Do NBA Players Choose Teams for Non-Basketball Reasons?

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Acknowledgements

I would like to acknowledge first and foremost, my advisor, Dr. Nara, who gave valuable insight on how to structure my project and what would make for useful and productive research. He helped to guide me on my first major data analytics project and I will always be grateful for that.

I would like to also thank the people around me for their helpful feedback on what I should look at. Specific people are my coworkers, especially, Ramil, for his insight in cost-of-living, since players would still want to manage finances and lifestyle even if they are getting paid millions. Also, it is from his experiences, due to his having a family and having a lifestyle that differs from mine due to different experiences, he tends to look at cost-of-living for different cities to plan for hypotheticals. This is something that players' agents would likely inform them of when they are looking to move and would work on so that those players could focus their energy on the more important parts, mainly basketball since that is what they are skilled and generally experienced in. I wanted to try and see if NBA players had similar motivations to people in other industries when changing locations and possibly having to uproot their lives and homes and other people with more experience in that were able to share their possible reasons for moving jobs and even to different cities and states.

Lastly, I would like to thank the helpful resources, namely, basketball-reference.com, REAP Project, Tax Foundation, Statistics Canada, and Open Meteo, for freely providing data to be used for analysis, both as teaching and learning tools. The world has a lot of data to provide and these databases are the keys for data analysts and data scientists to learn from and be able to translate for other people to read and also learn from. Additionally, I am thankful for the National Basketball Association for providing entertainment for many, opportunities for people that may not have had such a life without, and useful and interesting statistics for many others and myself to look at, as well as being fun to watch, of course.

Table of Contents

Introduction

In the world of professional basketball, player movement has become a topic of intense discussion among fans and analysts. A common perception is that star players, like many individuals in regular life, make decisions based on factors such as weather, taxes, or cost of living when choosing their next city. This project aims to investigate whether these factors play a significant role in player transitions, especially among high-profile athletes, and compare their motivations to those of the average person.

The saying “loyalty is a two-way street” applies not only to life in general but also to the dynamics of the National Basketball Association (NBA). In the modern workforce, individuals frequently shift jobs to seek better opportunities, as companies prioritize their interests and may replace employees to maximize benefits. Similarly, NBA teams operate as businesses, aiming to generate revenue, win championships, and maintain fan engagement. While players were once at the mercy of their contracts being sold to other teams, they now possess greater agency, ranging from negotiating contracts to forcing trades to their desired destinations. These moves often create significant challenges for both their former and future teams, requiring careful adjustments to align with league rules and financial structures.

The *NBA Player Movement Project* seeks to analyze trends in player transitions across teams. Specifically, it explores patterns in player relocations and examines the reasons behind such moves, whether they align with common perceptions or reveal new insights.

This analysis was conducted using publicly available data, with the code and dataset accessible on GitHub. Links to the GitHub repository and project website are provided in Appendices 6 and 7. Additionally, a video presentation summarizing the findings can be viewed on YouTube linked on Appendix 8.

Executive Summary

This research aimed to explore whether star players in the National Basketball Association (NBA) consider factors beyond basketball, such as economic and environmental aspects, when deciding to change teams. Specifically, the study focused on three key factors: per capita income, average annual temperature, and state tax rates. The data analyzed spanned from 1940 to 2023, sourced from basketball-reference.com, open-meteo.com, the REAP project, and the Tax Foundation.

To identify potential patterns, correlation analysis was conducted to assess the significance of these factors in player movement decisions. Additionally, QGIS was used to map the geographical shifts of players and visualize the temperature data, along with a comparison of trends across four distinct eras: pre-1980, 1981-2000, 2001-2016, and 2016-present.

The analysis found no significant correlation between the factors (income, temperature, tax rates) and the likelihood of players changing teams. However, trends were observed in the popularity of certain cities for free-agent signings, aligning with general public perceptions of desirable destinations, which also corresponded with team success.

This study contributes to the ongoing discussion of non-basketball factors influencing NBA player decisions and offers insights into how external factors may shape team dynamics in the league.

Problem Statement

Having been an avid follower of the NBA for over two decades and a keen observer of its statistical aspects for nearly a decade, I sought to apply data analytics to the league with a unique perspective. Rather than focusing solely on basketball-related factors, I wanted to explore whether players considered non-basketball aspects when changing teams, such as the characteristics of the cities they moved to.

I chose to examine quantifiable aspects of the cities, including average annual temperature, cost of living, and tax rates. The goal of this research was to determine if these factors had any impact on players' decisions, alongside the traditional basketball considerations. To achieve this, I analyzed player movement data, identified relevant cities and states, and collected data on the chosen city characteristics. Using correlation analysis and visualizing player movement, I aimed to explore whether players made decisions based on factors beyond basketball performance, such as the economic and environmental qualities of a city.

Literature Review

See Appendix 5 for a list of references.

The history of player movement in the NBA provides a rich context for analyzing the factors influencing decisions to change teams. Over the decades, several trends and systemic changes have shaped how and why players switch franchises.

Evolution of Player Movement

The NBA has experienced a significant increase in roster churn in recent years. As highlighted by NBC Sports, only 57% of minutes played in the 2019-2020 season were by players who remained with their previous team, a sharp decline from 70% a decade earlier. Several factors contributed to this shift, including changes to collective bargaining agreements (CBAs) in 2005 and 2011. These agreements introduced shorter maximum contract lengths to reduce deadweight contracts and added mechanisms like the stretch provision, which allows teams to waive players and spread their salary cap hits over multiple years. The relaxation of trade rules and increased

star player agency further catalyzed player movement, as players leveraged their value to dictate their destinations, even at financial costs.

SBNation discusses the role of "player empowerment" in reshaping the NBA landscape. Modern stars, building on the advocacy of earlier players like Oscar Robertson, have exercised unprecedented control over their careers. Notable examples include LeBron James and Kevin Durant, who used free agency and trade demands to form "superteams." These actions echo historical patterns of player agency but on a more aggressive scale.

Motivations Behind Player Movement

Field Insider categorizes the reasons for player movement into several key factors. Players often seek championship opportunities, driven by legacy and competitive drive. The rise of superteams reflects players' pursuit of shared goals and camaraderie, as well as a response to heightened competition. Other motivations include income disparities between franchises, team chemistry issues, and expiring contracts. For some, a fresh start offers a chance to maximize potential or address frustrations at their current location.

Fadeaway World expands on these reasons, emphasizing factors such as returning to a hometown team, seeking more playing time, or securing roles that better fit their abilities. Financial incentives, friendship, and the pursuit of a championship ring remain central themes.

The Trade Deadline and Its Impact

The NBA trade deadline serves as another focal point for player movement. Trades often stem from management's efforts to enhance team performance, address contract issues, or rebuild for the future. However, trades also have significant personal impacts on players, particularly those with deep ties to their teams. As NBA.com highlights, organizations like the San Antonio Spurs, known for their strong player relationships, aim to balance the business aspects of trades with the human element. Despite this, players such as Eric Bledsoe have acknowledged the reality of basketball as a business, where loyalty is often secondary to organizational priorities.

Conclusion

The reviewed literature paints a multifaceted picture of NBA player movement, blending professional, personal, and systemic factors. While players today enjoy greater autonomy, their decisions are shaped by a complex interplay of motivations, organizational strategies, and league-wide trends. This context provides a foundational understanding for examining whether non-basketball factors, such as city characteristics, influence player decisions—a key focus of this study.

Data

Player Data Collection:

To identify star players, I used a combination of general basketball knowledge and specific criteria detailed in Appendix 1. The player data was initially gathered and organized in CSV and Excel files located in the ‘nba_analysis/data’ directory. This dataset included all NBA players, which I gradually filtered down to those who had changed teams. A key challenge during this process was determining whether a player actively chose their next team, especially for earlier data where detailed free agency information was sparse. With the advent of the 24/7 news cycle, more comprehensive articles were available, making it easier to verify a player's intent when changing teams.

Data Transition to MongoDB:

Once the initial list of players was refined, the data was transferred from Excel to MongoDB. This transition allowed for more efficient data management and interaction with Python scripts and other analytical tools. The relevant scripts for this process are located in the ‘nba_analysis/scripts’ directory, while the corresponding maps and notebooks are stored in ‘nba_analysis/QGIS’ and ‘nba_analysis/notebooks’, respectively. Detailed documentation of these scripts is available in the README file and Appendix 2.

Temperature Data Collection:

The cities and states for each player's previous and new teams were identified, and annual temperature data for these locations was retrieved using API requests from open-meteo.com. A rolling two-year average was applied to smooth out fluctuations and provide a more stable comparison. The specific timing of transactions was not accounted for in this average, except for trades occurring in 2023 or 2024, where the end date was set to June 17, 2024, the date of the data lookup.

Cost of Living Index (PCI) Creation:

A relative cost-of-living index was created using per capita income (PCI) data. For U.S. states, PCI data was sourced from the REAP Project, while for Toronto, Ontario, data was obtained from Statistics Canada. The PCI values, which were not adjusted for inflation, were incorporated into MongoDB. This enabled the easy retrieval of cost-of-living information for each player’s previous and future destination states.

Tax Rate Data Compilation:

Tax rates were determined using data from the Tax Foundation. States were categorized into four tiers: none, low, moderate, and high, based on their tax rates relative to other states during the

same period. This classification accounted for changes in tax laws over time, leading to shifts in a state's tier. The tax data was structured into a MongoDB collection, where each state's tax rate history was stored for straightforward access during analysis.

Data Organization and Visualization:

The MongoDB database was organized into collections for each data category (temperature, cost of living, tax rate) to facilitate easier analysis and visualization in Jupyter notebooks. The data was subsequently downloaded into CSV files for further processing. Various notebooks were created to conduct regression analyses, generate bar charts of differences between previous and future destinations, and create frequency charts based on binned years. The analysis also included trend maps and QGIS-generated maps illustrating temperature changes and city-to-city paths.

Other Data Information

- Data was divided into four time periods: beginning to 1980, 1999, 2015, and the present.

- PCI graphs titles are incorrect and should be labeled for US States and Provinces, in the case of Ontario.

- PCI in graphs are for the value of currency without being adjusted for inflation or conversion.

- MongoDB databases were converted to JSON and are saved in the 'nba_analysis/notebooks' subfolder.

-Appendix 6 contains the link for the GitHub repository.

-Project website is listed on Appendix 7.

- If any graphs or Appendices are hard to view, they can be found on the above GitHub page and the README file there should be able to guide you to any file you are looking for.

Methodology

Star Player Identification:

As shown in Appendix 1, I set several metrics that I learned from my years of following the NBA to determine players that could be considered stars. Even these could be considered partial as the voting for some of the awards are by media and fans, not just other players or management on the team. These awards still generally represent the players that performed the best in those categories during those seasons, so players who were either one of the best or showed that they were elite would generally reach at least one of the criteria. For example, the best regular season player is usually the Most Valuable Player (MVP) and the one that performed the best in The Finals would win finals Most Valuable Player (FMVP). Making it to the All Star Team suggests

a player is top 30 for that season, out of over 450 players over the course of a season, while All-NBA means they are in the top 15 usually, so appearing in that enough times will make them be considered a star. Defensive Player of the Year (DPOY) means a player is the best player on defense although that award has had some scrutiny for being dependent on the narratives from the media in who they want to win at times and not who is the most deserving player, for example Marcus Smart winning in 2022 to be the first guard to win the award and Rudy Gobert winning his 4th DPOY last season over Anthony Davis who was considered by some fans and other people to be the best defensive player overall the past few seasons but because he was also elite on offense and won other awards, that might have hurt his consideration. Additionally Bam Adebayo was a player that people thought should win but might have not won due to his relative youth and it "not being his time yet".

The award pages on basketball-reference.com had all players who had won those awards along with a count which I used to sort players and copied onto an Excel sheet as long as they reached those criteria. An example is the MVP page that is shown on Appendix 3. After all the players were added, I combined them onto a single sheet that I would then filter for duplicates, players who had never left a team, and if a player left a team then their next team was not their choice, and removed all of them from the final sheet. I also had the hyperlink for the player's page added as a separate column for both easier research and for future convenience. I then had multiple entries for players who changed teams of their own choosing more than once so that the MongoDB would not be too convoluted and then each entry could be considered a separate entity in regards to analysis.

Data Transfer and Management:

I read the final player csv into MongoDB using Python, in particular, using MongoClient from pymongo. The client was titled 'nba_analysis' and the collection was 'player_movements' as that was the first collection so that I could eventually add more collections as needed.

Within both my local drive and on GitHub, scripts used for pulling data from the csv into MongoDB, making API requests, and then converting MongoDB into a csv for analysis are located within the 'scripts' subfolder. All maps made on QGIS, along with their output files, are located within the 'QGIS' subfolder. Jupyter notebooks for doing regression analysis, creating bar charts, and frequency analysis of binned years.

Data Collection

The API for the annual temperature was collected using API requests on Open Meteo by converting the city locations for the previous and new teams for all entries into longitude and latitude coordinates using Python. The exact time of year for the movements was not considered as I wanted to imagine a player was looking at the annual average temperature and not for a specific season so the year that the trade occurred along with the following year were collected

and then averaged, unless one of the years included 2024, then as stated in the Data section, the span would go from January 1, 2024, to June 12, 2024, which is 5 days before the API pull happened. In order to respect API limits, I had the program “sleep” for 1 second in between calls and also ran it over the course of a few days as it did not require an API key and was free so limits were understandable to not overload the server. Additionally I used their historical data which went as far back as 1940 to up to 5 days before the API request. I used a two-year average to try and reduce outliers and also consider that players would want to stay in a city for the near future (although some players did leave their team the immediate year after).

Cost-of-living data was taken from the REAP Project for the United States which provided csv’s since 1958. They had provided the per capita income (PCI) for both the current value of the dollar along with a standardized one which I did not use. Statistics Canada provided the Toronto PCI since 1985 which worked since the Toronto Raptors were not in existence until after then. Additionally, despite the fact that there used to be a team in Vancouver, BC, no movements involving “star players” were shown there so I did not need to pull any data for that city. All the PCI were added into MongoDB for each applicable entry and were saved in individual years. Additionally, I did not do any conversions between currency which does result in some odd results as then Toronto has a much larger PCI than all of the United States.

The tax rates for the states and provinces were taken from the Tax Foundation and then placed into tiers of none, low, moderate, and high, as I believed that minor differences in tax rates would not be a major reason that players would choose a specific city over another. Additionally, some states changed tiers as they added tax laws, with those states being Ohio which went from “low” to “moderate” in 1971, Louisiana which went from “moderate” to “high” in 2019, and Georgia which went from “low” to “moderate” in 1971. Washington increased its tax rates by codifying more things recently but it occurred after the Seattle SuperSonics became the Oklahoma City Thunder.

