_{it} + \beta_3 * count_{it} + \beta_4 * avgmobyscore_{it} +$$

$$\beta_5 * total\_incompany_{it} + \sum_{t=2015}^{2018} \lambda_t D_t + \alpha_i + \varepsilon_{it}$$

$Salary_{it}$ describes the dependent variable, where i indicates the individuals identified by their panel ID, and t refers to the time. The coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_4$ represent the effects of the Livability Index, Cost of Living Index, company performance variables, and company size on the salary. $\lambda_t D_t$ captures the time effects through dummy-coded year variables from the years 2015 to 2018, where λ_t are the coefficients associated with each year dummy. The year 2019 serves as the reference year. The time-invariant effects of the individuals are represented by α_i. The error term ε_{it} accounts for unobserved factors in individuals and time.

4. Results

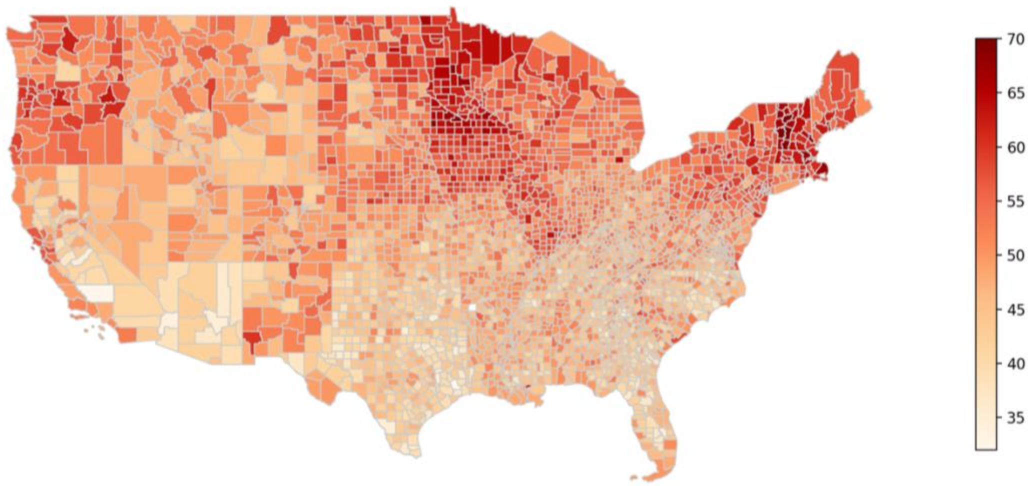
This chapter presents the results that test the influence of livability on salary, taking into account the Cost of Living Index, company performance and company size. The Livability Index is addressed first, with its robustness check and geographical distribution being thematized. Subsequently, the descriptive statistics of the variables and the correlation matrix are presented. The Sargan Hansen statistic is then briefly described before the results of the regression analyses are presented.

4.1 Overview of the Data and Model Selection

Figure 2 shows the Livability Score per county in 2019 (see Appendix, Figure A1, for years 2015-2018). The shading represents the index values, with darker regions corresponding to higher index scores.

Figure 2

Livability Score by County in 2019



Note. The Map was generated using Python 3.9.10 with Geopandas, Pandas, and Matplotlib. Data sources include the U.S. Census Bureau's TIGER/Line shapefiles (U.S. Census Bureau, 2023) and the author's custom dataset, which contains the livability scores on the county level.

The robustness check of the Livability Index shows that the Pearson correlation coefficient between the overall Livability Scores of this study and the AARP's Scores is .82 ($p < 0.001$). The correlation matrix is shown in the Appendix in Table A2.

Before the descriptive statistics and the results of the panel regression are presented, an overview of the geographical distribution of the gaming companies is provided. The dataset shows California, New York, Texas, Washington and New Jersey as the five key states of the company locations. This includes seven different counties in California, two in New York, four in Texas, three in New Jersey, and one in Washington.

Table 1 presents the descriptive statistics of the variables after adjustment. The data set contains combinations of companies and their locations, along with the associated salaries for each year from 2015 to 2019. Adjustments were made to exclude salary values based on a single observation represented by the variable count, resulting in variations in the number of observations per year. The data consists of 245 observations for salary and score data from 2015-2019. The mean salary is $99,582.13 (*SD* = 25,341.45), ranging from $44,990.00 to $195,336.00. The Livability Score ranges between 39.00 and 67.00, with a mean value of 54.64 (*SD* = 7.20).

The control variables contain fewer observations due to missing values. The Cost of Living Index includes 195 observations and ranges between 65.80 and 103.40 with a mean of 83.91 (*SD* = 10.04). The company performance variable has 147 observations, with the number of newly released games ranging from 0 to 26.00 with a mean of 2.07 (*SD* = 4.17). The average MobyScore is between 0 and 8.90, with a mean of 1.79 (*SD* = 3.24). The number of employees with 141 observations ranges from 0 to 2,290, with a mean of 318.55 (*SD* = 476.68).

Table 1

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	245	2017.037	1.395	2015	2019
Salary in USD	245	99582.131	25341.455	44990	195336
count	245	14.988	23.478	2	147
FIPS	245	19091.424	16911.449	6001	53033
Livability Score	245	54.645	7.201	39	67
Health Score	245	76.273	10.932	45	87
Neighborhood Score	245	44.094	8.213	24	73
Opportunity Score	245	41.261	11.333	22	72
Environment Score	245	33.212	16.372	9	83
Engagement Score	245	53.604	9.853	36	80
Housing Score	245	76.482	18.436	6	100
Transportation Score	245	57.065	8.918	32	83
Cost of Living Index	195	83.92	10.037	65.9	103.4
Company Size	141	318.553	476.678	1	2290
New Games	147	2.075	4.171	0	26
MobyScore	147	1.795	3.235	0	8.9
Company+Location	245	28.984	16.615	1	58

The correlations of the variables show a first assessment of the relationships between the variables and are shown in the correlation matrix in Table A3 in the Appendix. Of interest here is the relationship between salary and the Livability Score, which shows a positive but rather weak relationship with a Pearson coefficient of .35 ($p < .001$). Concerning the control variables and their relationship to the salary, the strongest but still rather weak relationship is shown with the Cost of Living Index ($r = .31$; $p < .001$). One correlation that should be emphasized here is the one between the Livability Score and Cost of Living Index, as a strong relationship ($r = .83$; $p < .001$) can be identified here.

The results of the test for overidentifying restrictions, which was carried out for the suitability of a fixed effects versus a random effects model, are briefly reviewed. The Sargan-Hansen statistic shows a significant value ($p < .001$), thereby rejecting the null hypothesis of valid overidentifying restrictions (see Appendix, Table A4).

4.2 Results of the Panel Data Regression Analysis

As a first step, the overall Livability Score is considered, answering the research question. This is followed by an examination of the individual categories.

4.2.1 The Livability Score

The two-way fixed effects regression results are represented in Table 2. The Livability Score, Cost of Living Index, company performance variables, and company size serve as regressors to assess their influence on the mean salary. Additionally, dummy variables for the years 2015-2018 are included in the model, with 2019 serving as the reference year. The standard errors were adjusted for the 27 clusters defined by the panel ID.

First, the number of observations is explained in more detail. Taking all variables into account, a total of 104 observations are considered. Clustering by company and location results in 27 groups containing an average of 3.90 observations. This means that the combination of company and location occurs 3.90 times on average. A group contains a maximum of five observations if all five years of the panel are included.

A look at the R-squared values provides information about the variance in the data explained by the model. As the fixed-effects model aims to eliminate the differences between groups and focus on the variation within the groups, the within R-squared is described. The R-squared shows that 31.4 % of the variance in salary within the groups over time is explained by the regressors in the model. The F-statistic (F (9,26) = 3.96) is significant (p = .003), indicating that at least one of the explanatory variables has a significant influence on salary.

The results show that the livability score has a negative coefficient of –252.68, but no significant influence on salary (p = .788). Consequently, the hypothesis that a higher livability score negatively affects salary is rejected.

The Cost of Living Index (p = .832), the average MobyScore (p = .256) and the number of employees (p = .073) also show no significant influence on salary. The number of new games has a significant influence with a negative coefficient of –1258.79 (p = .009), which means that an increase in the number of published games is associated with a decrease in salary.

The dummy variables of 2015 and 2016 show a significant influence with a negative coefficient of –18400.19 (p = .001) and –14,226.10 (p = .002) on the salary, while the years 2017 (p = .058) and 2018 (p = .903) also show negative coefficients, but no significant influence. The dummy variable of 2019 serves as a reference year for the years 2015-2018 and is excluded from the regression to avoid multicollinearity.

Table 2

Fixed Effects Regression Analysis: Livability Score

salary	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
Livability Score	-252.679	931.97	-0.27	.788	-2168.371	1663.014	
Cost of Living Index	79.946	372.36	0.21	.832	-685.45	845.342	
New Games	-1258.79	448.068	-2.81	.009	-2179.806	-337.774	**
MobyScore	749.169	645.234	1.16	.256	-577.129	2075.467	
Company Size	-26.937	14.436	-1.87	.073	-56.611	2.736	
Dummy 2015	-18400.286	4824.622	-3.81	.001	-28317.439	-8483.134	**
Dummy 2016	-14226.007	4093.277	-3.48	.002	-22639.859	-5812.156	**
Dummy 2017	-11055.379	5571.238	-1.98	.058	-22507.223	396.465	
Dummy 2018	-553.527	4481.295	-0.12	.903	-9764.962	8657.907	
o	0	.	.	.	.	.	
Constant	126832.45	70770.745	1.79	.085	-18638.903	272303.79	

Mean dependent var	101241.394	*SD* dependent var	25013.212
R-squared	0.314	Number of obs	104
F-test	3.963	Prob > *F*	0.004
Akaike crit. (AIC)	2244.998	Bayesian crit. (BIC)	2268.797

**** p<.001, ** p<.01, * p<.05*

4.2.2 *Categories of the Livability Index*

In the following, the seven categories will be examined to analyze the Livability Index in more detail. Table 3 shows the results of the two-way fixed effects regression analysis.