Data Integration and Analysis

The data was binned into four distinct periods—beginning to 1980, 1999, 2015, and the present—to capture the evolution of player movement trends over time. This binning allowed for a comparative analysis across different eras of the NBA, reflecting significant shifts in player agency and market dynamics.

The MongoDB main collection was divided into smaller collections that focused on the main three categories of analysis: annual average temperature, PCI, and tax tier, with a unique player ID being used as the primary key to link each document to the main collection ‘player_movements’. This made it easier to view the collection to make analysis cleaner and also each individual collection was used for their specific Jupyter notebooks to reduce chances of the wrong data being used in a notebook after all were downloaded as JSON files.

In Jupyter and on QGIS, regression, general graphing, trend mapping, and binned frequency analysis were run on the complete MongoDB that was converted to JSON to be compatible with those programs. The regression analysis was a significance test on whether there was a significant difference between new and former cities and states or provinces for annual average temperature for cities and states or provinces for PCI and tax tiers. The general graphing was on the new and former as well, along with the difference between temperature and PCI. These results were binned based on the resulting values to not make the graphs too crowded. Trend mapping was done on all three categories along with their differences but were binned according to the different eras and also were the average of year one and year two. Binned frequency analysis was on city to city movement along with most popular destinations divided by the binned years to show how destinations changed through the years. QGIS used the same JSON file to map temperature bubbles for new and former cities, destination bubbles, and city-to-city paths.

Results

Notes

- See ‘Other Data Information’ in Data Section for corrections on Per Capita Income (PCI)
- See Appendix 4 for NBA teams locations

Significance Test from ‘regression1.ipynb’

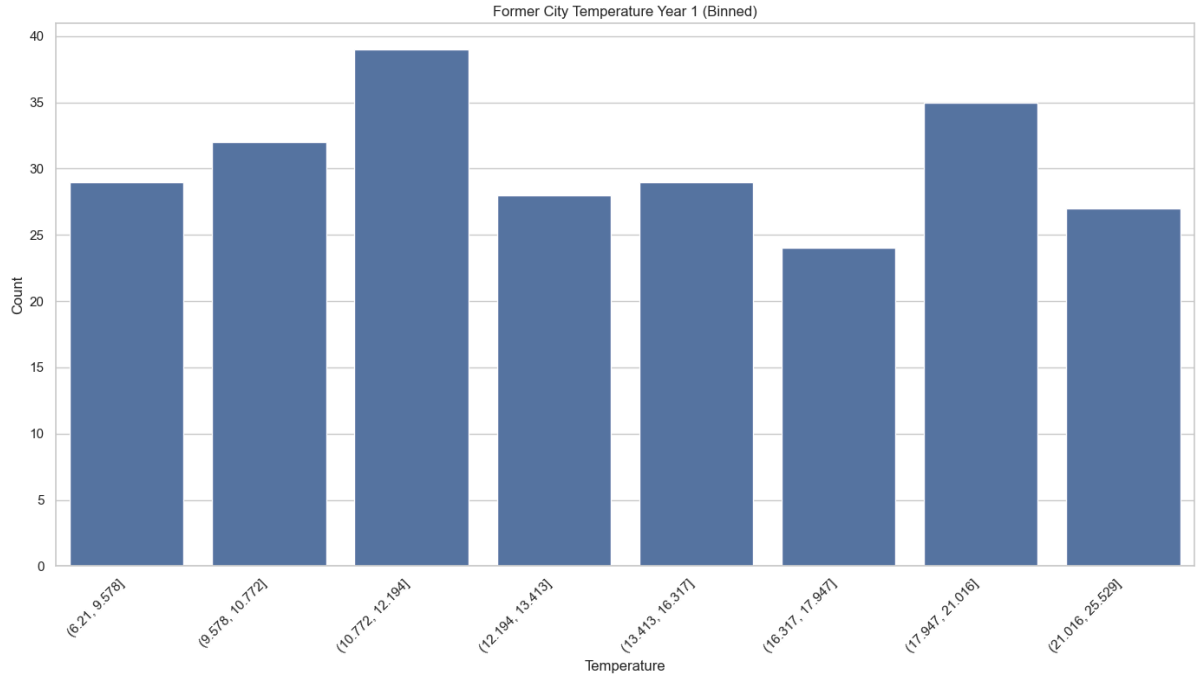
Temperature differences - t-statistic: -0.69962809136618, p-value: 0.48483154381081073

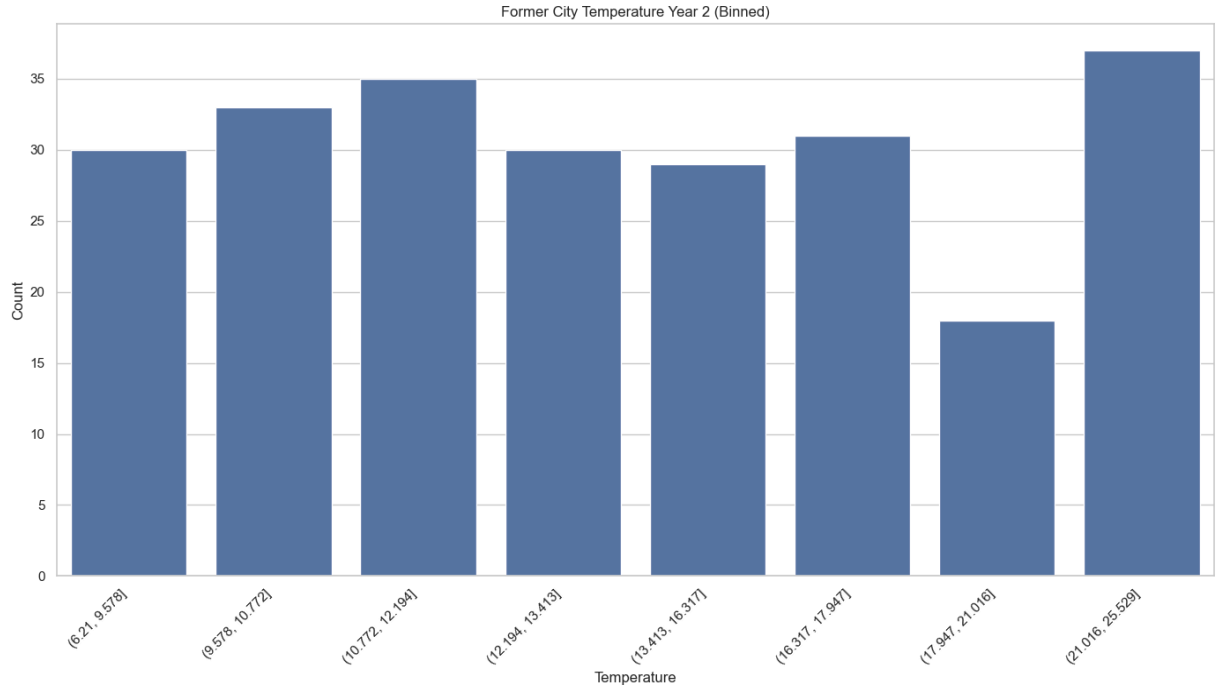
PCI differences - t-statistic: -0.8894896300814626, p-value: 0.3746653616580382

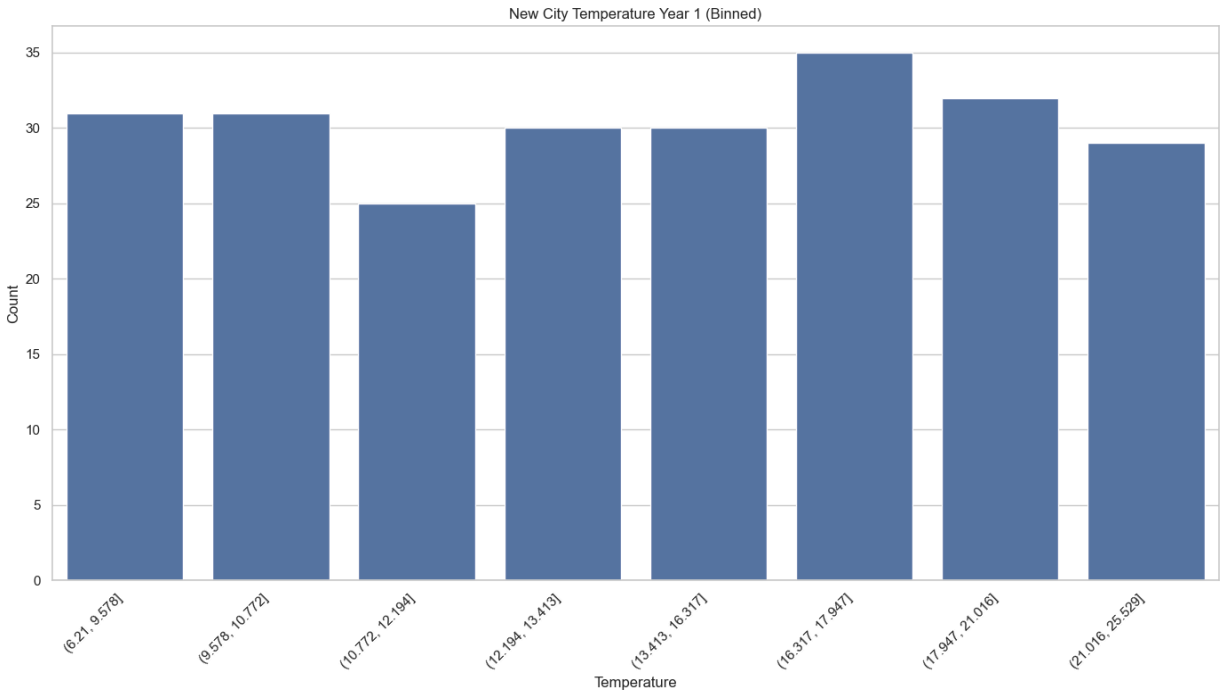
Not enough data for tax significance test.

Graphs from ‘graphing.ipynb’

Graphs for Average Annual Temperature



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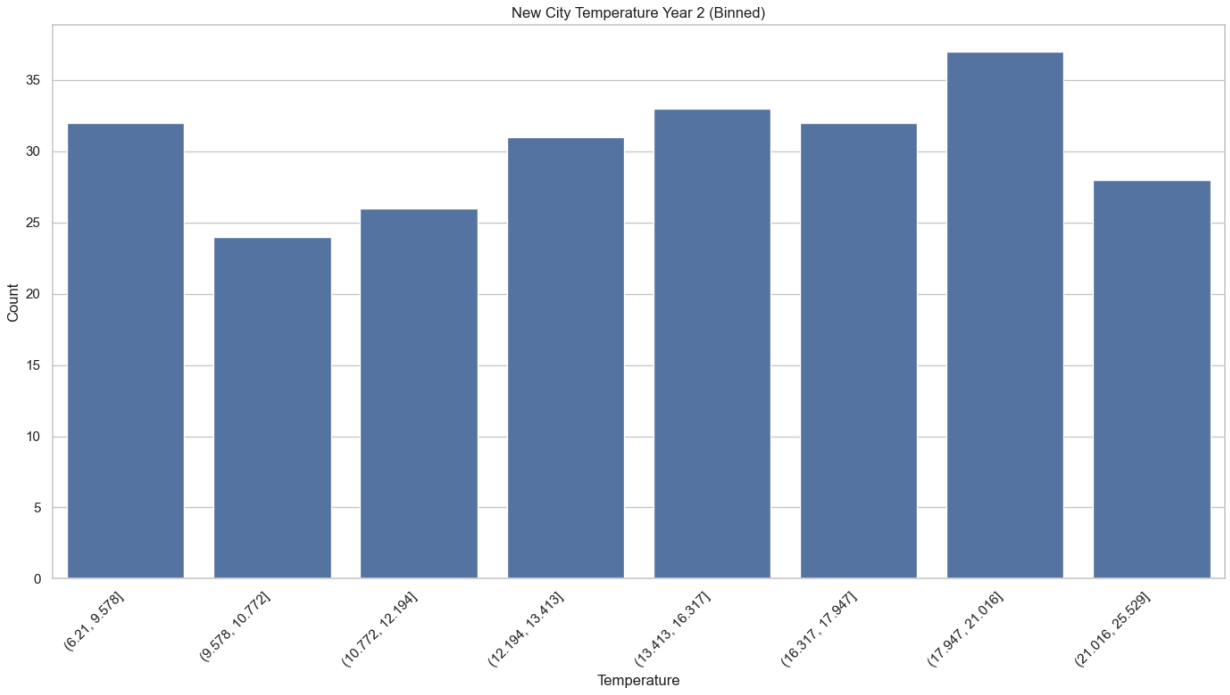
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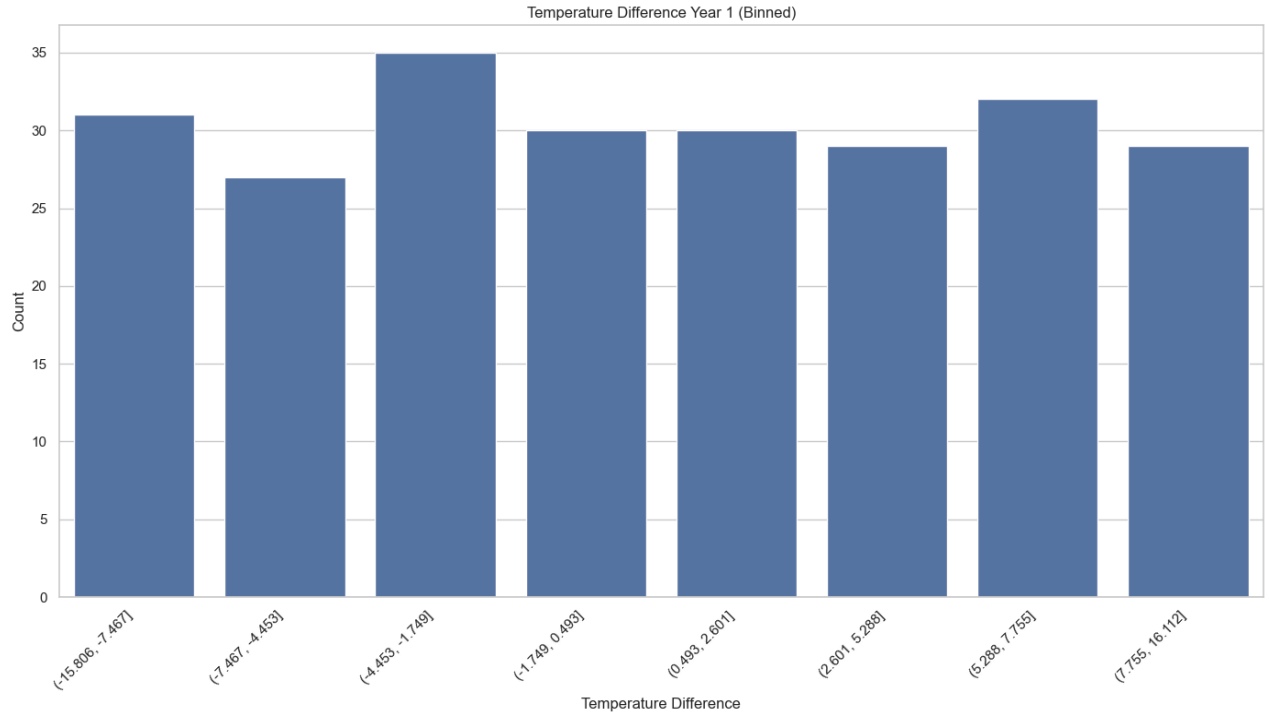
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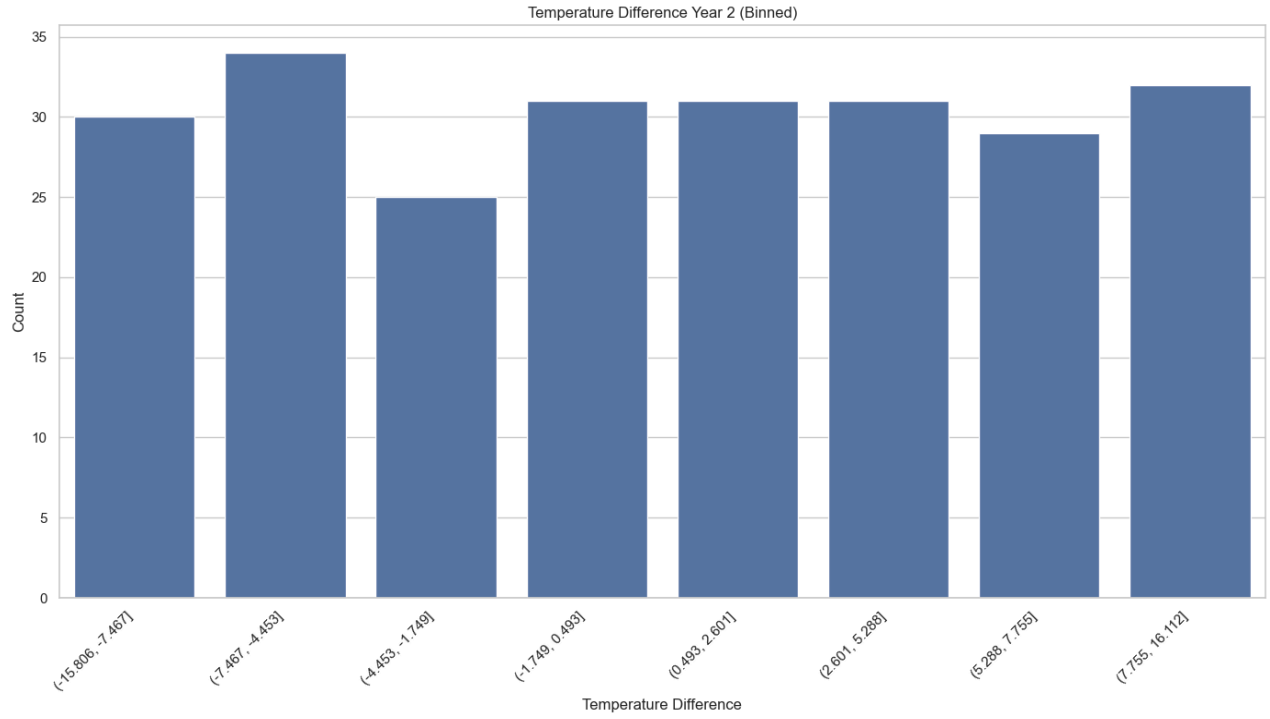
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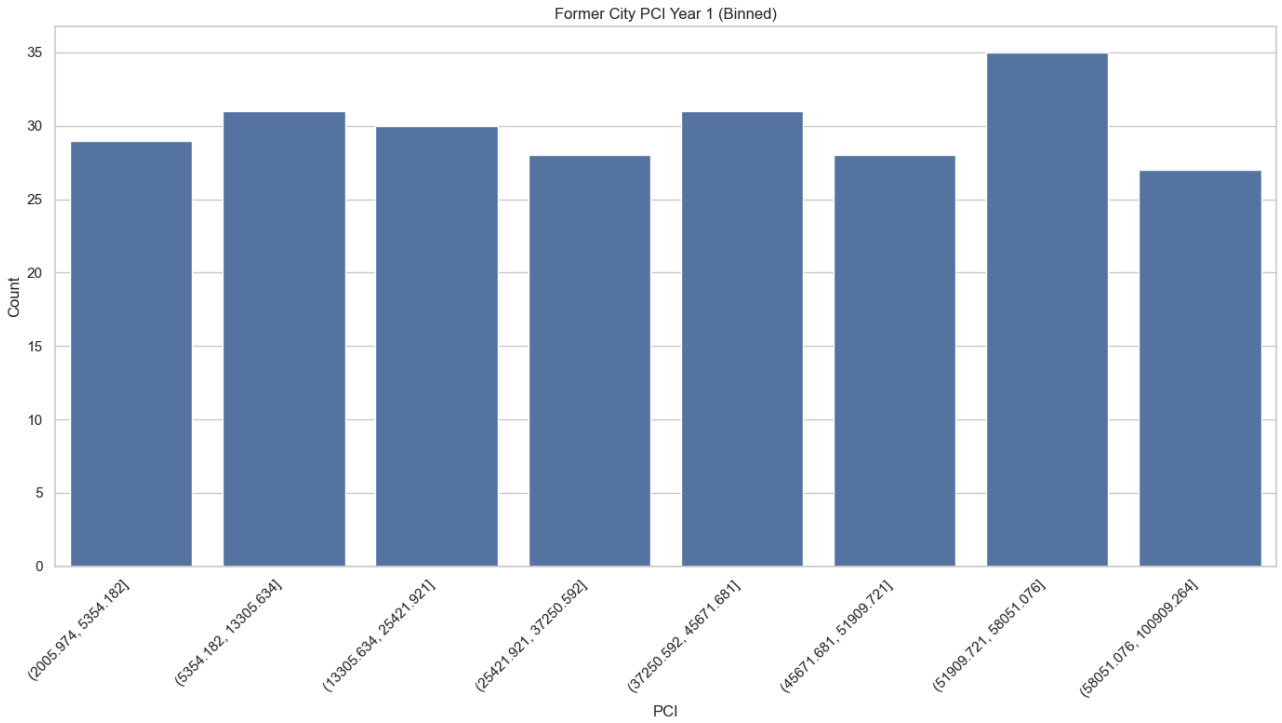
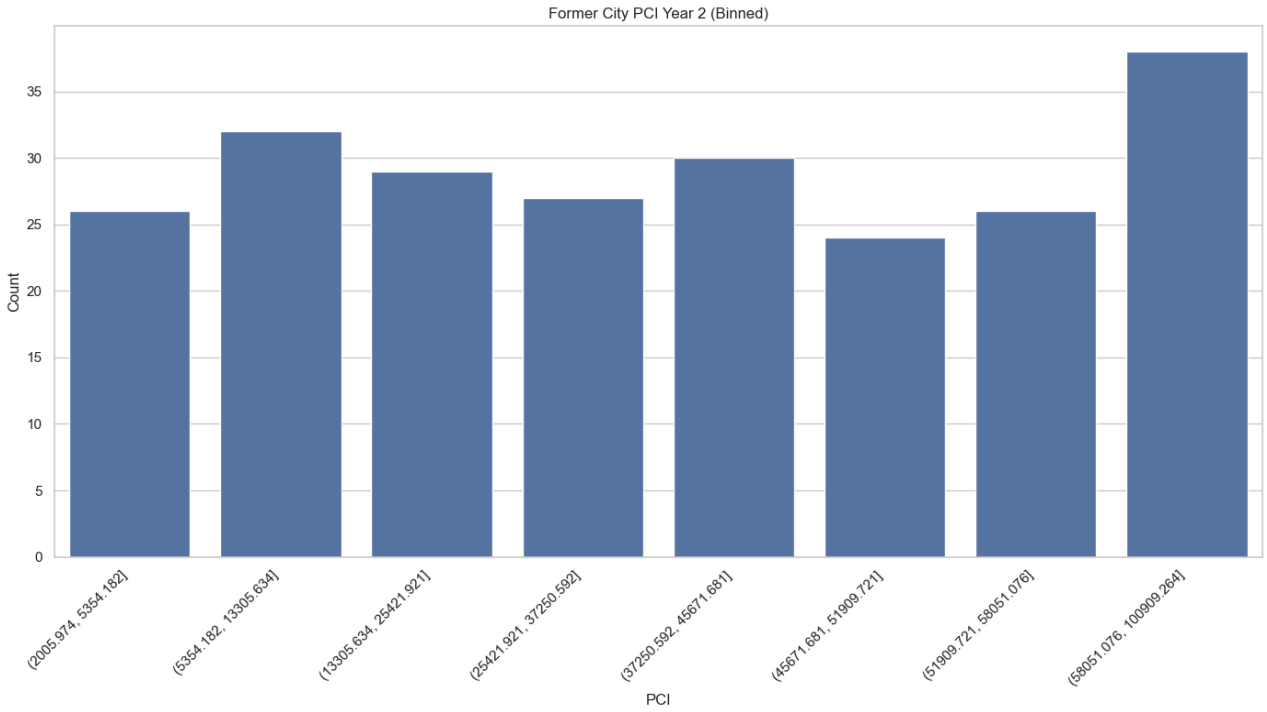
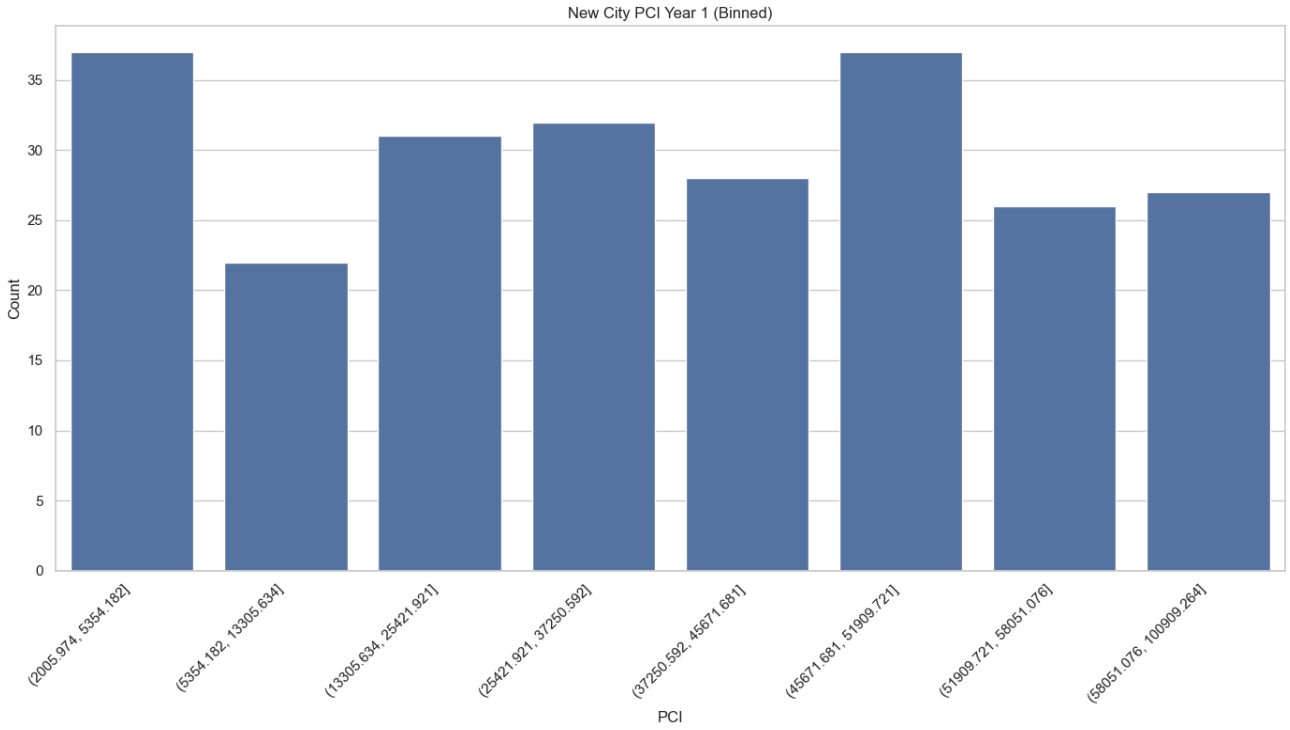
Temperature Difference