The sample size of 104 observations and 27 groups remains the same. The F-statistic (F (15,26) = 7.63) is significant ($p < .001$), which shows that at least one of the explanatory variables has a significant influence on salary. 36.1 % of the variance in salary within the groups is explained by the regressors. Two scores have a significant influence on salary. The Health Score shows a coefficient of 3252.83 (p = .048), and the Engagement Score also shows a positive coefficient of 1722.07 (p = .047).

As a result, better Health or Engagement Scores have a positive influence on salary. The remaining five scores and the control variables also have positive and, in some cases, negative coefficients, although no significant influence can be identified here.

Table 3

Fixed Effects Regression Analysis: Categories

salary	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
Health Score	3252.826	1567.564	2.08	.048	30.653	6475	*
Neighborhood Score	-419.416	304.086	-1.38	.18	-1044.472	205.641	
Opportunity Score	811.926	688.784	1.18	.249	-603.889	2227.741	
Environment Score	-237.079	145.978	-1.62	.116	-537.14	62.983	
Engagement Score	1722.072	825.583	2.09	.047	25.062	3419.082	*
Housing Score	1287.522	2720.082	0.47	.64	-4303.687	6878.732	
Transportation Score	329.237	926.264	0.36	.725	-1574.726	2233.2	
Cost of Living Index	168.248	418.848	0.40	.691	-692.705	1029.202	
New Games	-1068.149	532.12	-2.01	.055	-2161.937	25.638	
MobyScore	474.67	719.243	0.66	.515	-1003.756	1953.096	
Company Size	-31.578	19.135	-1.65	.111	-70.911	7.754	
Dummy 2015	-14453.477	8978.504	-1.61	.12	-32909.056	4002.102	
Dummy 2016	-6728.34	6324.497	-1.06	.297	-19728.529	6271.849	
Dummy 2017	-7568.559	5561.72	-1.36	.185	-19000.839	3863.721	
Dummy 2018	1955.605	5057.718	0.39	.702	-8440.684	12351.894	
o	0	.	.	.	.	.	
Constant	-378246.72	272168.02	-1.39	.176	-937696.1	181202.66	

Mean dependent var	101241.394	*SD* dependent var	25013.212
R-squared	0.361	Number of obs	104
F-test	7.630	Prob > *F*	0.000
Akaike crit. (AIC)	2249.544	Bayesian crit. (BIC)	2289.210

*** *p<.001*, ** *p<.01*, * *p<.05*

In conclusion, the results demonstrate that the Livability Score exerts no significant influence on the salary, thereby rejecting the proposed hypothesis. However, an examination of the categories shows significant influences of the Health and Engagement Scores on salary. The following discussion will examine the findings in greater detail and contextualize them.

5. Discussion

The first part of the discussion includes the theoretical implications. Subsequently, the thesis presents its managerial implications. Finally, the potential limitations and prospects for future research are addressed.

5.1 Theoretical Discussion

First, the findings on the Livability Index are addressed. This is followed by a discussion of the findings regarding the influence of the Livability Index on salary, which answers the research question. In addition, the findings on the categories are examined as they provide additional insights and thus a basis for further research.

5.1.1 Discussion of the Livability Index

Firstly, the robustness check of the Livability Scores calculated in this study shows a strong correlation with the Livability Scores of the AARP. The high Pearson coefficient emphasizes the robustness and validity of the calculated index. The fact that the scores does not correspond precisely with the values of the AARP Livability Index seems logical, as a different timeline was analyzed and, in some cases, different metrics or data sources were utilized. However, this ensures a robust basis for the subsequent panel regression. The geographical analysis of the data also shows promising results. Except for New Jersey rather than Florida, the key states correspond to the key states mentioned in the economic impact report of the Entertainment Software Association (Grueber & Yetter, 2024), meaning that the gaming companies analyzed are located in the states considered to be key states for the gaming industry. These findings speak in favor of the representativeness of the dataset.

The map of the United States in Figure 2 provides an overview of the distribution of the Livability Scores. Geographical differences are apparent, such as areas in the north and northeast that show high scores based on the dark red tones. In the south, on the other hand, lighter tones tend to indicate a lower score. The maps for the years 2015 to 2018 (see Appendix Figure A1) show a similar structure.

5.1.2 Discussion of the Livability Score Results

This section discusses the analysis of Table 2, which examines the Livability Score. Although the F-statistic is significant, indicating that at least one of the independent variables influences salary, the explanatory power of the model remains moderate. The R-squared value shows that the fixed effects model explains 31.4 % of the total variance in salary within the groups over time. There may be other relevant factors that were not considered in the model and could have a stronger influence on salary. According to the hypothesis, the Livability Score would be expected to have a negative influence on the salary. The coefficient of -252 suggests that a one-unit increase in livability would result in a decrease in salary by $252. Although this finding is in line with the expected relationship, the coefficient is relatively minor compared to the annual salary range of $41,000 to $150,000. However, the effect is not significant, thereby rejecting the hypothesis. This answers the research question by showing that livability does not influence the mean salary in the years 2015 to 2019, regarding the respective livability of various company locations.

This finding can be related to the findings of previous studies that have found an influence of livability on salary. First, it is important to note that this study focused on the analysis of average company salaries. In contrast, previous research (Deng & Gao, 2013; Li et al., 2021) that has found an effect of livability on salary investigated executive compensation. A possible conclusion could be that, for higher-level executives, compensation packages are more likely to be shaped by the non-monetary factor of livability. In contrast, for the broader workforce, salary structures might be more closely tied to traditional economic metrics, with livability playing a much smaller role, even though Roback (1982) or Shi et al. (2021) were able to demonstrate effects in this area.

Additionally, the temporal component can be discussed, which may yield dissimilar results. Deng & Gao (2013) considered a longer period (1993-2008) than the period presented in this paper (2015-2019). They also considered temporal lags, which indicates a different methodological approach. In contrast, this study has applied the fixed effects model for analyzing the combination of company and location over time, focusing on contemporaneous relationships and within-group variations.

Furthermore, it should be noted that previous studies have used a different geographical basis for investigation, by focusing on livability in cities (Li et al., 2021; Roback, 1982; Shi et al. 2021) or states (Deng & Gao, 2013). Although this study differentiates between counties, providing a more detailed level of analysis than states, most jobs are concentrated in five key states with a limited number of counties, which limits geographic differentiation. For instance, seven counties are analyzed in California, and New York only incorporates one county in the analysis, despite these states being divided into many more counties. Texas, the state with the highest number of counties (254) in the USA, is represented by only four counties in this study, due to company locations. This concentration appears reasonable, as companies in the same industry often cluster in specific geographic areas, such as the computer industry in Texas (Pouder & John, 1996). Nevertheless, since only a limited number of regions are mapped, this could potentially affect the findings of the analysis.

In addition, the consideration of the gaming industry can be discussed, as an industry may affect the salary structures of companies in the industry. This thesis aims to provide insights into the gaming industry, which is an industry that relies on skilled employees. McCausland et al. (2020) show that macroeconomic factors, such as the general demand for labor in the industry, play a central role in salary development. In technical industries such as gaming, this could mean that competition for skilled labor is a key driver of salaries. Furthermore, as Christofferson et al. (2023) noted, the gaming industry has so far focused on the passion and motivation of its employees, which could mitigate the consideration of livability in regard to salary. It is also important to consider that remote working is also a working model in the industry (Grueber & Yetter, 2024). Consequently, the company location may not necessarily be identical to the residence of all employees. For companies that rely on remote working, livability could therefore play a less important role in the compensation plan.

Following the discussion of the findings regarding the influence of the Livability Score on salary, this section will present a brief overview of the control variables. The Cost of Living Index shows a positive, but insignificant, influence on salary. Regarding the salary range, the coefficient of (β_2 = 79.95) is rather low. The positive influence seems logical, since higher cost of living requires higher wages as compensation. Based on the negative coefficient of the overall score and the positive coefficient of the cost of living, a potential balance can be seen that is consistent with the assumptions of the Spatial Equilibrium Theory (Roback, 1982). Accordingly, higher local amenities would lead to lower wages, while higher cost of living would lead to higher wages. However, since the results are not significant, this assumption must be treated with caution.

The number of published games demonstrates a significant negative effect on salary, challenging the assumption that stronger firm performance translates into higher wages. Several factors could account for this discrepancy. First, unlike the studies by Bronars and Famulari (2001) and Bell and Van Reeven (2012), firm performance in this analysis is not measured through financial indicators such as stock returns, which may contribute to differing results. The analysis also does not include data on game sales. If game releases increase without a corresponding rise in sales, profit margins may shrink, leaving companies with fewer financial resources for salary increases.

Furthermore, the variables number of released games and salaries of the same year were considered. However, there could be a potential time lag between newly released games and their influence on salaries. In this case, the salary increase would occur at a later point in time, once the commercial success of the games becomes clearer. This time lag could distort the results, which supports the idea of further analyses with time lags or financial indicators. The quality of the games shows no significant influence on the salary. The Pearson coefficient (r = .38) between the number of new games and the average MobyScore shows that there seems to be no strong relationship between the two performance indicators.