Graphs for Average PCI for States and Provinces



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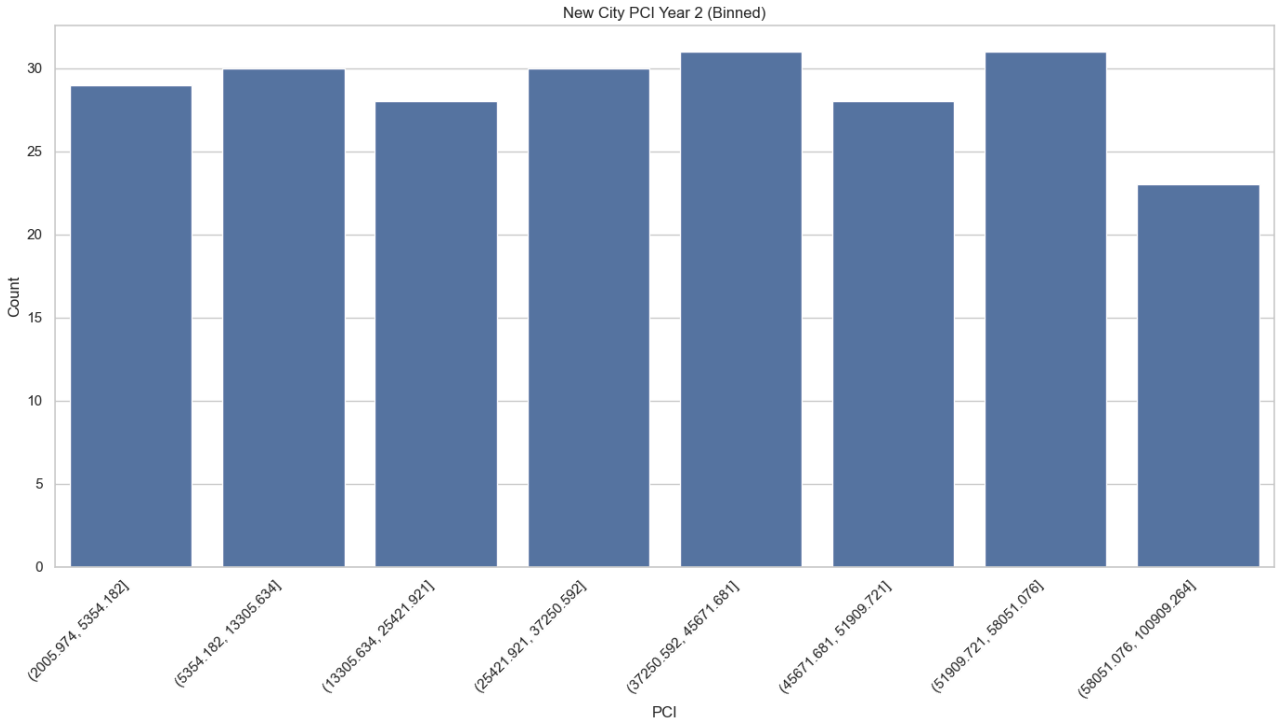
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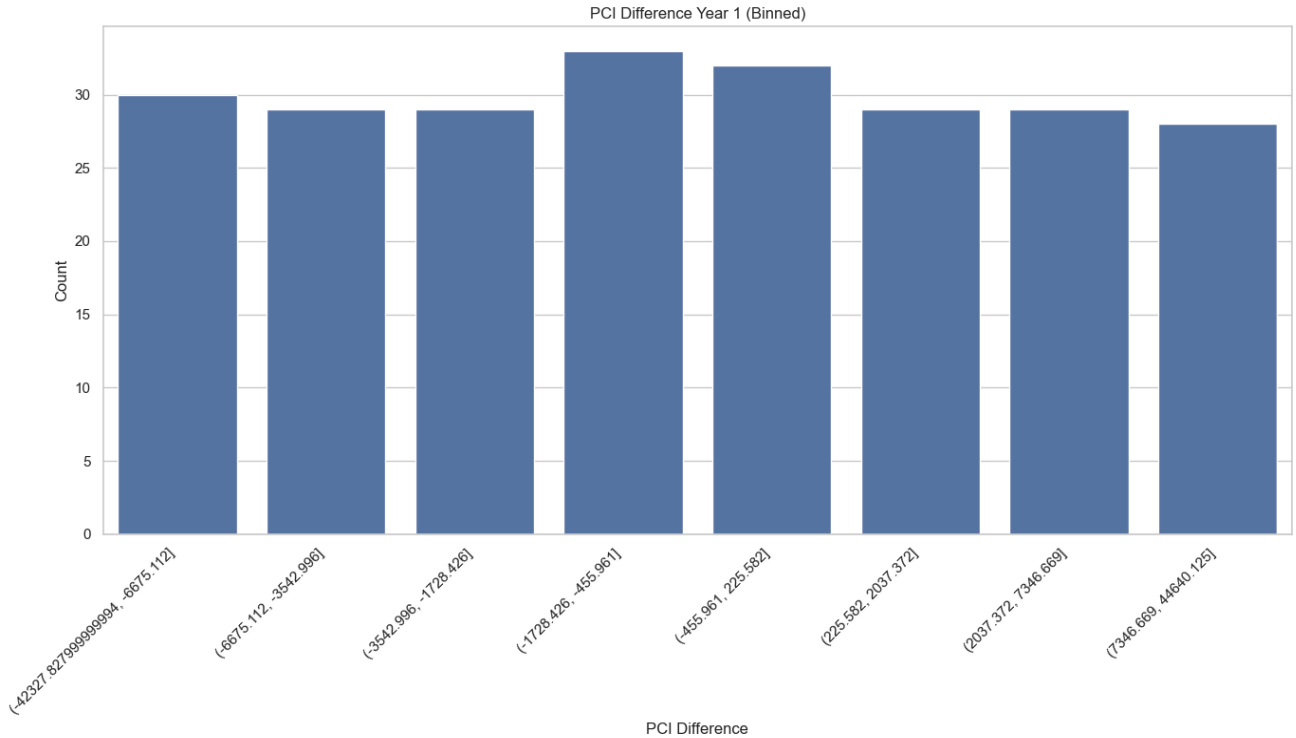
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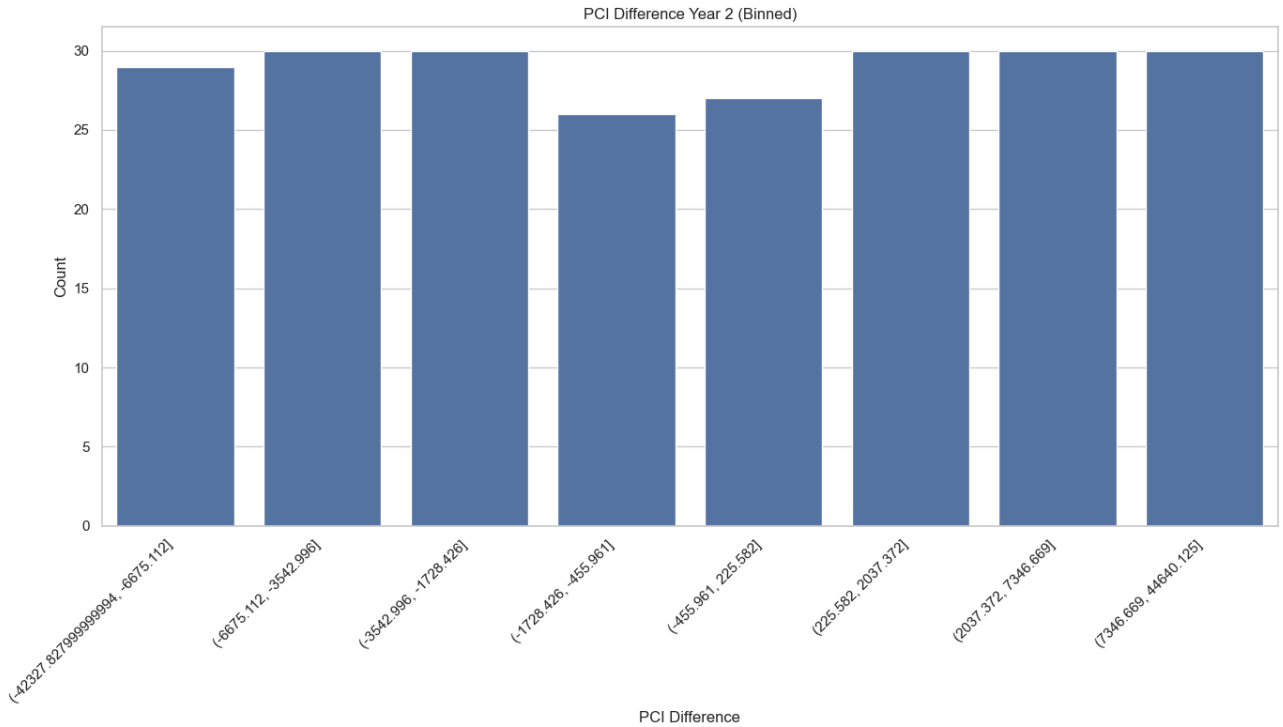
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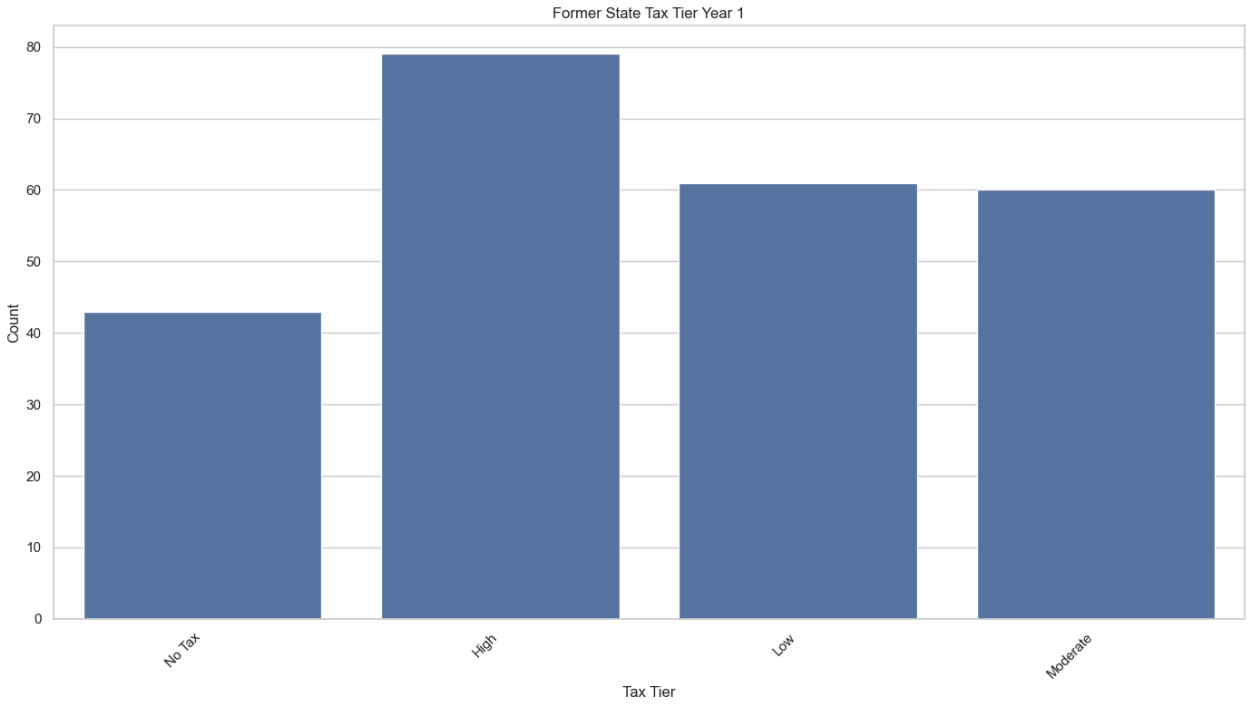
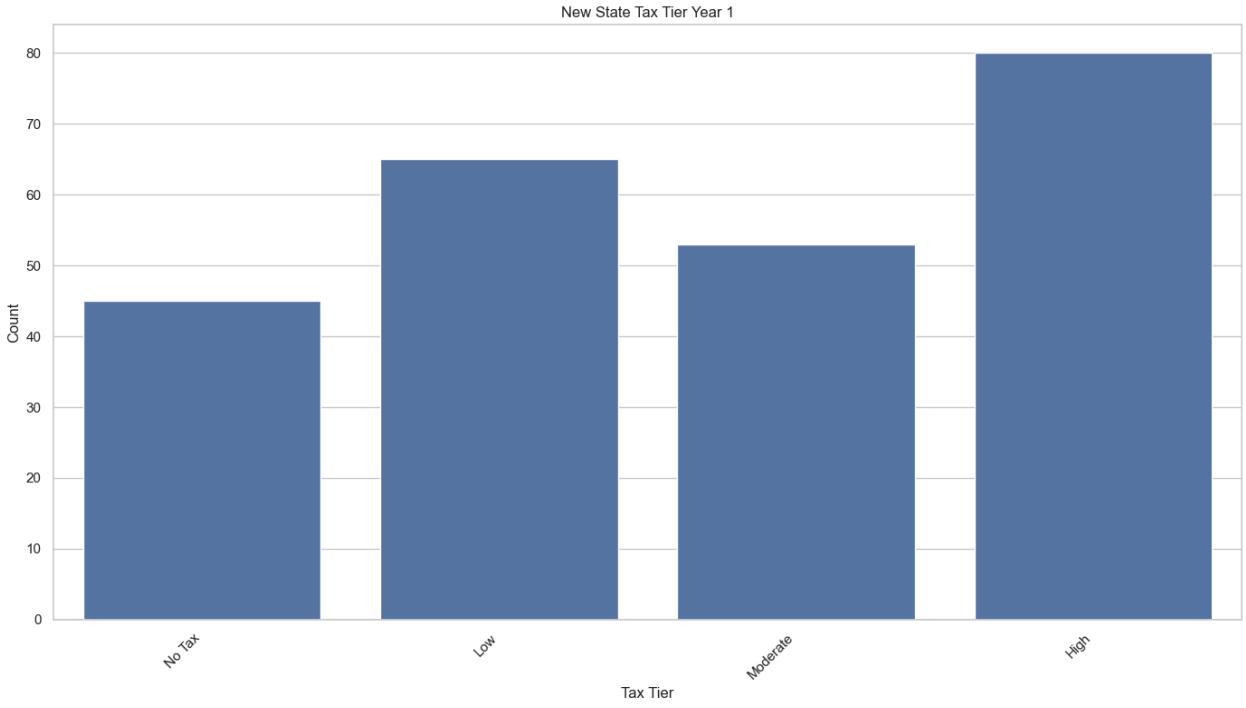
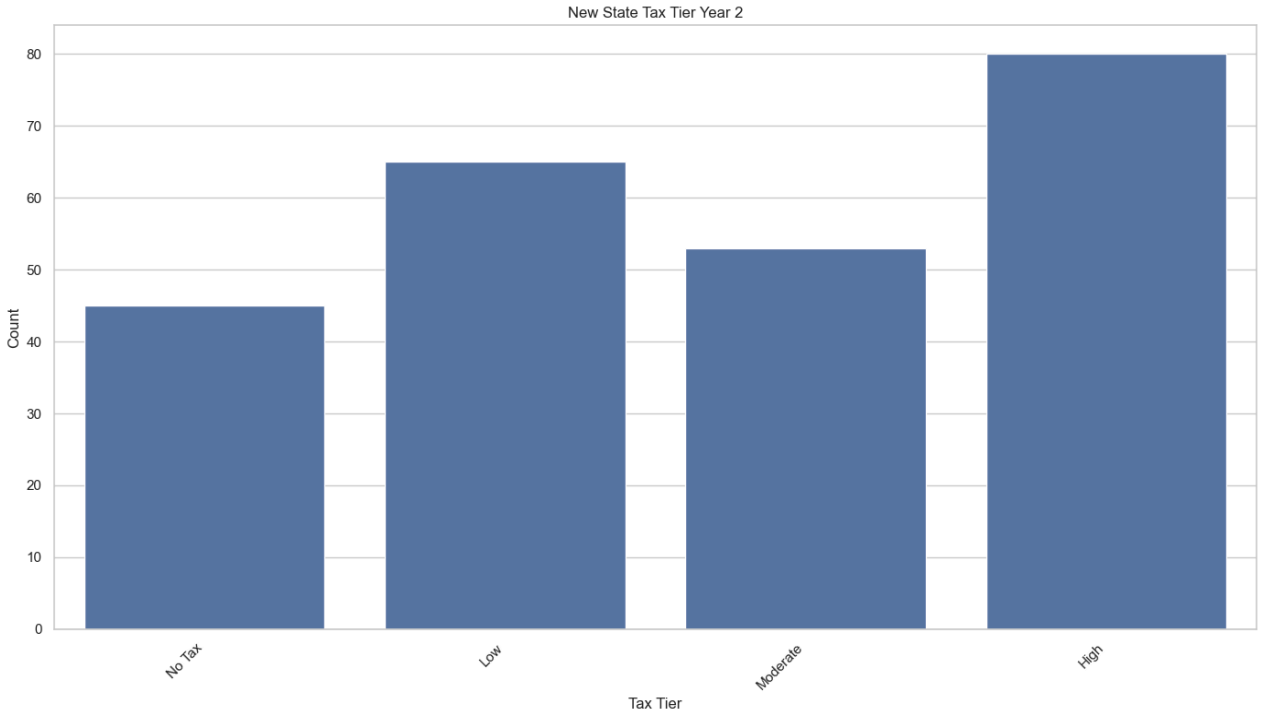
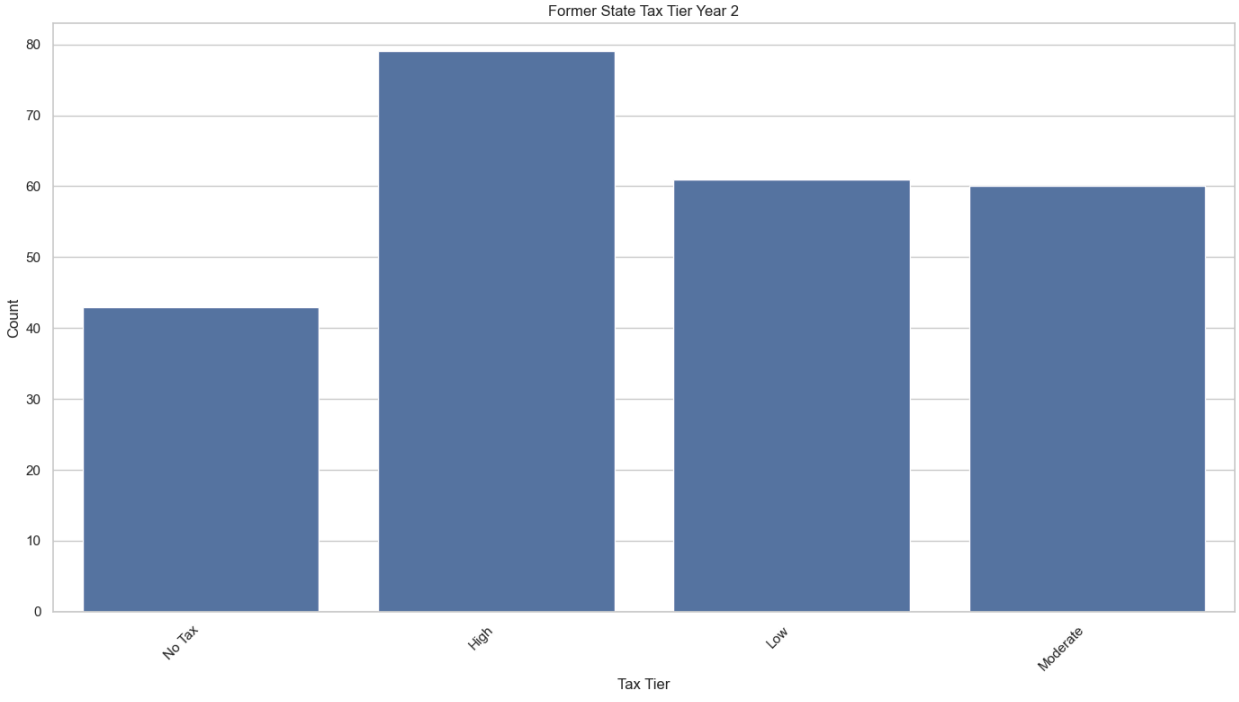
PCI Difference

Graphs for Tax Tiers for States and Provinces



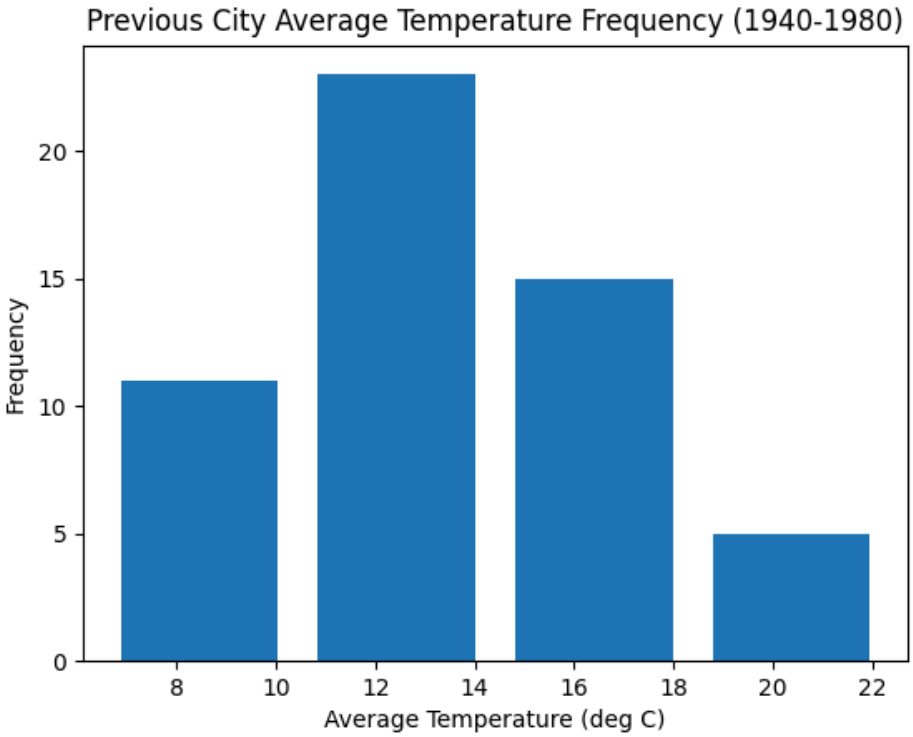


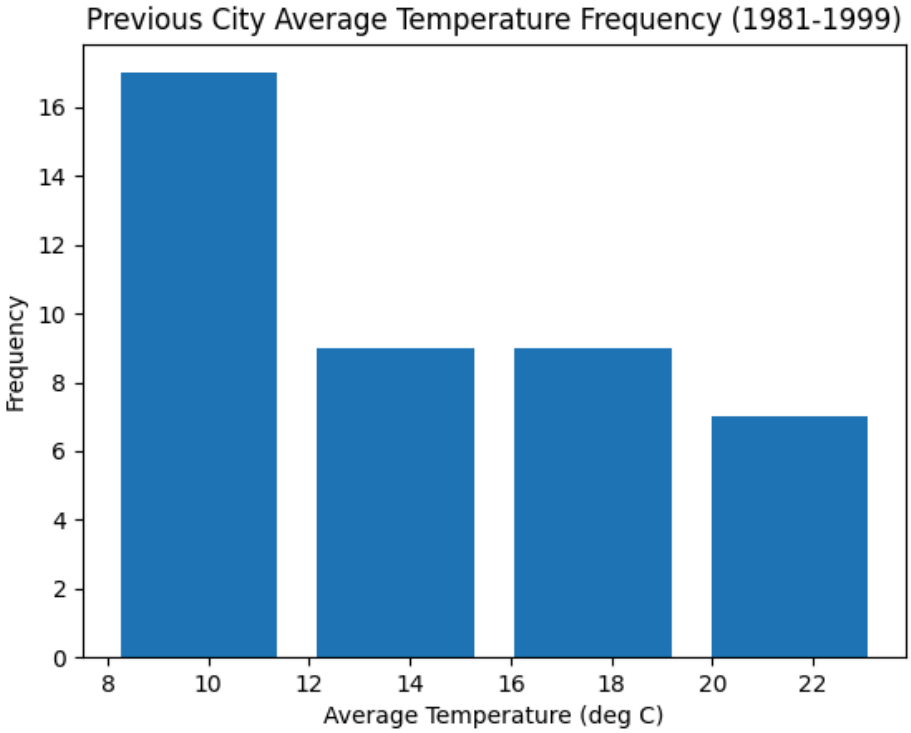


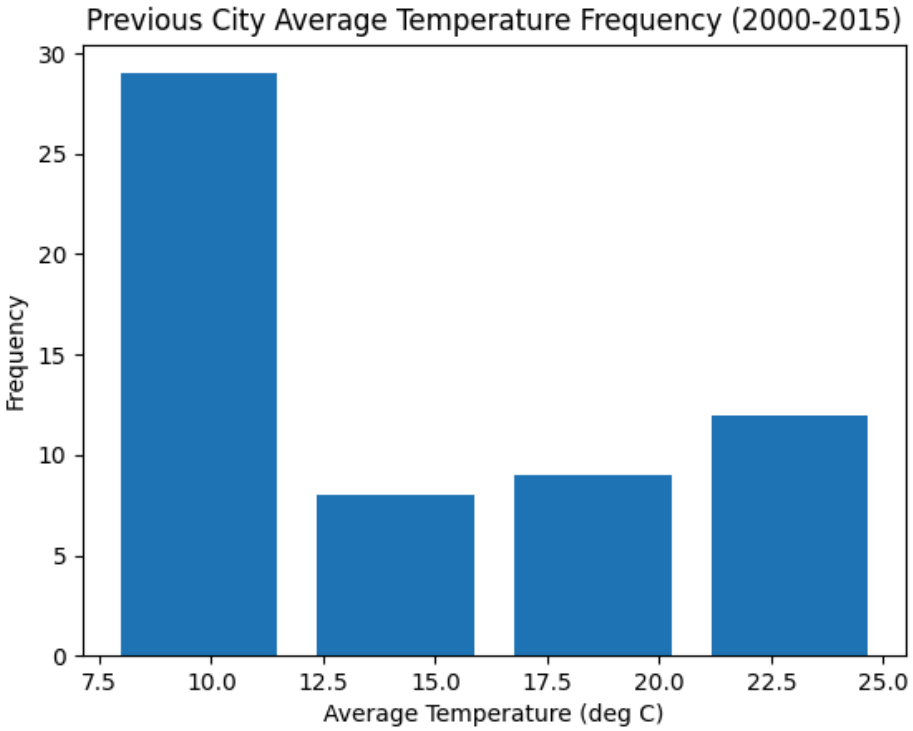


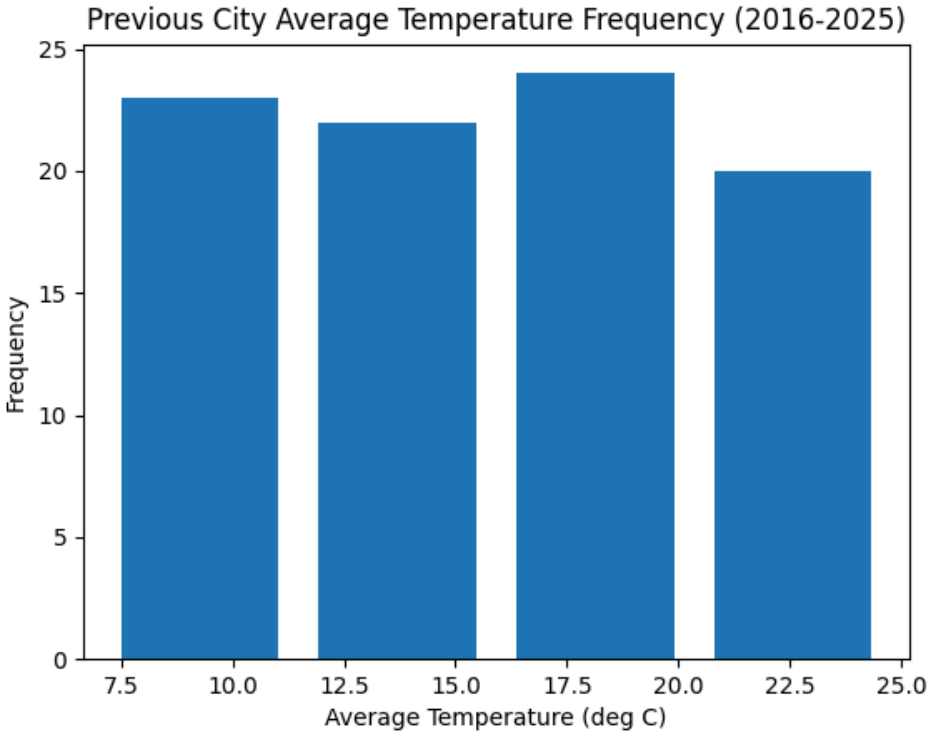
Trend Graphs from 'trend mapping.ipynb'

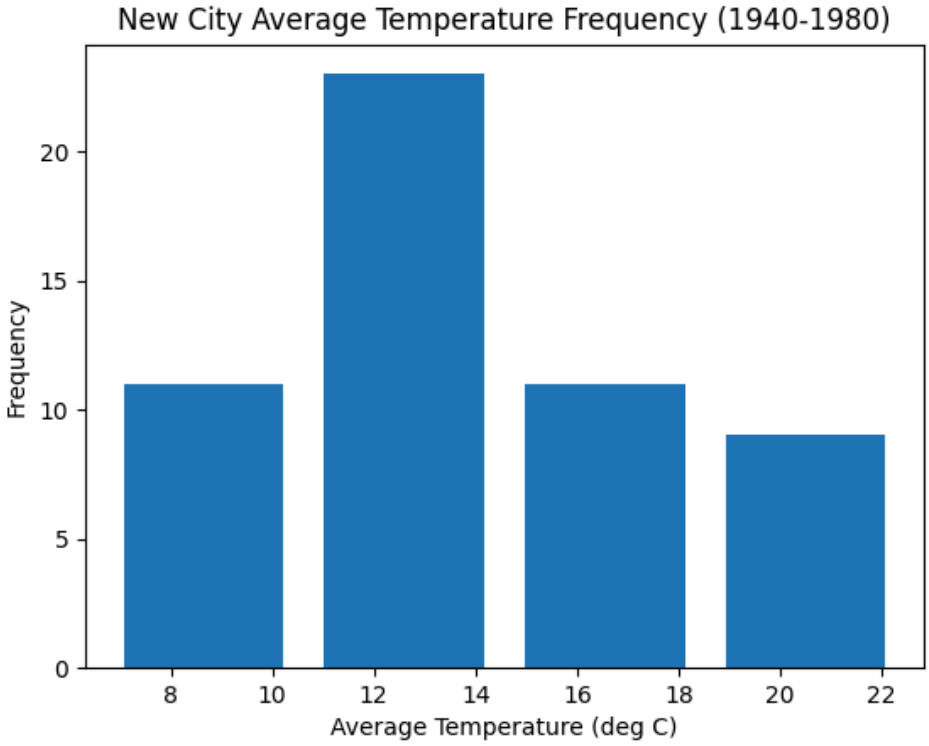
Trend Mapping for Average Temperature for States and Provinces