The dummy variables for the years 2015 and 2016 show a negative and significant influence on salaries compared to the reference year 2019. This finding suggests that time effects contributed to the changes in salary.

5.1.3 Discussion of the Category Results

The second regression analysis incorporating the Category Scores shows a higher variance in the salary variable (R^2 = .361) and a higher significance of the F-statistics (F (15,26) = 7.63; p < .001).

Nevertheless, the explanatory power remains moderate, which also indicates additional factors influencing the salary. The detailed analysis of the individual categories shows a deviation from the analysis of the overall Livability Score, with the Health and Engagement Score showing a significant influence on salary. Both scores show positive coefficients, indicating a higher salary in response to better Health and higher Engagement scores. This result contradicts the initial hypothesis and requires further investigation. A plausible explanation for the positive coefficients is that local amenities can enhance a company's productivity, which in turn leads to higher wages being both offered by employers and accepted by residents (Shi et al., 2021). This is consistent with the Theory of Spatial Equilibrium (Roback, 1982), which states that productivity factors into the equilibrium of local amenities and wages. A more detailed discussion of this is provided in the following sections, which examine the Health and Engagement Score in more detail.

The Health Score includes the current smoking and obesity of adults, access to exercise opportunities, the satisfaction of hospital patients, Health Professional Shortage Areas, and the Preventable Hospitalization Rate. Therefore, better health conditions for both individuals and the healthcare system appear to exert a positive influence on salary. An explanation for this effect could be that a healthy lifestyle of employees may enhance productivity, which subsequently reflects in higher salaries. A poor state of health, on the other hand, is associated with reduced wages, suggesting that individuals may earn less than their potential human capital would allow (Alvarez & Rodriguez-Gutierrez, 2018). In addition, hours worked decrease with health problems (Pelkowski & Berger, 2004), which may contribute to lower overall productivity, particularly if such health restrictions also affect work performance.

Improving health conditions can contribute to the development of a more efficient wage-setting mechanism (Alvarez & Rodriguez-Gutierrez, 2018). For instance, the National Reform Agenda of the Australian Government aims for productivity growth and workforce participation, including strategies to reduce the prevalence of diseases such as diabetes and cancer (Forbes et al., 2010). In addition to individual health factors, such as smoking, obesity, and access to exercise opportunities, the Health Score also includes healthcare system indicators like patient satisfaction and the effectiveness of hospitalization. An efficient healthcare system could result in lower costs for employers, which may, in turn, allow for greater flexibility in wage-setting. However, the extent to which these savings are reflected in higher salaries remains uncertain. Nevertheless, the significant positive influence of the health score on salary suggests that the health score of a county not only plays a crucial role in the well-being of its population but, as a local amenity, also positively influences salaries.

The Engagement Score includes social associations, the Social Involvement Index, cultural institutions, voter turnout, and Broadband cost and speed. A higher level of engagement shows a positive influence on salary although the coefficient is lower than for the Health Score. Increased civic participation may reflect active and involved residents, who are likely to be similarly engaged in the workforce. Moreover, the presence of social facilities, cultural institutions, and robust broadband infrastructure may serve as indicators of a thriving economic region, which is associated with favorable working conditions and, consequently, higher salaries. Broadband infrastructure is recognized as a key driver of economic growth (Kelly et al., 2010), with its capacity to enhance productivity. Cultural resources further underscore the potential for individual development and community engagement. Markusen and Gadwa (2010) emphasize the importance of investment in the cultural sector for cities and highlight its potential for creating employment and income streams, as a result of which urban economic development is strengthened. The Social Involvement Index indicates that social networks may be present that facilitate career opportunities and advancement, which can lead to higher salaries. These factors may explain the observed positive influence of the engagement score as a local amenity on salary.

A distinction must be drawn between the Engagement Score and the Opportunity Score, the latter of which emphasizes factors such as income inequality, age diversity, employment, and educational attainment. However, the Opportunity Score, along with other categories such as Neighborhood, Transportation, Environment, and Housing, does not exhibit a significant influence on salary. Despite the lack of statistical significance, it is noteworthy that the Opportunity, Housing, and Transportation Scores display a positive impact while the Environment and Neighborhood Scores exhibit a negative impact. Building on the framework presented by Shi et al. (2021), these variations could also be explained by the Theory of Spatial

Equilibrium by Roback (1982), which states that certain factors can increase the productivity of companies and in turn lead to higher wages. However, these interpretations should be treated with caution as no statistically significant results for these Scores are found.

The control variables show similar results to the overall score analysis. The Cost of Living Index remains statistically insignificant but exhibits a slightly higher positive coefficient. The number of new games continues to show a negative influence but in contrast to the overall score analysis, the effect does not reach the significance level ($p > 0.05$). Nor does the quality of the games show a significant influence ($p > 0.05$). Consequently, the performance indicators show no significant influence on the salary. As mentioned at the beginning of the paper, there is no clear definition of livability, as it is a very complex construct. The results of the Category Scores analysis suggest that it is valuable to take the complexity of livability into account.

5.2 Managerial Implications

In general, non-monetary incentives play an important role in compensation policy (Mathios, 1989) and contribute to improved employee performance (Condly et al. 2003; Jenkins et al., 1998; Prendergast, 1999). Of course, companies only have limited influence over the livability of a location since this factor is rather the responsibility of policy and administration. Nevertheless, companies can contribute to livability by promoting factors such as access to exercise opportunities through sports facilities or by promoting social exchange. Employee surveys on the perceived quality of life can provide a subjective assessment and expand the concept of livability to include these components. In this way, companies can respond to the needs of their employees, which is an important aspect when it comes to retaining talent.

Christofferson et al. (2023) point out that the gaming industry needs to find ways to attract and retain talent. The results show that livability currently appears to not influence salary. However, these findings may encourage companies in the industry to consider incorporating livability into their compensation decisions in the future to offer more attractive pay to their employees. Since work-life balance also appears to be an important factor for gaming industry employees (Christofferson et al., 2023), based on Rosen's theory of Equalizing Differences (1986), this could be used to create a balance and attract employees to less attractive locations with higher salaries. Although remote working options may reduce the importance of location factors, only 17% of employees in the industry fall into this category (Grueber & Yetter, 2024). Companies should therefore not ignore location factors.

Another factor that should be mentioned is geographic diversification. Many gaming companies are located in the same states (Grueber & Yetter, 2024), an aspect that is also reflected in the data of this study. Fast-growing geographic clusters, known as hot spots, can initially offer advantages in terms of growth and innovation, but with adverse effects over time (Pouder & John, 1996). As land prices and salaries rise (Arthur, 1990; Grove, 1987), other locations may become more attractive for companies (Malecki, 1984). Furthermore, employees from the local university are often employed at one location, which can lead to the employees having a similar way of working (DiMaggio & Powell, 1983). Thus, accessing new locations can provide companies with opportunities for development outside a cluster. In the future, livability should be included in decision-making processes for location selection, as well as in compensation strategies, to create new incentives for talent.

5.3 Limitations and Future Research

In the following, the limitations of the study are discussed, whereby a distinction is made between various considerations. First, the Livability Index and its limitations are addressed, followed by an examination of the research model and the underlying analysis. In addition, this thesis identifies areas for further research, which are also presented in this chapter.

First of all, data availability is a limitation, since not all data are available for all counties and years (see Appendix A, Table A1, for an overview), which requires the use of calculation methods such as interpolation and state means. Interpolation estimates values for missing years, which may result in lower accuracy of the metrics. When calculating the state means for missing counties, it is assumed that the county corresponds to the state average. This could obscure regional differences within the state. Individual counties may differ greatly from the average, which can lead to distorted conclusions.

Additionally, another factor requiring mention is the percentile ranking method. This method allows for standardizing data from different units, which is necessary for calculating the Livability Index. However, this method shows the relative positions of values within the distribution, not the absolute differences between the values. As a result, differences in the data may be obscured.

As mentioned in the chapter on definition, the concepts of livability and quality of life differ in terms of the subjective component. In this research, the Livability Index is based on metrics that do not capture the opinions of residents or employees. One possibility would therefore be to conduct interviews to capture the perceived quality of life. On this occasion, further factors for research models could be surveyed, which are discussed in more detail in the following chapter.

Furthermore, the AARP is an institute targeting people aged 50 and up. Even though the AARP emphasizes that the AARP Livability Index covers residents of all ages, this point should still be kept in mind. Variables such as those relating to health facilities or providing barrier-free transport are important for residents of all ages but become increasingly essential as people grow older. Further variables could be included for an analysis relevant to the labor market. Regarding transportation, one variable could be the average commuting time, as analyzed in the Urban Mobility Report (Schrank et al., 2023) for urban areas. The AARP Livability Index also includes policies that focus on the future development of the location based on current actions. In this study, the Livability Index was created using metrics. While this allows an analysis of the current state of the location, policies for potential future improvement of amenities are not considered.

In contrast to the AARP Livability Index, the data was not collected at the neighborhood level, but at the county level. This factor represents a limitation to the overall research model concerning the salary and control variables since the data was not compiled at the county level. The salary data as well as the company performance and size variables are mapped based on the specific company locations. The Cost of Living Index is based on cities in the United States. By aggregating all data at the county level, the underlying geographical level represents a difference. Depending on the availability of data, future research could conduct analyses that focus on a differentiated examination of specific company locations, thereby analyzing regional differences more precisely.