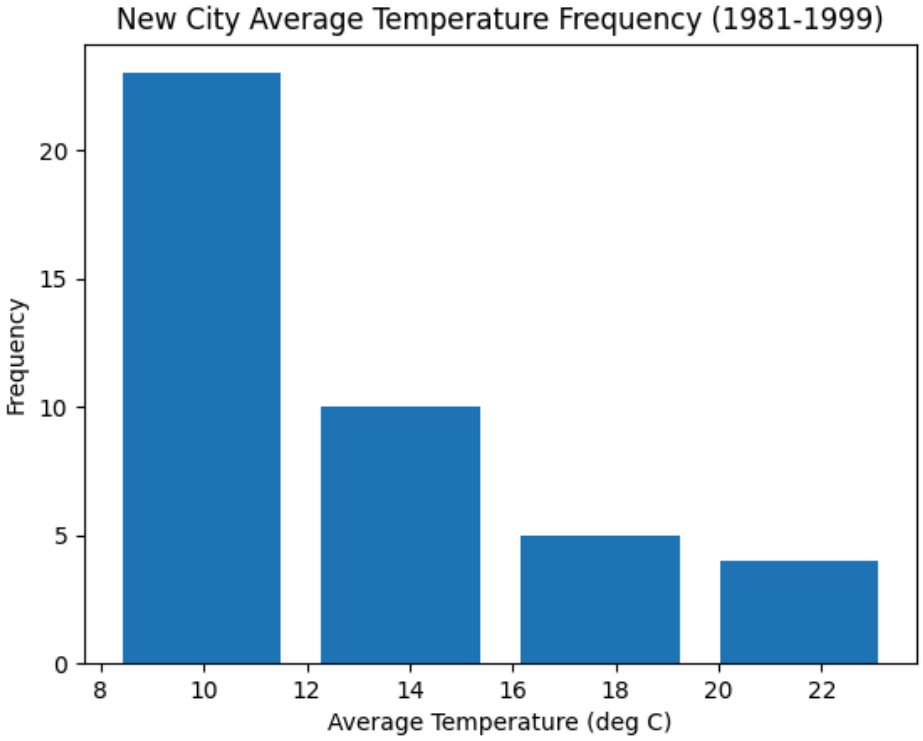

Previous City Average Temperature Frequency (1940-1980)
Frequency
0
5
10
15
20
8
10
12
14
16
18
20
22
Average Temperature (deg C)

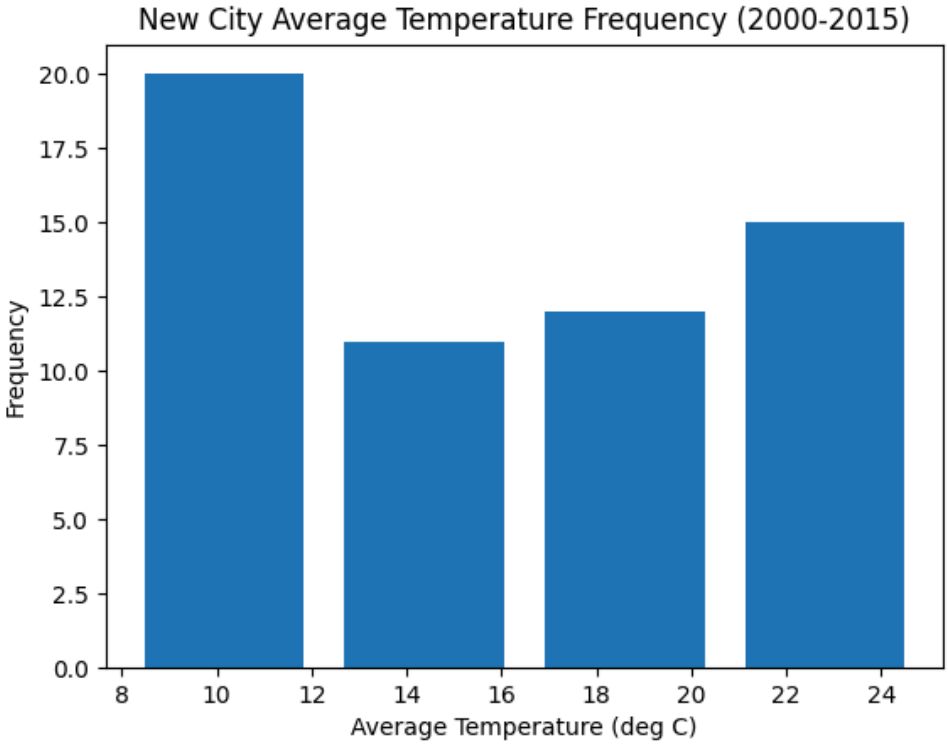

Previous City Average Temperature Frequency (1981-1999)
Frequency
0
2
4
6
8
10
12
14
16
8
10
12
14
16
18
20
22
Average Temperature (deg C)

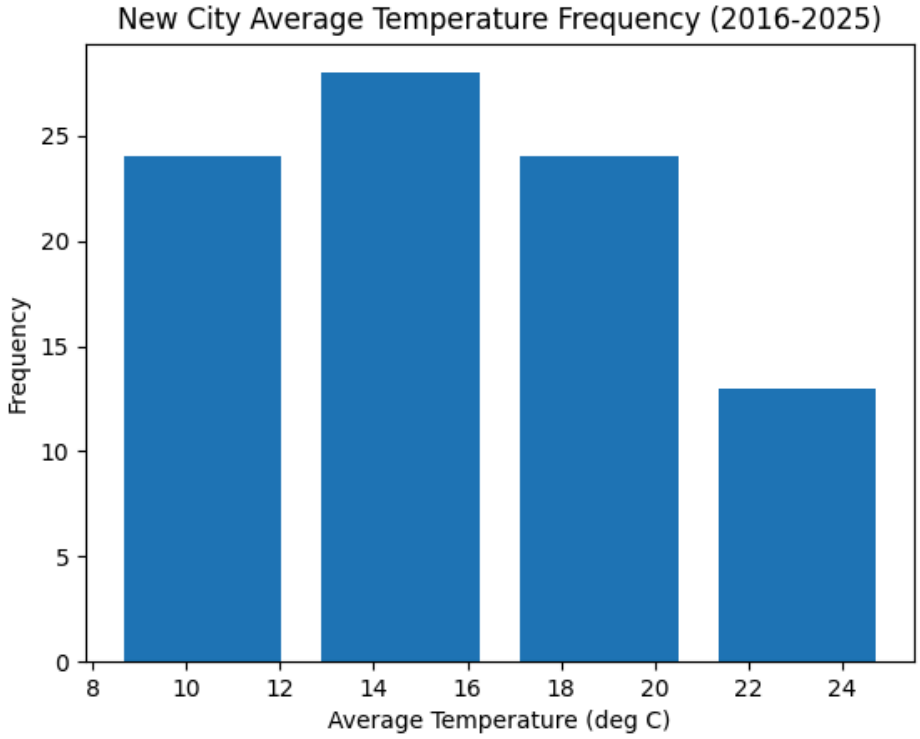

Previous City Average Temperature Frequency (2000-2015)
Frequency
Average Temperature (deg C)
0
5
10
15
20
25
30
7.5
10.0
12.5
15.0
17.5
20.0
22.5
25.0

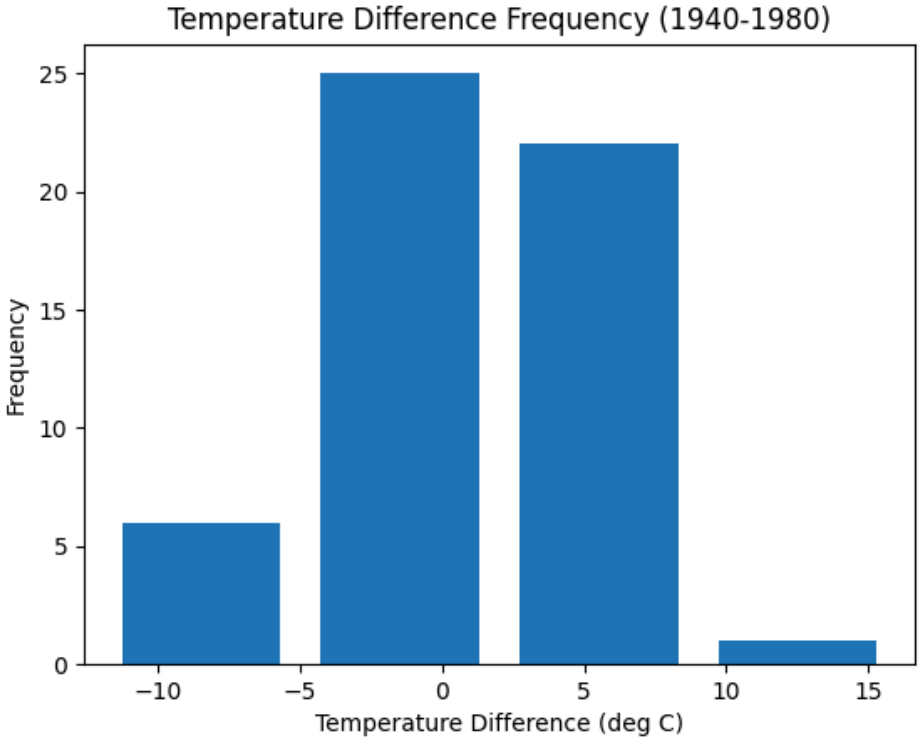

Previous City Average Temperature Frequency (2016-2025)
Frequency
Average Temperature (deg C)
0
5
10
15
20
25
7.5
10.0
12.5
15.0
17.5
20.0
22.5
25.0

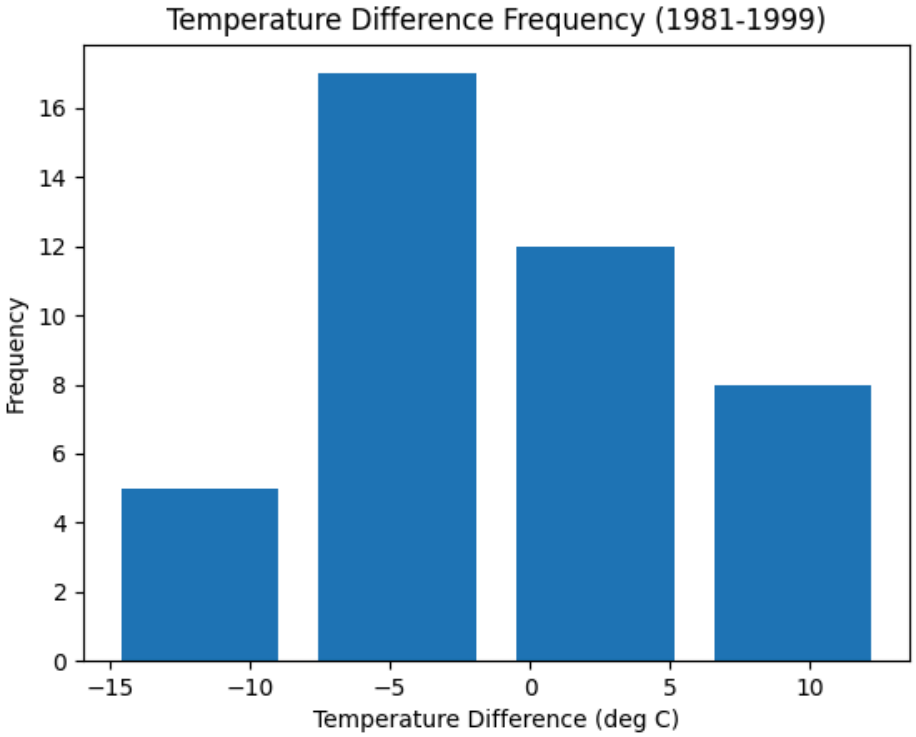

New City Average Temperature Frequency (1940-1980)
Frequency
0
5
10
15
20
8
10
12
14
16
18
20
22
Average Temperature (deg C)

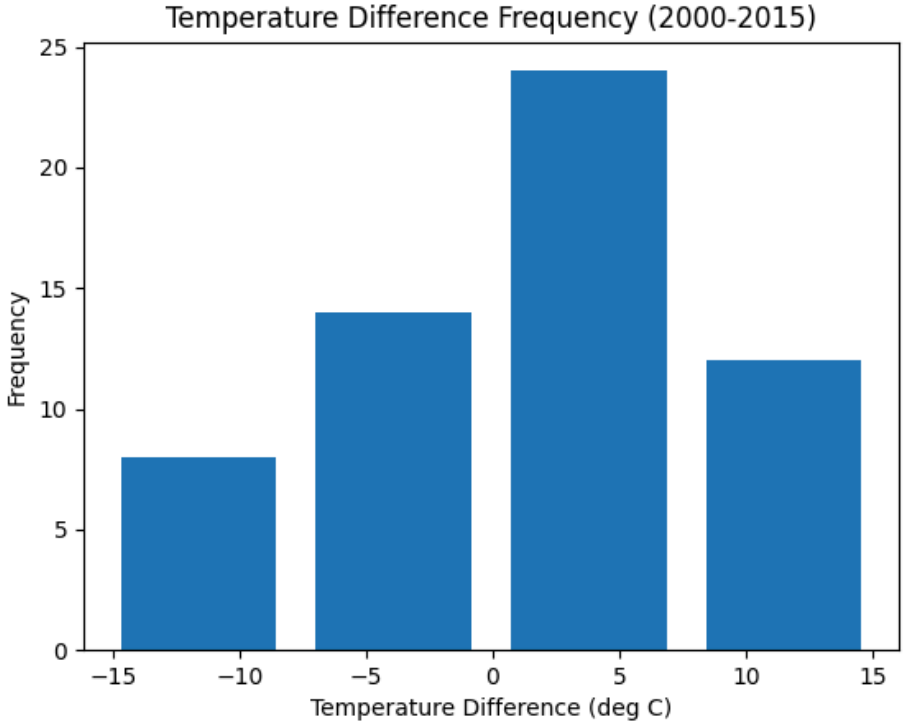

New City Average Temperature Frequency (1981-1999)
Frequency
0
5
10
15
20
8
10
12
14
16
18
20
22
Average Temperature (deg C)

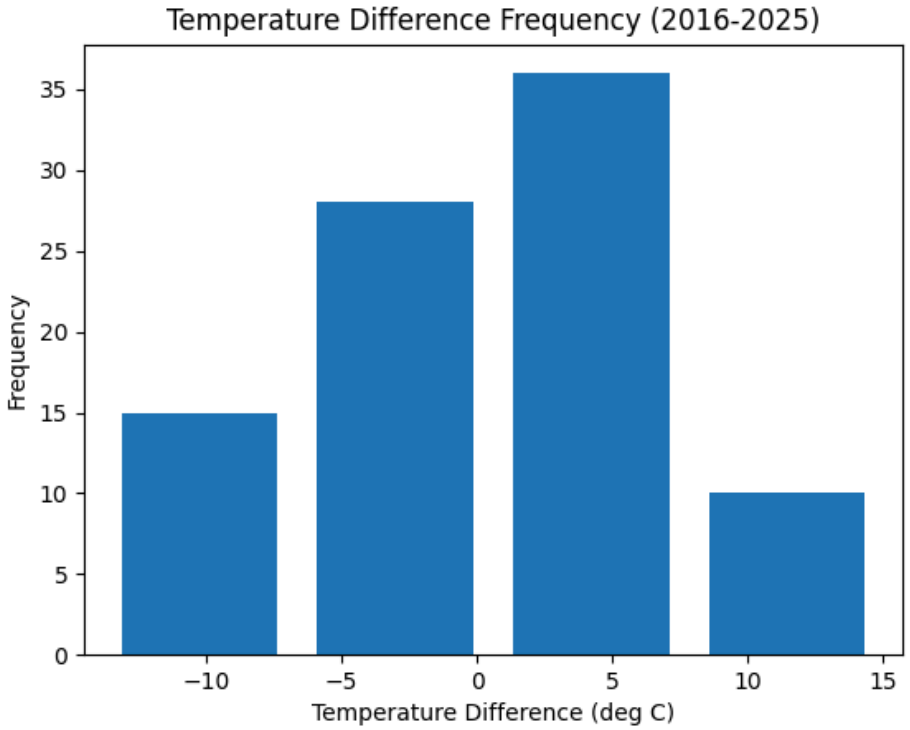

New City Average Temperature Frequency (2000-2015)
Frequency
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
8
10
12
14
16
18
20
22
24
Average Temperature (deg C)


New City Average Temperature Frequency (2016-2025)
Frequency
0
5
10
15
20
25
8
10
12
14
16
18
20
22
24
Average Temperature (deg C)

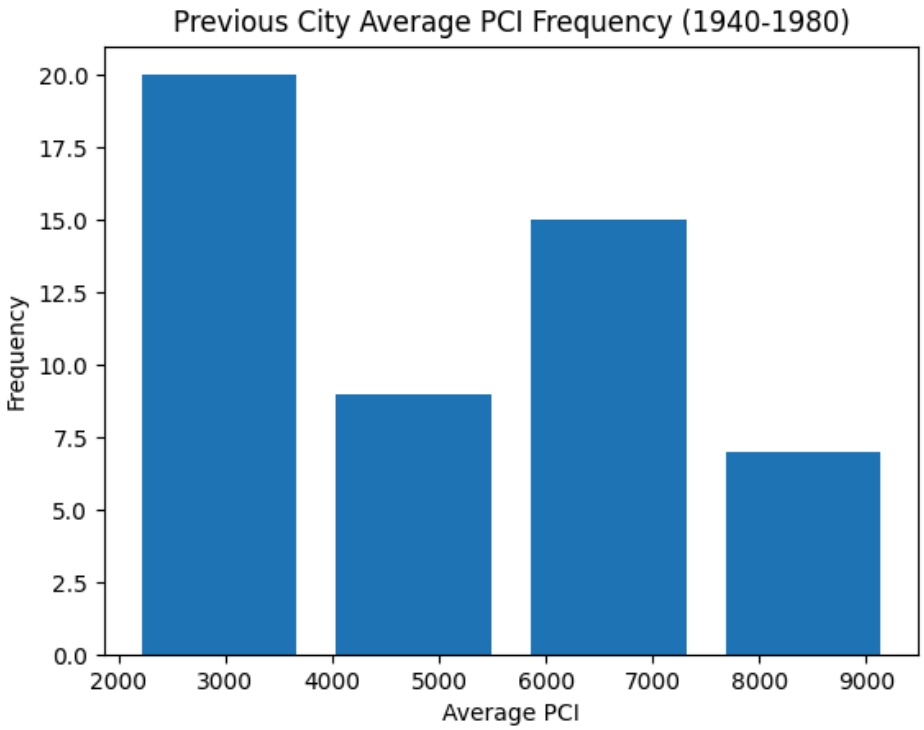

Temperature Difference Frequency (1940-1980)
Frequency
Temperature Difference (deg C)
25
20
15
10
5
0
−10
−5
0
5
10
15

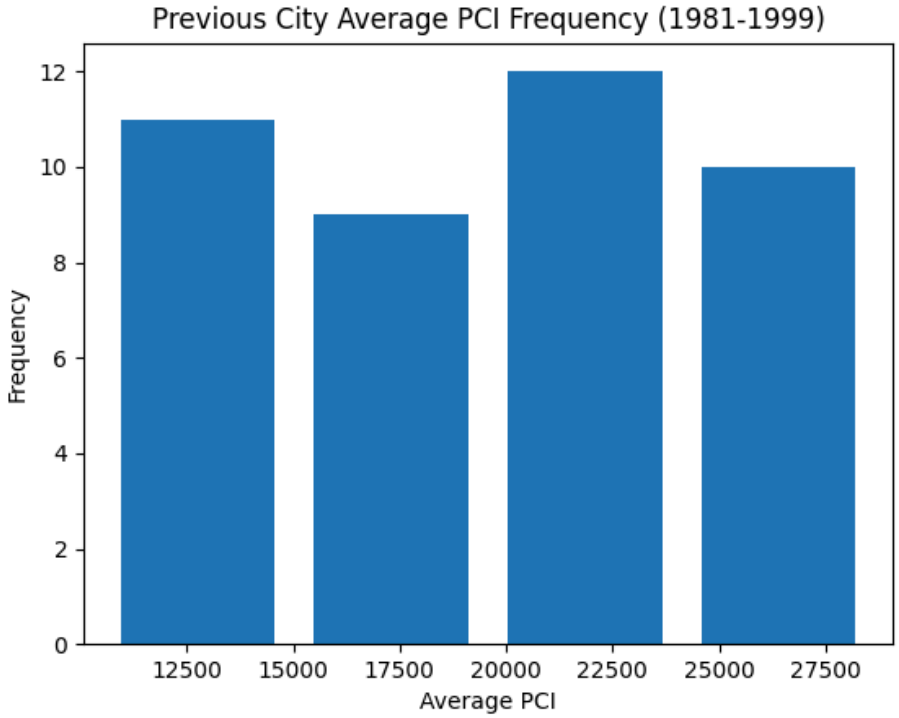

Temperature Difference Frequency (1981-1999)
Frequency
Temperature Difference (deg C)
16
14
12
10
8
6
4
2
0
−15
−10
−5
0
5
10

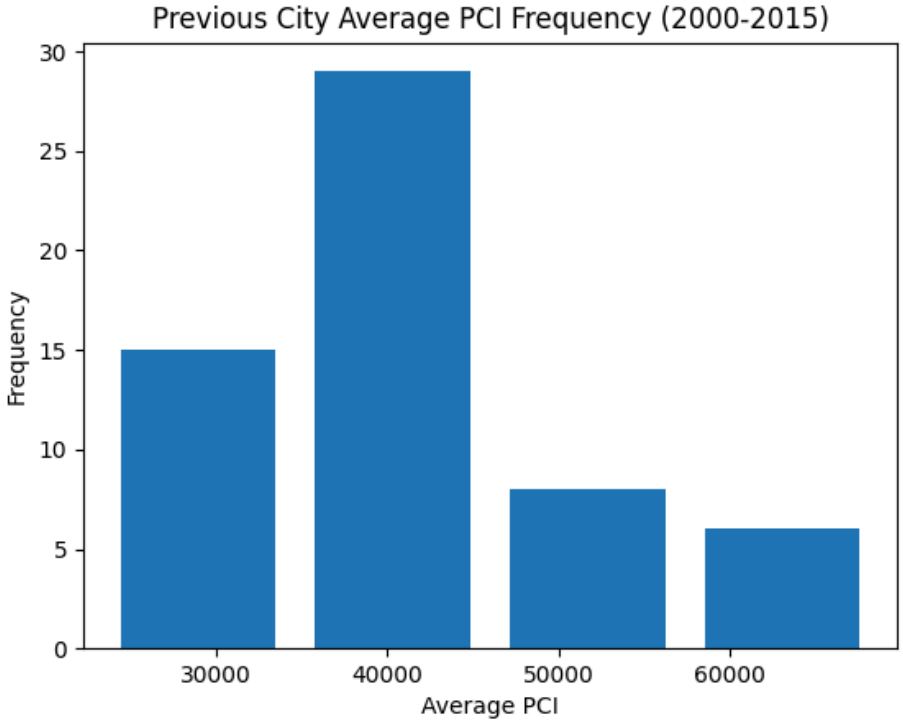

Temperature Difference Frequency (2000-2015)
Frequency
Temperature Difference (deg C)
0
5
10
15
20
25
−15
−10
−5
0
5
10
15

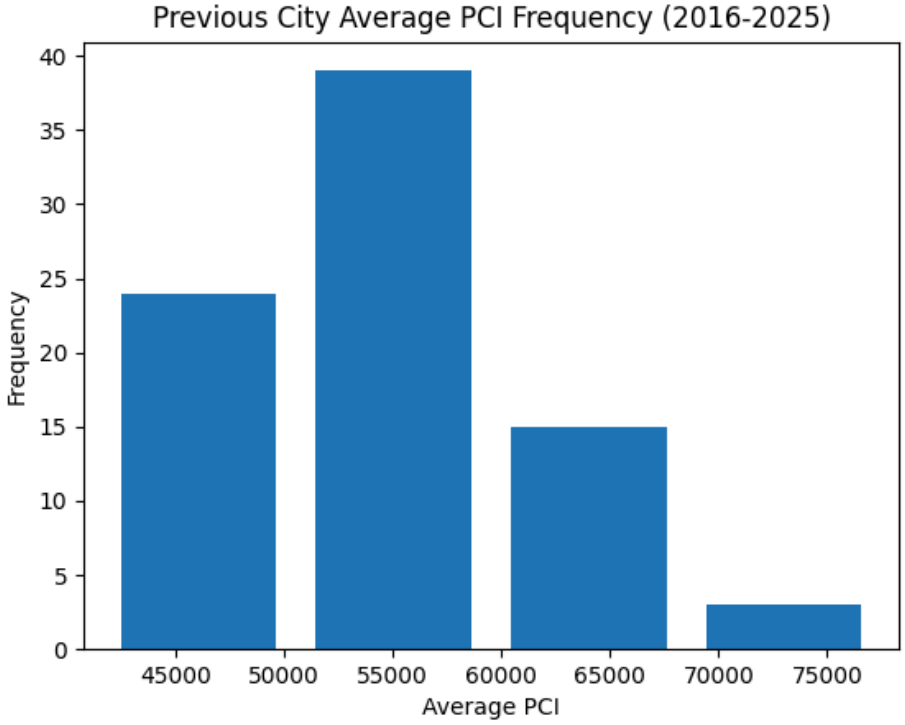

Temperature Difference Frequency (2016-2025)
Frequency
Temperature Difference (deg C)
0
5
10
15
20
25
30
35
−10
−5
0
5
10
15

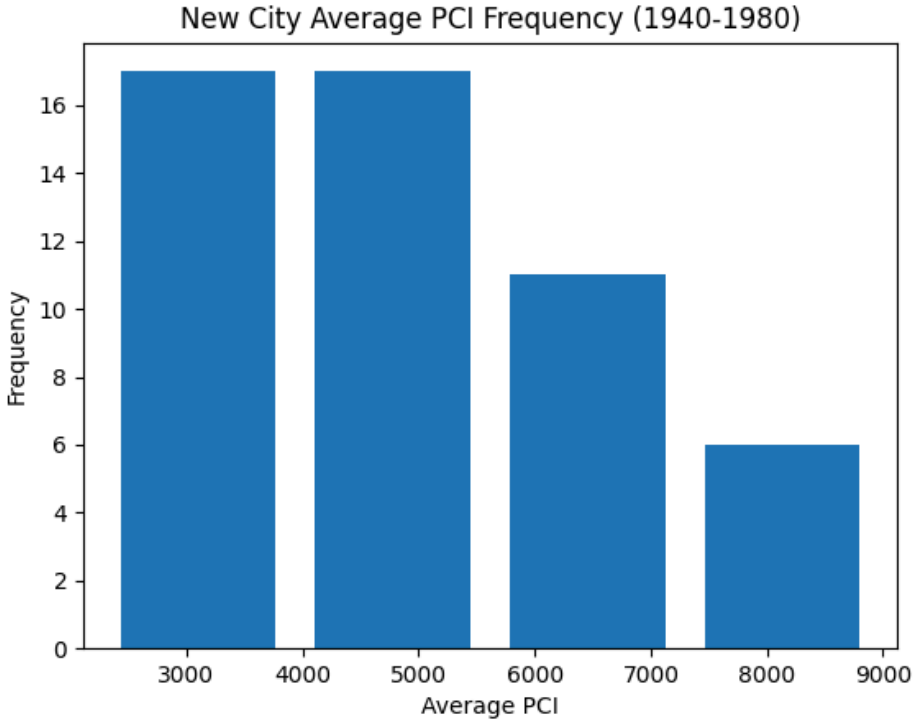
Trend Mapping for PCI for States and Provinces