One factor that could be an interesting subject of investigation here, in addition to the costs of living considered in this study, is housing prices. Besides the Spatial Equilibrium Theory (Roback, 1982), studies also address rising rents in the context of geographic clusters (Arthur, 1990; Grove, 1987). A differentiated geographic analysis would offer the opportunity to specifically consider rents in conjunction with livability and salary. One option would be to use the Rent Index by Numbeo (Numbeo, 2015-2019) in addition to the Cost of Living Index, although the geographical scope of the Livability Index in combination with rent prices must be taken into account, as further differentiation may be necessary.

Another possibility lies in adding the variable of housing costs and housing cost burden to the Livability Index. However, since theoretical assumptions consider local amenities and rent separately, the interaction of the factors should be kept in mind.

Another area for differentiation lies in the salary variable. This study aimed to analyze the overall salaries within gaming companies, with control variables reflecting company characteristics. Future research could expand on this by examining salaries at the employee level. Distinguishing between hierarchy levels could offer more nuanced insights into the impact of livability on salary structures, while also considering employee characteristics.

The study showed that time effects also appear to influence salary. A more detailed examination of variables in the economic environment during this period could contribute to a further explanation of the negative effects on salaries. When analyzing panel data, incorporating macroeconomic factors such as GDP and inflation rates could offer valuable insights. In terms of time, there is another limitation to be noted that offers scope for future research. This study focused on the years 2015 to 2019. Since the maps do not indicate any major changes during this period, analyzing a longer time frame could help identify larger temporal changes within the groups and provide therefore further insights. Furthermore, the methodological approach of lead-lag ordinary least squared regression, as conducted by Deng & Gao (2013), could also be applied to further research on temporal dynamics.

Additionally, this study focused specifically on the gaming industry, providing a detailed insight into the dynamics of this industry. Future research could generate further insights in the context of other industries. Especially about industries in which geographic clusters are less common and companies and employees are therefore geographically dispersed, analyses covering larger regions of the United States could offer valuable insights into how livability influences salary. By observing more companies or locations over a longer period, a larger number of observations and groups could be achieved. This could increase the explanatory power of statistical analysis and provide broader insights into variations within companies and their locations. A comparison between these groups could also provide interesting insights, although care must be taken to ensure that the methodological approach is appropriate.

Finally, it should be made clear that the differentiation in the Livability Index makes an important contribution to research and that the analysis of the categories shows interesting insights. In addition to further research into these category-related influences, future research could also be motivated by the possibility of reverse causality. This study examined the influence of the categories on salary, while other research suggests, for instance, that higher income can have a positive effect on health (Woolf et al., 2015). Thus, exploring the impact of salaries on the Health Score or other categories could also offer valuable insights.

This chapter shows that this thesis provides a foundation for further studies that can contribute interesting insights into the research of livability and salary.

6. Conclusion

This thesis aimed to examine the influence of livability on salaries at company level in the research context of the gaming industry. A Livability Index at the county level of the United States for the years 2015–2019 was used as a central element of the analysis and calculated using the AARP's model based on seven categories (AARP, n.d.-b).

The results of the fixed effects panel data regression analysis did not provide any evidence of a significant influence of the Livability Score on salaries from 2015 to 2019. These results contradict the hypothesis that higher livability is associated with lower salaries. It was originally expected that regions with a high Livability Score would show a negative influence on wages, since employees in such regions might be willing to accept a lower wage to live in a more pleasant environment. However, this hypothesis could not be confirmed.

In addition to the Livability Score, other factors such as cost of living, company performance and company size were included in the research model. Interestingly, most of these variables also showed no significant influence on salaries. Solely the number of new games released had a negative impact on salaries.

However, a differentiated analysis of the individual categories of the Livability Index showed that certain aspects of livability do indeed have an influence on wages. In particular, the Health Score, which reflects health care and general health in the form of smoking and obesity in a county, as well as the Engagement Score, which measures social participation, showed a positive influence on wages. This assumption contradicts the original hypothesis due to the positive influence, suggesting that specific categories of livability, especially those directly related to health and the social environment, could be able to positively influence the compensation structure in the gaming industry.

In conclusion, a differentiated analysis of livability can provide valuable insights. While the total score does not show significant effects on salary, the individual categories offer potential starting points for a deeper understanding of the relationships between the Livability Index and salary. These results suggest that a broad assessment of livability may not be sufficient to capture its effects on salary structure. Instead, a more differentiated level of analysis is required to identify variations in the direction of influence.

The overall goal of this research is to expand on existing studies on livability and gain new insights into compensation policy in the research context of the gaming industry. The gaming industry is a growing industry in the United States that faces talent management challenges due to its need for highly skilled workers. In an industry that is characterized by innovation and technological development, incentives play a crucial role in attracting and retaining talent. With this in mind, it is important to consider both monetary and non-monetary incentives that can contribute to employee satisfaction and retention.

The concept of livability is particularly interesting in this context, as it represents a non-monetary incentive that could have an impact on monetary factors such as salaries. The Spatial Equilibrium Theory (Roback, 1982) provides a theoretical basis for examining the relationship between local amenities and salaries. It states that residents are willing to pay a premium for local amenities, which can be reflected in both housing prices and salaries. Previous studies have already shown that the attractiveness of a location influences salaries, with some focusing on executive compensation. The present work stands out by examining the average salary in the gaming industry to draw company-level conclusions.

The fact that this study was unable to demonstrate a significant influence of livability on salaries could be seen as an incentive for companies to integrate livability into their compensation packages. It is feasible that companies could pay more attention to the livability at their locations in the future, to attract employees, particularly in less attractive regions, with appropriate incentives. A highly developed compensation package that includes both monetary and non-monetary incentives could play an important role here and help to make locations with a lower livability more attractive to talented individuals.

Nevertheless, the study also shows limitations, including the limited availability of data for certain years and counties, as well as the challenge of different geographical levels of data availability. Future studies could benefit from a more differentiated geographical approach, an examination of the salary at the employee level, or further research into period-specific effects, which could yield further insights. A particularly noteworthy element is the differentiated Livability Index, which allows for an analysis of various components. The results show great potential for further research into the categories to gain detailed insights into the complex construct of livability.

Overall, the thesis analyzed an area of interest that is highly relevant for further research. The study has contributed to existing research on livability and factors influencing salary and has addressed a research gap by examining the complexity of livability and its influence on salaries at the company-level. Findings from this area can contribute to the design of effective compensation packages that cover employees' needs with both monetary and non-monetary incentives. This area has significant potential when it comes to achieving a balance between corporate goals and employee well-being and can make a significant contribution to the sustainable development of the industry.

References

AARP. (2015). *Livability Index FAQs*. [Archived Version]. https://web.archive.org/web/20150906113031/http://livabilityindex.aarp.org/faqs

AARP. (2023-2024.). *Livable communities.* AARP Policy Book. Retrieved October 3, 2024, from https://policybook.aarp.org/policy-book/livable-communities

AARP. (2024-a). *What does "AARP" stand for?.* Retrieved October 3, 2024, from https://help.aarp.org/s/article/what-does-aarp-stand-for

AARP. (2024-b). *What is AARP?*. Retrieved October 3, 2024, from https://help.aarp.org/s/article/what-is-aarp

AARP. (n.d.-a). *Methods and sources: Livability Index*. Retrieved October 3, 2024, from https://livabilityindex.aarp.org/methods-sources

AARP. (n.d.-b). *Livability Index FAQs*. Retrieved October 3, 2024, from https://livabilityindex.aarp.org/faqs

Allison, P. D. (2009). *Fixed effects regression models*. SAGE Publications, Inc., https://doi.org/10.4135/9781412993869

Arthur, W. B. (1990). 'Silicon Valley' locational clusters: when do increasing returns imply monopoly?. *Mathematical social sciences*, *19*(3), 235-251. https://doi.org/10.1016/0165-4896(90)90064-E

Bell, B., & Van Reenen, J. (2012). *Firm Performance and Wages: Evidence from Across the Corporate Hierarchy* [CEP Discussion Paper No. 1088]. London School of Economics and Political Science, Centre for Economic Performance. http://eprints.lse.ac.uk/id/eprint/121751

Black, D., Kolesnikova, N., & Taylor, L. (2009). Earnings functions when wages and prices vary by location. *Journal of Labor Economics*, *27*(1), 21-47. https://doi.org/10.1086/592950

Bollinger, L., Hope, K., & Utterback, J. M. (1983). A review of literature and hypotheses on new technology-based firms. *Research Policy*, *12*(1), 1-14. https://doi.org/10.1016/0048-7333(83)90023-9

Bronars, S. G., & Famulari, M. (2001). Shareholder wealth and wages: Evidence for white-collar workers. *Journal of Political Economy*, *109*(2), 328-354. https://doi.org/3078421

Brown, C., & Medoff, J. (1989). The employer size-wage effect. *Journal of Political Economy*, *97*(5), 1027-1059. https://doi.org/10.1086/261642

Bérenger, V., & Verdier-Chouchane, A. (2007). Multidimensional Measures of Well-Being: Standard of Living and Quality of Life Across Countries. *World Development*, *35*(7), 1259-1276. https://doi.org/10.1016/j.worlddev.2006.10.011

Centers for Disease Control and Prevention. (2017). *500 Cities: Census tract-level data (GIS-friendly format)* [Data set]. U.S. Department of Health and Human Services. https://data.cdc.gov/500-Cities-Places/500-Cities-Census-Tract-level-Data-GIS-Friendly-Fo/kucs-wizg/about_data

Centers for Disease Control and Prevention. (2018). *500 Cities: Census tract-level data (GIS-friendly format)* [Data set]. U.S. Department of Health and Human Services. https://data.cdc.gov/500-Cities-Places/500-Cities-Census-Tract-level-Data-GIS-Friendly-Fo/k25u-mg9b/about_data

Centers for Disease Control and Prevention. (2019). *500 Cities: Census tract-level data (GIS-friendly format*) [Data set]. U.S. Department of Health and Human Services. https://data.cdc.gov/500-Cities-Places/500-Cities-Census-Tract-level-Data-GIS-Friendly-Fo/k86t-wghb/about_data

Centers for Medicare & Medicaid Services. (2015–2019). *Archived hospital data* [Data set]. U.S. Department of Health and Human Services. https://data.cms.gov/provider-data/archived-data/hospitals

Christofferson, A., James, A., & Rowland, T. (2023, October 04). *Beyond the love of the game: Talent in the video game industry*. Bain & Company. https://www.bain.com/insights/beyond-the-love-of-the-game-talent-in-the-video-game-industry/

Condly, S. J., Clark, R. E., & Stolovitch, H. D. (2003). The effects of incentives on workplace performance: A meta-analytic review of research studies 1. *Performance improvement quarterly*, *16*(3), 46-63. https://doi.org/10.1111/j.1937-8327.2003.tb00287.x

Crifo, P., & Diaye, M. A. (2011). The Composition of Compensation Policy: From Cash to Fringe Benefits. *Annals of Economics and Statistics*, *101-102*, 307-326. https://ssrn.com/abstract=1103115

Deng, X., & Gao, H. (2013). Nonmonetary Benefits, Quality of Life, and Executive Compensation. *Journal of Financial and Quantitative Analysis*, *48*(1), 197–218. https://doi.org/10.1017/S0022109013000033

DiMaggio, P. J., & Powell, W. W. (1983). The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review*, *48*(2), 147-160. https://doi.org/10.17323/1726-3247-2010-1-34-56

DuMond, J. M., Hirsch, B. T., & Macpherson, D. A. (1999). Wage differentials across labor markets and workers: Does cost of living matter? *Economic Inquiry*, *37*(4), 577-598.

Economic Research Service. (2015, 2019). *Food Access Research Atlas [Data set]*. U.S. Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/data-products/food-access-research-atlas/download-the-data/

Faust, A. (2021). *The effects of gamification on motivation and performance*. Springer Gabler. https://doi.org/10.1007/978-3-658-35195-3

Federal Communications Commission. (2016–2019). *Compare broadband availability in different areas* [Web application]. Retrieved October 3, 2024, from https://broadband477map.fcc.gov/#/area-comparison?version=jun2021&tech=acfosw&speed=25_3&searchtype=county

Federal Emergency Management Agency (FEMA). (2020, July 7). *Community*. https://www.fema.gov/about/glossary/community#:~:text=A%20group%20of%20people%20living,jurisdiction%20over%20a%20particular%20area

Federal Transit Administration. (2015–2019a). *National Transit Database: Annual database Transit stations* [Data set]. U.S. Department of Transportation. https://www.transit.dot.gov/ntd/data-product/2019-annual-database-transit-stations

Federal Transit Administration. (2015–2019b). *National Transit Database: Annual database – Revenue vehicle inventory* [Data set]. U.S. Department of Transportation. https://www.transit.dot.gov/ntd/data-product/2019-annual-database-revenue-vehicle-inventory

Feldman, M. (1985). Patterns of biotechnology development. In J. Brotchie, P. Newton, P. Hall, & P. Nijkamp (Eds.), *The Future of Urban Form: The Impact of New Technology* (pp. 93–107). Croom Helm.

Forbes, M., Barker, A., & Turner, S. (2010). *The effects of education and health on wages and productivity* [Productivity Commission Staff Working Paper]. Australian Government Productivity Commission.

Fuchs, V. R. (1967). Hourly Earnings Differentials by Region and Size of City. *Monthly Labor Review*, *90*(1), 22–26.

Gerking, S. D., & Weirick, W. N. (1983). Compensating differences and interregional wage differentials. *Review of Economics and Statistics*, *65*(3), 483-487.

Ghasemi, K., Hamzenejad, M., & Meshkini, A. (2018). The spatial analysis of the livability of 22 districts of Tehran Metropolis using multi-criteria decision-making approaches. *Sustainable Cities and Society, 38*, 382-404. https://doi.org/10.1016/j.scs.2018.01.018

Gibson, J., & Stillman, S. (2009). Why do big firms pay higher wages? Evidence from an international database. *Review of Economics and Statistics*, *91*(1), 213-218. http://www.jstor.org/stable/25651329

Greene, W. (2012). *Econometric analysis* (7th ed.). Pearson.

Grove, A. (1987). Executive Forum: The Future of Silicon Valley. *California Management Review*, *29*(3), 154-160. https://doi.org/10.2307/41165258

Grueber, M., & Yetter, D. (2024). *Video games in the 21st century: The 2024 economic impact report*. The Entertainment Software Association. https://www.theesa.com/wp-content/uploads/2024/02/EIR_ESA_2024.pdf

Hanck, C., Arnold, M., Gerber, A., & Schmelzer, M. (2024, February 13). *Introduction to Econometrics with R.* University of Duisburg-Essen. https://www.econometrics-with-r.org/10.3-fixed-effects-regression.html

Health Resources & Services Administration. (n.d.). *Shortage areas data, HPSA – Primary Care [Data set]*. U.S. Department of Health and Human Services. Retrieved October 3, 2024, from https://data.hrsa.gov/data/download?data=SHORT#SHORT

Henderson, R. I. (2000). *Compensation management in a knowledgebased world*. Upper Saddle River, NJ: Prentice Hall.

Hoch, I. (1974). Inter-urban differences in the quality of life. In Rothenberg, J.G., Heggie, I.G. (Eds.), *Transport and the Urban Environment. Internnational Econnomic Association Series* (pp. 54-98). Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-02007-2_3

Hoechle, D. (2007). Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. *The Stata Journal*, *7*(3), 281-312. https://doi.org/10.1177/1536867X0700700301

Holtbrügge, D. (2010). Instrumente des Personalmanagement. In Springer-Lehrbuch, *Personalmanagement* (pp. 95–239). Springer. https://doi.org/10.1007/978-3-642-14580-3_5

Huang, G. (2021). Missing data filling method based on linear interpolation and lightgbm. In *Journal of Physics: Conference Series*, *1754* (1), id. 012187. https://doi.org/10.1088/1742-6596/1754/1/012187

Imai, K., & Kim, I. S. (2020). On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data. *Political Analysis*, *29*(3), 405–415. https://doi.org/10.1017/pan.2020.33

Institute of Museum and Library Services. (2014). *Museum, Aquariums, and Zoos* [Data set]. Kaggle. https://www.kaggle.com/datasets/imls/museum-directory

Institute of Museum and Library Services. (2015–2019). *Public Libraries Survey* [Data set]. https://www.imls.gov/research-evaluation/data-collection/public-libraries-survey

Insurance Institute for Highway Safety. (2024, February). *Speed limit laws* [Webpage]. https://www.iihs.org/topics/speed/speed-limit-laws

Jenkins, G. D., Mitra, A., Gupta, N., & Shaw, J. D. (1998). Are financial incentives related to performance? A meta-analytic review of empirical research. *Journal of Applied Psychology*, *83*(5), 777-787. https://doi.org/10.1037/0021-9010.83.5.777

Jensen, M. C., and K. J. Murphy. (1990). "CEO Incentives—It's Not How Much You Pay, But How." *Harvard Business Review, May-June 1990*(3), 138–153. http://dx.doi.org/10.2139/ssrn.146148

Kalita, D. (2013). *Fixed Effects (within) Estimator* [Conference presentation]. Stata Users Group Meeting, India. https://www.stata.com/meeting/india13/materials/in13_kalita.pdf

Kelly, T., Mulas, V., Raja, S., Zhen-Wei Qiang, C., & Williams, M. (2010). What Role Should Governments Play in Broadband Development? In OECD (Eds.), *Development Dimension ICTs for Development* (pp. 119–137). OECD Publishing. https://doi.org/10.1787/9789264077409-6-en

Khorrami, Z., Ye, T., Sadatmoosavi, A., Mirzaee, M., Fadakar Davarani, M. M., & Khanjani, N. (2021). The indicators and methods used for measuring urban liveability: a scoping review. *Reviews on Environmental Health*, *36*(3), 397-441. https://doi.org/10.1515/reveh-2020-0097

Kim, D., Liu, F., & Yezer, A. (2009). Do inter-city differences in intra-city wage differentials have any interesting implications?. *Journal of Urban Economics*, *66*(3), 203-209. https://doi.org/10.1016/j.jue.2009.07.004

Lam, E. (2023, December 1). *FuzzyWuzzy*. HKUST Library. https://library.hkust.edu.hk/sc/fuzzywuzzy/

Li, L., Zhong, S., Guo, F., Guo, X., & Guo, X. (2021). Paying for the quality of life: The impacts of urban livability on CEO compensation. *Habitat International*, *116*, 102416. https://doi.org/10.1016/j.habitatint.2021.102416

MIT Election Data and Science Lab. (2021). *County presidential election returns 2000-2020* [Data set]. Harvard Dataverse. https://doi.org/10.7910/DVN/VOQCHQ

Malecki, E. J. (1984). High technology and local economic development. *Journal of the American Planning Association*, *50*(3), 262-269. https://doi.org/10.1090/01944368408976593

Markusen, A., & Gadwa, A. (2010). *Creative placemaking.* National Endowment for the Arts. https://www.arts.gov/sites/default/files/CreativePlacemaking-Paper.pdf

Mathios, A. D. (1989). Education, Variation in Earnings, and Nonmonetary Compensation. *Journal of Human Resources*, *24*(3), 456-468. https://doi.org/10.2307/145823

McCausland, W. D., Summerfield, F., & Theodossiou, I. (2020). The effect of industry-level aggregate demand on earnings: Evidence from the US. *Journal of Labor Research, 41*(2), 102–127. https://doi.org/10.1007/s12122-020-09299-z

McHenry, P., & McInerney, M. (2014). The Importance of Cost of Living and Education in Estimates of the Conditional Wage Gap Between Black and White Women. *The Journal of Human Resources*, *49*(3), 695–722. https://doi.org/10.3368/jhr.49.3.695

MobyGames. (n.d.). *Frequently Asked Questions.* https://www.mobygames.com/info/faq4/

Myers, D. (1987). Internal Monitoring of Quality of Life for Economic Development. *Economic Development Quarterly, 1*(3), 268–278. https://doi.org/10.1177/089124248700100309

National Highway Traffic Safety Administration. (2015-2019). *Fatality and Injury Reporting System Tool (FIRST)* [Web application]. U.S. Department of Transportation. Retrieved October 3, 2024, from https://cdan.dot.gov/query

Nshimirimana, D. A., Kokonya, D., Gitaka, J., Wesonga, B., Mativo, J. N., & Rukanikigitero, J. M. V. (2023). Impact of COVID-19 on health-related quality of life in the general population: A systematic review and meta-analysis. *PLOS Global Public Health, 3*(10), e0002137. https://doi.org/10.1371/journal.pgph.0002137

Numbeo. (2015–2019). *Cost of Living: North America Rankings.* [Web Application]. Retrieved October 3, 2024, from https://www.numbeo.com/cost-of-living/region_rankings.jsp?title=2019&region=021

Numbeo. (n.d.-a). *Numbeo Homepage.* https://www.numbeo.com/common/

Numbeo. (n.d.-b). *Understanding our Cost of Living Indexes.* https://www.numbeo.com/cost-of-living/cpi_explained.jsp

Ofer, D. (2017). *Zipcodes and county FIPS crosswalk [Data set].* Kaggle. https://www.kaggle.com/datasets/danofer/zipcodes-county-fips-crosswalk?resource=download

Oi, W. Y. (1983). Heterogeneous firms and the organization of production. *Economic Inquiry*, *21*(2), 147-171. https://doi.org/10.1111/j.1465-7295.1983.tb00623.x

Oi, W. Y., & Idson, T. L. (1999). Firm size and wages. In Ashenfelter, O. & Card, D. (Eds.) *Handbook of Labor Economics* (pp. 2165-2214). Elsevier.

Pelkowski, J. M., & Berger, M. C. (2004). The impact of health on employment, wages, and hours worked over the life cycle. *The Quarterly Review of Economics and Finance*, *44*(1), 102-121. https://doi.org/10.1016/j.qref.2003.08.002

Porell, F. W. (1982). Intermetropolitan Migration and Quality of Life. *Journal of Regional Science*, *22*(2), 137-158. https://doi.org/10.1111/j.1467-9787.1982.tb00741.x

Porter, M. E. (1990). The Competitive Advantage of Nations. *Harvard Business Review*, *68*(2), 73-93.

Pouder, R., & St. John, C. H. (1996). Hot spots and blind spots: Geographical clusters of firms and innovation. *Academy of Management Review*, *21*(4), 1192-1225. https://doi.org/10.2307/259168

Power, T. M. (1980). *The Economic Value of the Quality of Life* (1st ed.). Routledge. https://doi.org/10.4324/9780429310256

Prendergast, C. (1999). The Provision of Incentives in Firms. *Journal of Economic Literature*, *37*(1), 7–63. https://doi.org/10.1257/jel.37.1.7

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy, 90*(6), 1257–1278. http://dx.doi.org/10.1086/261120

Rodriguez-Alvarez, A., & Rodriguez-Gutierrez, C. (2018). The impact of health on wages: evidence for Europe. *The European journal of Health Economics*, *19*(8), 1173–1187. https://doi.org/10.1007/s10198-018-0966-2

Rosen, S. (1979). Wage-based indexes of urban, quality of life. In Mieszkowski, P. (Eds.) *Current issues in urban economics* (pp. 74-104). Johns Hopkins University Press.

Rosen, S. (1986). The theory of equalizing differences. *Handbook of Labor Economics*, *1*, 641-692. https://doi.org/10.1016/S1573-4463(86)01015-5

Schaffer, M. E., & Stillman, S. (2010). *xtoverid: Stata module to calculate tests of overidentifying restrictions after xtreg, xtivreg, xtivreg2, and xthtaylor*. Boston College Department of Economics. http://ideas.repec.org/c/boc/bocode/s456779.html

Schick, J. (2024, October 15). *Livability-Index-Analysis.* [GitHub Repository]. https://github.com/jasmin-1807/Livability-Index-Analysis

Schrank, D., & Eisele, B. (n.d.). *Urban Mobility Report.* Texas A&M Transportation Institute. https://mobility.tamu.edu/umr/

Schudey, A., Kasperovich, P., Ikram, A., & Panhans, D. (2023, June 9). *Drivers of global gaming industry growth*. Boston Consulting Group. https://www.bcg.com/publications/2023/drivers-of-global-gaming-industry-growth

Shi, T., Zhu, W., & Fu, S. (2021). Quality of life in Chinese cities. *China Economic Review*, *69*(1), 101682. https://doi.org/10.1016/j.chieco.2021.101682

Smith, A. (with Todd, W.B.). (1981). *The Wealth of Nations.* Liberty Classics. (Original work published 1776)

Sturman, M. C., Ukhov, A. D., & Park, S. (2017). The Effect of Cost of Living on Employee Wages in the Hospitality Industry. *Cornell Hospitality Quarterly*, *58*(2), 179-189. https://doi.org/10.1177/1938965516649691

the pandas development team. (n.d.). *pandas.Series.rank.* https://pandas.pydata.org/pandas-docs/version/1.0.1/reference/api/pandas.Series.rank.html

The SciPy community. (n.d.). *scipy.stats.pearsonr*. https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html

Tilburg Science Hub. (n.d.). *The Fixed Effects Model (Within Estimator).* https://tilburgsciencehub.com/topics/analyze/causal-inference/panel-data/within-estimator/#:~:text=The%20fixed%20effects%20(FE)%20model,effects%20to%20obtain%20unbiased%20results.

Tosi, H. L., Werner, S., Katz, J. P., & Gomez-Mejia, L. R. (2000). How much Does Performance Matter? A Meta-Analysis of CEO Pay Studies. *Journal of Management*, *26*(2), 301-339. https://doi.org/10.1177/014920630002600207

Trust for Public Land. (2015, 2016, 2017, 2019). *Park Data Downloads, Historic ParkScore Rankings* [Data set]. https://www.tpl.org/park-data-downloads

U.S. Census Bureau. (2015–2019a). *LED Extraction Tool, Quarterly Workforce Indicators (QWI)* [Web application]. Retrieved October 3, 2024, from https://ledextract.ces.census.gov/

U.S. Census Bureau. (2015-2019b). *DP04: Selected housing characteristics* [Data set]. https://data.census.gov/table?t=Families%20and%20Household%20Characteristics:Renter%20Costs&g=010XX00US,$0500000

U.S. Census Bureau. (2015–2019c). *B19083: Gini Index of Income Inequality* [Data set]. https://data.census.gov/table?q=B19083&g=010XX00US$0500000

U.S. Census Bureau. (2015–2019d). *American Community Survey, 1-year estimates: Age and sex* [Data set]. https://data.census.gov/table/ACSST1Y2019.S0101?q=national%20age&g=010XX00US,$0500000

U.S. Census Bureau. (2015–2019e). *American Community Survey: S0101 Age and Sex* [Data set]. https://data.census.gov/table?q=national%20age

U.S. Census Bureau. (2015–2019f). *County Population Totals: 2010 - 2019* [Data set]. https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html

U.S. Census Bureau. (2019). *Volunteering and civic life, Current Population Survey* [Data set]. https://www.census.gov/data/datasets/time-series/demo/cps/cps-supp_cps-repwgt/cps-volunteer.2019.html

U.S. Census Bureau. (2022). *Geography Program Glossary*. https://www.census.gov/programs-surveys/geography/about/glossary.html#par_textimage_5

U.S. Census Bureau. (2023). *TIGER/Line shapefiles: County layer* [Data set]. https://www2.census.gov/geo/tiger/TIGER_RD18/LAYER/COUNTY/

U.S. Census Bureau. (n.d.). *States, Counties, and Statistically Equivalent Entities. Chapter 4.* [PDF]. https://www2.census.gov/geo/pdfs/reference/GARM/Ch4GARM.pdf

U.S. Department of Agriculture, Agricultural Marketing Service, & Michigan State University. (n.d.). *Local Food Directories – Farmers Markets* [Data set]. Retrieved October 3, 2024, from https://www.usdalocalfoodportal.com/fe/datasharing/

U.S. Department of Education. (2016–2020). *EdFacts data files: Adjusted cohort graduation rate, school years 2015–2016 to 2019–2020* [Data set]. https://www2.ed.gov/about/inits/ed/edfacts/data-files/index.html#acgr

U.S. Department of Housing and Urban Development. (2015–2019a). *Assisted housing: national and local, Picture of Subsidized Households* [Data set]. https://www.huduser.gov/portal/datasets/assthsg.html#data_2009-2023

U.S. Department of Housing and Urban Development. (2015–2019b). *Section 8 income limits [Data set]*. https://www.huduser.gov/portal/datasets/il.html#data_2019

U.S. Department of Housing and Urban Development & U.S. Department of Transportation. (n.d.). *Location Affordability Index (LAI), version 3* [Web application]. Retrieved October 3, 2024, from https://hudgis-hud.opendata.arcgis.com/datasets/location-affordability-index-v-3/explore?location=42.054580%2C-81.917933%2C6.64

U.S. Department of Justice, & Federal Bureau of Investigation. (2014). *Uniform Crime Reporting Program Data: Detailed Arrest and Offense Data, United States, 2014* (ICPSR 36399; Version 2) [Data set]. ICPSR. https://doi.org/10.3886/ICPSR36399.v2

U.S. Department of Justice, & Federal Bureau of Investigation. (2016). *Uniform Crime Reporting Program Data: Detailed Arrest and Offense Data, United States, 2016* (ICPSR 37059; Version 3) [Data set]. ICPSR. https://doi.org/10.3886/ICPSR37059.v3

U.S. Department of Labor. (n.d.). *H-1B Program*. https://www.dol.gov/agencies/whd/immigration/h1b

U.S. Department of Transportation. (2022). *National Transit Database: Annual data breakdowns* [Data set]. Retrieved in 2024, from https://datahub.transportation.gov/Public-Transit/2022-NTD-Annual-Data-Breakdowns/amkt-4ehs/data

U.S. Environmental Protection Agency. (2015–2019). *Annual AQI by county* [Data set]. https://aqs.epa.gov/aqsweb/airdata/download_files.html

U.S. Environmental Protection Agency. (n.d.-a). *SDWIS Federal reports: Violations* [Web application, search report for 2015, 2016, 2017, 2018, and 2019]. Retrieved October 3, 2024, from https://sdwis.epa.gov/ords/sfdw_pub/r/sfdw/sdwis_fed_reports_public/9?p9_report=VIO

U.S. Environmental Protection Agency. (n.d.-b). *Easy RSEI: Risk-Screening Environmental Indicators* [Web application, search report for 2015, 2016, 2017, 2018, and 2019]. Retrieved October 3, 2024, from https://edap.epa.gov/public/extensions/EasyRSEI/EasyRSEI.html

University of Wisconsin Population Health Institute. (2018–2022). *County Health Rankings: National data documentation* [Data set]. https://www.countyhealthrankings.org/health-data/methodology-and-sources/data-documentation/national-data-documentation-2010-2022

VanZerr, M., Seskin, S., & Carr, T. (2011). Recommendations Memo #2 Livability and Quality of Life Indicators [PDF]. https://www.jwneugene.org/wp-content/uploads/2020/02/Livability-Indicators-CH2M-Hill.pdf

Williams, R. (2018). *Panel Data 4: Fixed Effects vs. Random Effects Models* [PDF]. University of Notre Dame. https://www3.nd.edu/~rwilliam/stats3/Panel04-FixedVsRandom.pdf

Winters, J. V. (2009). Wages and prices: Are workers compensated for cost of living differences? *Regional Science and Urban Economics*, *39*(5), 632-643. https://doi.org/10.1016/j.regsciurbeco.2009.05.001

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. The MIT Press Cambridge.

Woolf, S. H., Laudan, A., Dubay, L., Simon, S.M., Zimmerman, E., & Luk, K.X. (2015). *How Are Income and Wealth Linked to Health and Longevity?* [PDF]. Urban Institute & Center on Society and Health. https://www.urban.org/sites/default/files/publication/49116/2000178-How-are-Income-and-Wealth-Linked-to-Health-and-Longevity.pdf

Yang, C., Singh, P., & Wang, J. (2020). The effects of firm size and firm performance on CEO pay in Canada: A Re-Examination and Extension. *Canadian Journal of Administrative Sciences*, *37*(3), 225-242. https://doi.org/10.1002/cjas.1542

Ye, R., Chen, Y., & Kelly, K. A. (2023). The Effects of Firm Performance on CEO Compensation and CEO Pay Ratio Before and During COVID-19. *Research in Economics*, *77*(4), 453–458. https://doi.org/10.1016/j.rie.2023.07.002

Appendix List

Appendix

Table A1 *Metrics Overview*

Category	Metric	Years	Geographic Level	Number of Units	Additional Data & Source	Source
Health	Patient Satisfaction	2015-2019	County-Level	2,496 Counties		Centers for Medicare & Medicaid Services, 2015–2019
	Smoking Prevalence	2015, 2016, 2017	County-Level; based on Tract-FIPS aggregated by mean	326 Counties		Centers for Disease Control and Prevention, 2017, 2018, 2019
	Obesity Prevalence	2015, 2016, 2017	County-Level; based on Tract-FIPS aggregated by mean	326 Counties		Centers for Disease Control and Prevention, 2017, 2018, 2019
	Preventable Hospitalization Rate	2015-2019	County-Level	3,142 Counties		University of Wisconsin Population Health Institute, 2018–2022
	Healthcare Shortage	2023	County-Level; multiple entries per county are aggregated using the mean	3,208 Counties		Health Resources & Services Administration, n.d.
	Access to Exercise Opportunities	2016, 2018, 2019	County-Level	3,142 Counties		University of Wisconsin Population Health Institute, 2018–2022
Housing	Multi Family Housing	2015, 2016, 2017, 2019	County-Level	831 Counties	County Population Estimates (U.S. Census Bureau, 2015–2019f)	U.S. Census Bureau, 2015-2019b
	Housing Costs	2015-2019	County-Level	831 Counties		U.S. Census Bureau, 2015-2019b
	Housing Costs Burden	2015-2019	County-Level	831 Counties	Income (U.S. Department of Housing and Urban Development, 2015–2019b)	U.S. Census Bureau, 2015-2019b
	Subsidized Housing Units	2015-2019	County-Level	3,139 Counties	County Population Estimates (U.S. Census Bureau, 2015–2019f)	U.S. Department of Housing and Urban Development, 2015–2019a

Category	**Metric**	**Years**	**Geographic Level**	Number of Units	**Add**itional **Data & Source**	**Source**
Environment	Air Pollution	2015-2019	County-Level	1,042 Counties		U.S. Environmental Protection Agency, 2015-2019
	Drinking Water Quality	2015-2019	State-Level	17 States		U.S. Environmental Protection Agency, n.d.-a
	Local Industrial Pollution	2015-2019	County-Level	2,315 Counties		U.S. Environmental Protection Agency, n.d.-b
Engagement	Social Associations	2015-2019	County-Level	3,143 Counties		University of Wisconsin Population Health Institute, 2018–2022
	Cultural Institutions	2014	State-Level	51 States		Institute of Museum and Library Services, 2014
	Social Involvement	2019	County-Level	329 Counties		U.S. Census Bureau, 2019
	Broadband Cost and Speed	2016-2019	County-Level	3,155 Counties		Federal Communications Commission, 2016–2019
	Voting Rate	2016, 2020	County-Level	3,155 Counties		MIT Election Data and Science Lab, 2021
Neighborhood	Crime Rate	2014,2016	County-Level	3,137 Counties		U.S. Department of Justice, & Federal Bureau of Investigation, 2014, 2016
	Vacancy Rate	2015-2019	County-Level	837 Counties		U.S. Census Bureau, 2015-2019b
	Park Score	2015,2016,2017,2019	State-Level based on Cities	33 States	Allocation of the cities to the corresponding states	Trust for Public Land., 2015, 2016, 2017, 2019
	Access to Libraries	2015-2019	County-Level	2,766 Counties		Institute of Museum and Library Services, 2015–2019
	Grocery Stores	2015,2019	County-Level	3,007 Counties		Economic Research Service, 2015, 2019
	Farmers Markets	2024	County-Level based on ZIP Codes	2,207 Counties	ZIP Codes to FIPS (Ofer, D., 2017)	U.S. Department of Agriculture, Agricultural Marketing Service, & Michigan State University, n.d.

Category	Metric	Years	Geographic Level	Number of Units	Additional Data & Source	Source
Opportunity	Income Inequality	2015-2019	County-Level	830 Counties		U.S. Census Bureau, 2015–2019c
	High School Graduation Rate	2015-2019	County-Level	824 Counties		U.S. Department of Education, 2016–2020
	Age Diversity	2015-2019	County-Level	830 Counties	National Age (U.S. Census Bureau, 2015-2019e)	U.S. Census Bureau, 2015–2019d
	Jobs per Worker	2015-2019	County-Level	3,223 Counties		U.S. Census Bureau, 2015–2019a
Transportation	Crash Rate	2015-2019	County-Level	2,852 Counties	County Population Estimates (U.S. Census Bureau, 2015–2019f)	National Highway Traffic Safety Administration, 2015-2019
	Speed Limits	2024	State-Level	51 States		Insurance Institute for Highway Safety, 2024
	ADA accessible Stations and Vehicles	2015-2019	State-Level based on NTD IDs	50 States	NTD ID to States (U.S. Department of Transportation, 2022)	Federal Transit Administration, 2015-2019a, 2015-2019b
	Household Transportation Costs	2024	County-Level; multiple entries per county are aggregated using the mean.	3,140 Counties		U.S. Department of Housing and Urban Development & U.S. Department of Transportation, 2024

Figure A1

Livability Score by County 2015-2018

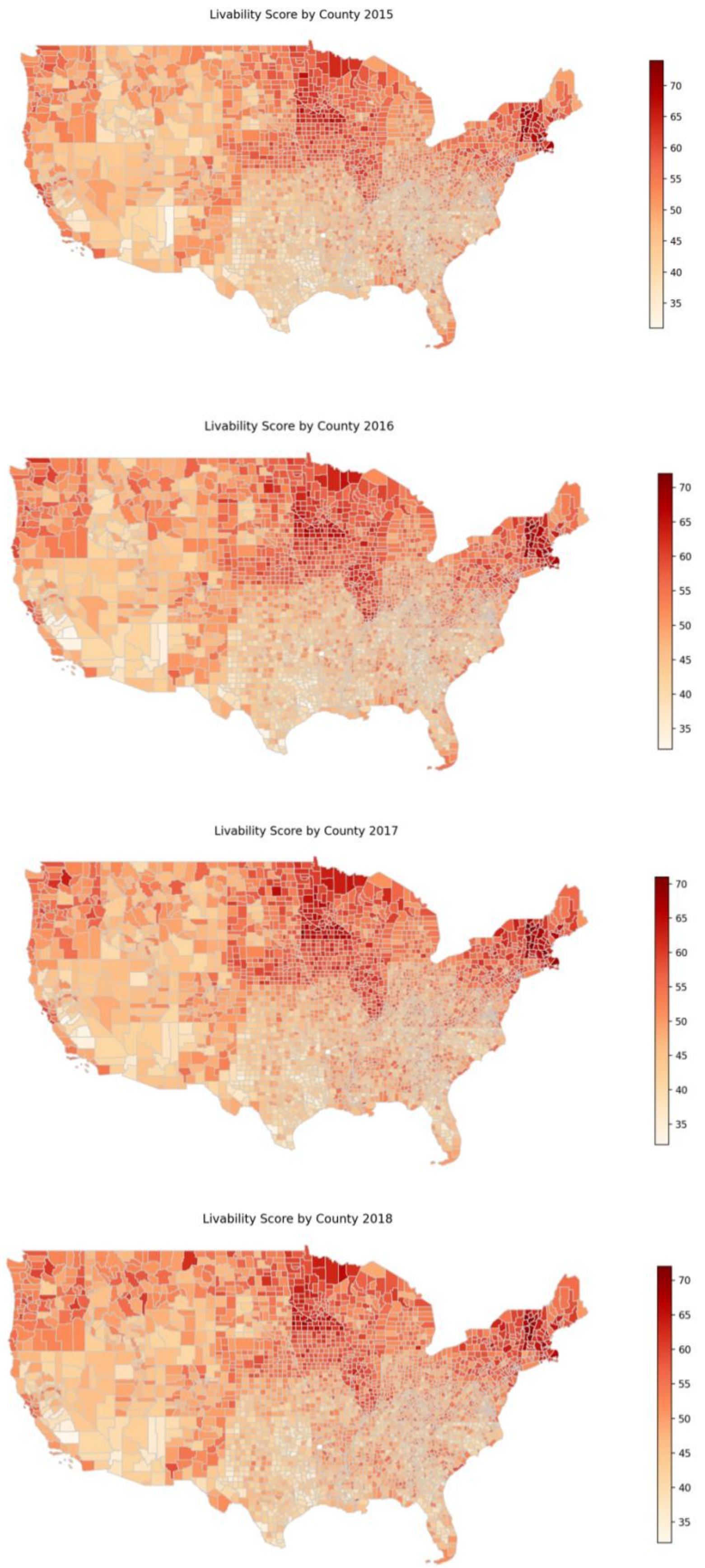


Table A2

Robustness Check: Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) AARP Livability Score	1.000															
(2) Livability Score	0.823	1.000														
	(0.000)															
(3) AARP Housing Score	0.192	0.242	1.000													
	(0.001)	(0.000)														
(4) Housing Score	0.559	0.715	0.431	1.000												
	(0.000)	(0.000)	(0.000)													
(5) AARP Neighborhood Score	0.680	0.608	0.027	0.648	1.000											
	(0.000)	(0.000)	(0.645)	(0.000)												
(6) Neighborhood Score	0.202	0.499	0.153	0.372	0.429	1.000										
	(0.001)	(0.000)	(0.009)	(0.000)	(0.000)											
(7) AARP Transportation Score	0.736	0.753	0.444	0.740	0.776	0.487	1.000									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)										
(8) Transportation Score	0.325	0.613	-0.070	0.497	0.386	0.337	0.493	1.000								
	(0.000)	(0.000)	(0.232)	(0.000)	(0.000)	(0.000)	(0.000)									
(9) AARP Environment Score	0.648	0.522	0.266	0.176	0.064	0.032	0.345	0.200	1.000							
	(0.000)	(0.000)	(0.000)	(0.003)	(0.280)	(0.591)	(0.000)	(0.001)								
(10) Environment Score	0.494	0.569	0.273	0.156	0.118	0.065	0.271	0.030	0.358	1.000						
	(0.000)	(0.000)	(0.000)	(0.008)	(0.045)	(0.267)	(0.000)	(0.609)	(0.000)							
(11) AARP Health Score	0.854	0.638	-0.150	0.344	0.681	0.051	0.450	0.199	0.359	0.442	1.000					
	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.386)	(0.000)	(0.001)	(0.000)	(0.000)						
(12) Health Score	0.505	0.288	-0.274	0.084	0.451	-0.127	0.113	-0.006	0.245	0.193	0.767	1.000				
	(0.000)	(0.000)	(0.000)	(0.152)	(0.000)	(0.030)	(0.056)	(0.920)	(0.000)	(0.001)	(0.000)					
(13) AARP Engagement Score	0.644	0.536	0.181	0.426	0.275	0.007	0.326	0.116	0.518	0.345	0.493	0.368	1.000			
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.909)	(0.000)	(0.049)	(0.000)	(0.000)	(0.000)	(0.000)				
(14) Engagement Score	0.647	0.705	0.211	0.379	0.216	0.356	0.479	0.295	0.698	0.288	0.353	0.096	0.593	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.104)	(0.000)			
(15) AARP Opportunity Score	-0.277	-0.396	-0.498	-0.606	-0.560	-0.422	-0.643	-0.280	-0.150	-0.007	-0.084	-0.123	-0.357	-0.192	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.909)	(0.151)	(0.037)	(0.000)	(0.001)		
(16) Opportunity Score	0.518	0.632	-0.006	0.200	0.187	0.296	0.420	0.505	0.457	0.290	0.341	-0.121	0.196	0.589	0.075	1.000
	(0.000)	(0.000)	(0.916)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.040)	(0.001)	(0.000)	(0.206)	

Table A3

Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) salary	1.000												
(2) Livability Score	0.355	1.000											
	(0.000)												
(3) Health Score	0.239	0.325	1.000										
	(0.000)	(0.000)											
(4) Neighborhood Score	-0.008	0.498	-0.072	1.000									
	(0.904)	(0.000)	(0.265)										
(5) Opportunity Score	0.195	0.636	-0.076	0.280	1.000								
	(0.002)	(0.000)	(0.236)	(0.000)									
(6) Environment Score	0.194	0.589	0.193	0.064	0.310	1.000							
	(0.002)	(0.000)	(0.002)	(0.319)	(0.000)								
(7) Engagement Score	0.304	0.715	0.178	0.351	0.579	0.314	1.000						
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)							
(8) Housing Score	0.316	0.714	0.087	0.384	0.203	0.180	0.380	1.000					
	(0.000)	(0.000)	(0.174)	(0.000)	(0.001)	(0.005)	(0.000)						
(9) Transportation Score	0.129	0.613	0.025	0.315	0.556	0.064	0.302	0.474	1.000				
	(0.044)	(0.000)	(0.702)	(0.000)	(0.000)	(0.321)	(0.000)	(0.000)					
(10) Cost of Living Index	0.307	0.832	0.516	0.381	0.596	0.532	0.693	0.689	0.397	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(11) Company Size	0.051	-0.144	0.130	-0.115	-0.103	-0.094	-0.123	-0.168	-0.130	0.001	1.000		
	(0.547)	(0.088)	(0.123)	(0.174)	(0.225)	(0.268)	(0.147)	(0.046)	(0.124)	(0.989)			
(12) New Games	0.072	0.142	0.150	0.239	0.135	0.047	0.134	0.033	0.058	0.095	-0.030	1.000	
	(0.387)	(0.087)	(0.070)	(0.003)	(0.104)	(0.568)	(0.106)	(0.694)	(0.486)	(0.272)	(0.751)		
(13) MobyScore	-0.200	0.000	-0.041	0.085	0.089	-0.060	0.021	-0.056	0.047	-0.019	0.239	0.380	1.000
	(0.015)	(0.998)	(0.623)	(0.305)	(0.283)	(0.467)	(0.804)	(0.497)	(0.570)	(0.824)	(0.010)	(0.000)	

Table A4

Test of Overidentifying Restrictions

Test of overidentifying restrictions: fixed vs random effects
Cross-section time-series model: xtreg re robust cluster(panel_id)
Sargan-Hansen statistic 57.765 Chi-sq(9)   P-value = 0.0000