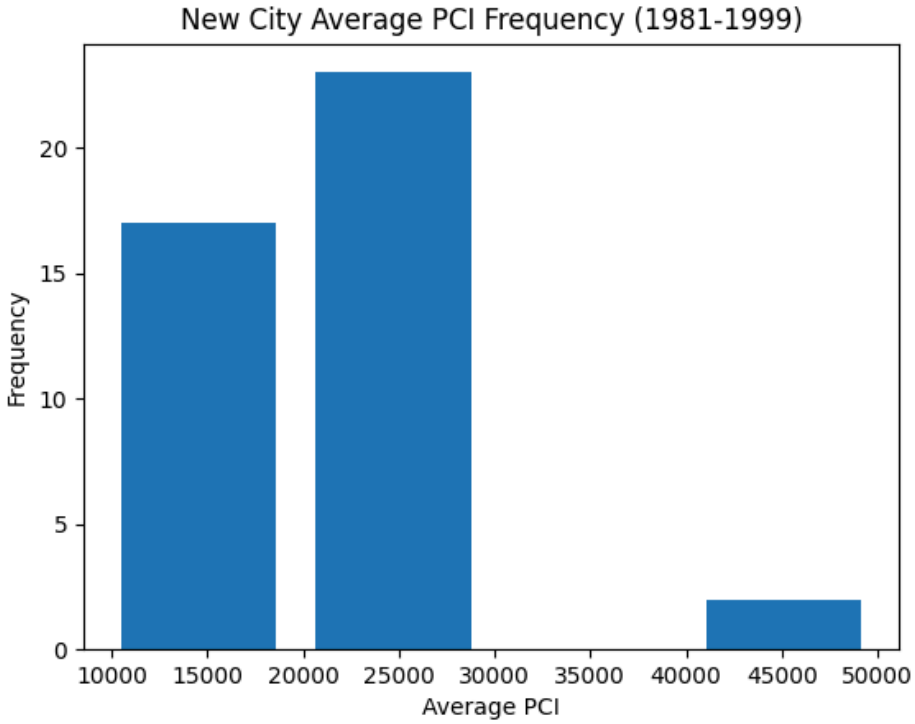


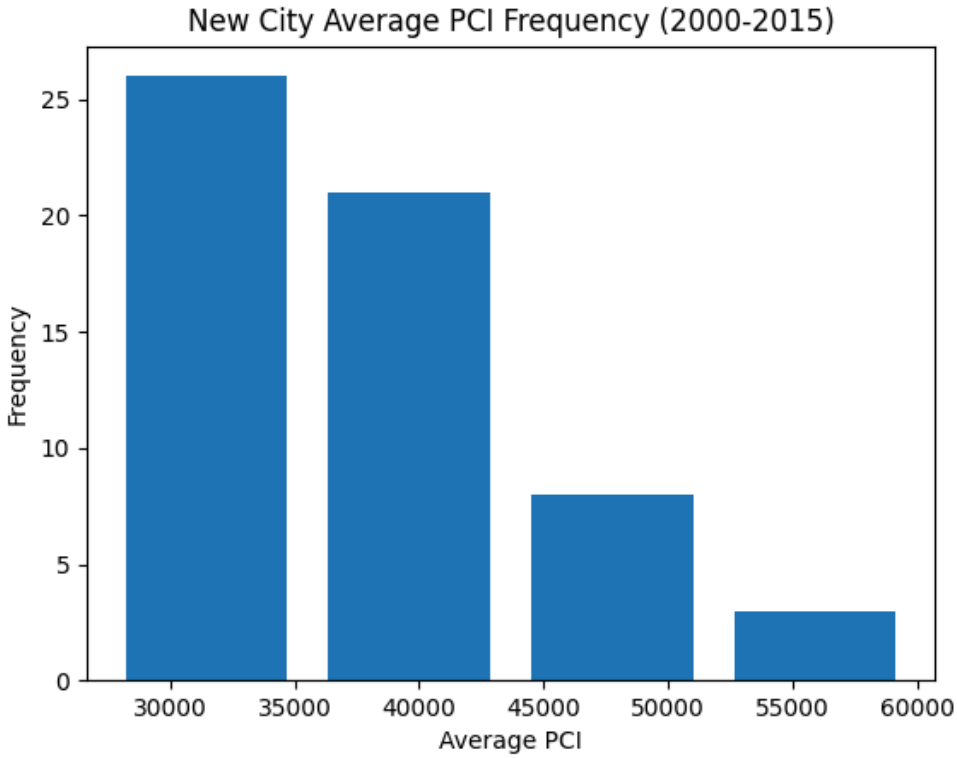


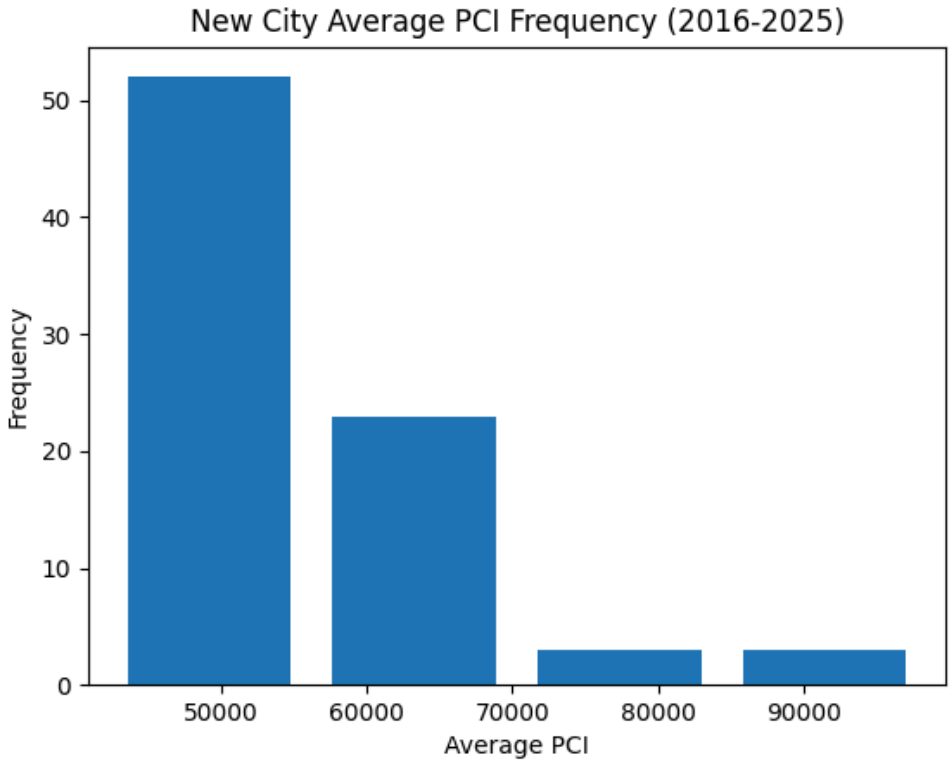

Previous City Average PCI Frequency (2000-2015)
Frequency
Average PCI
0
5
10
15
20
25
30
30000
40000
50000
60000

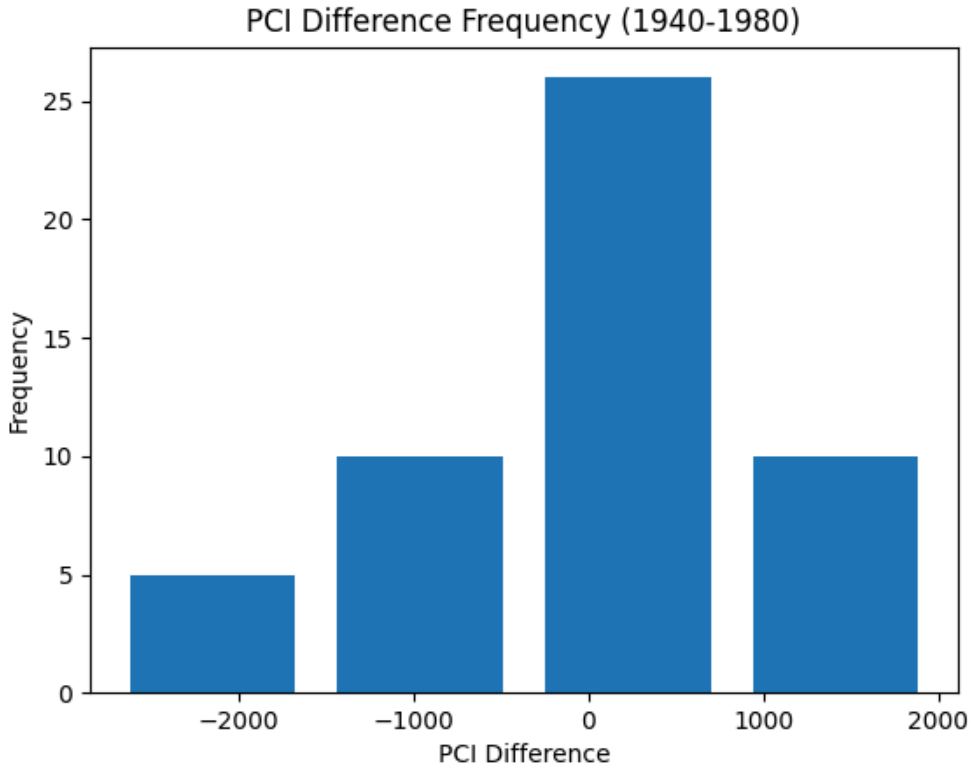

Previous City Average PCI Frequency (2016-2025)
Frequency
Average PCI
0
5
10
15
20
25
30
35
40
45000
50000
55000
60000
65000
70000
75000

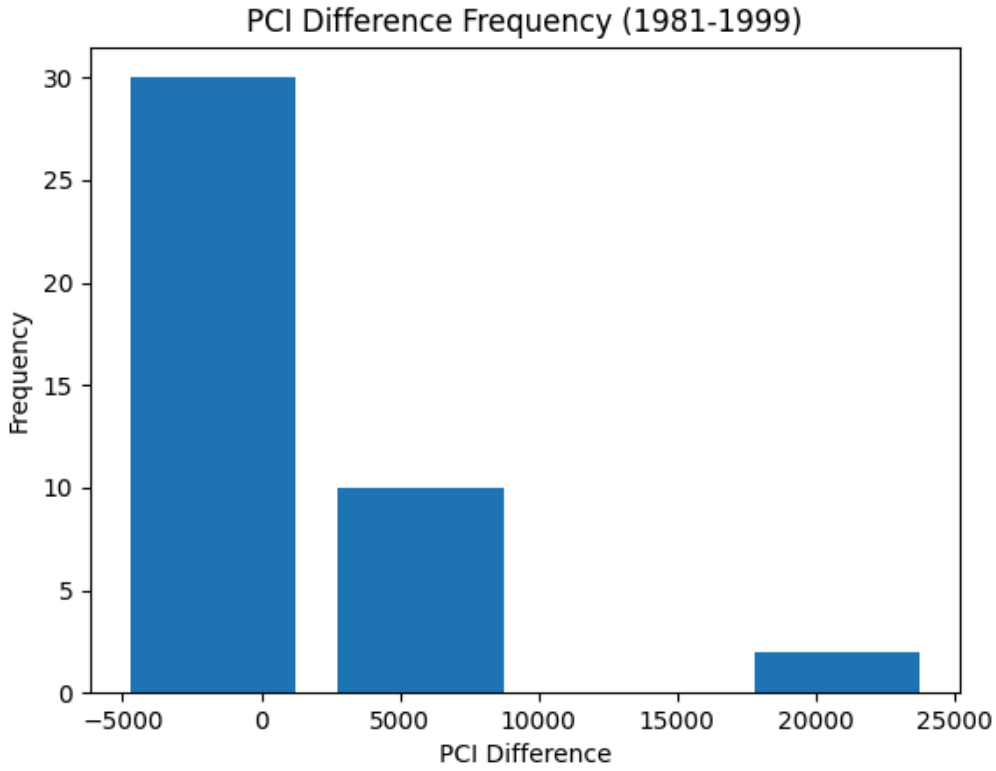

New City Average PCI Frequency (1940-1980)
Frequency
0
2
4
6
8
10
12
14
16
3000
4000
5000
6000
7000
8000
9000
Average PCI

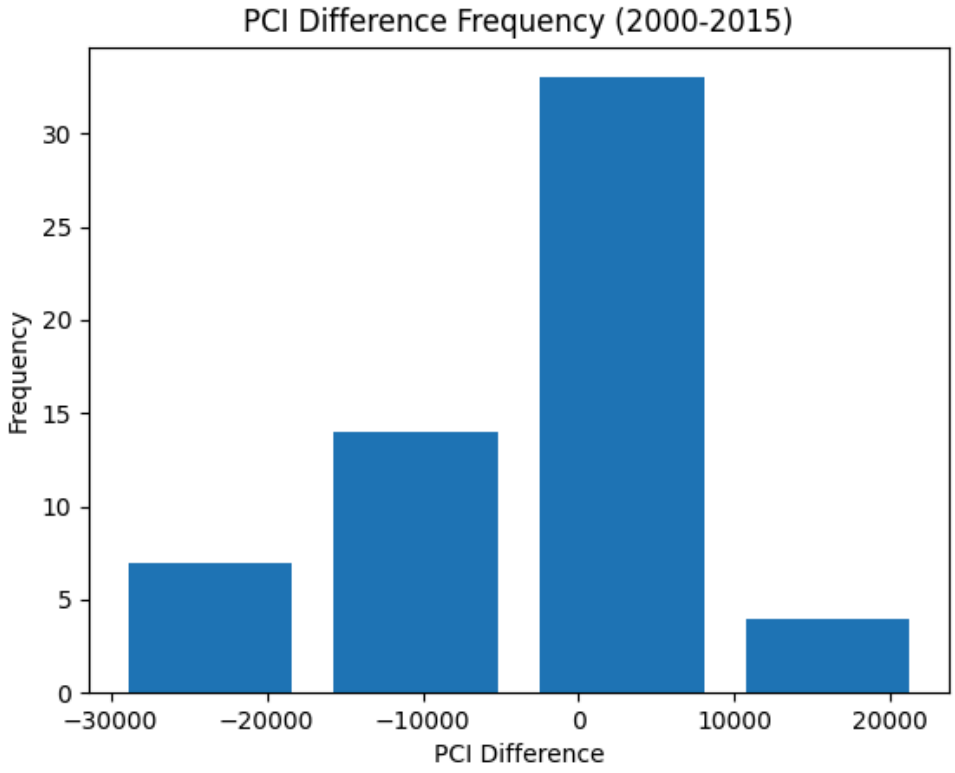

New City Average PCI Frequency (1981-1999)
Frequency
0
5
10
15
20
10000
15000
20000
25000
30000
35000
40000
45000
50000
Average PCI

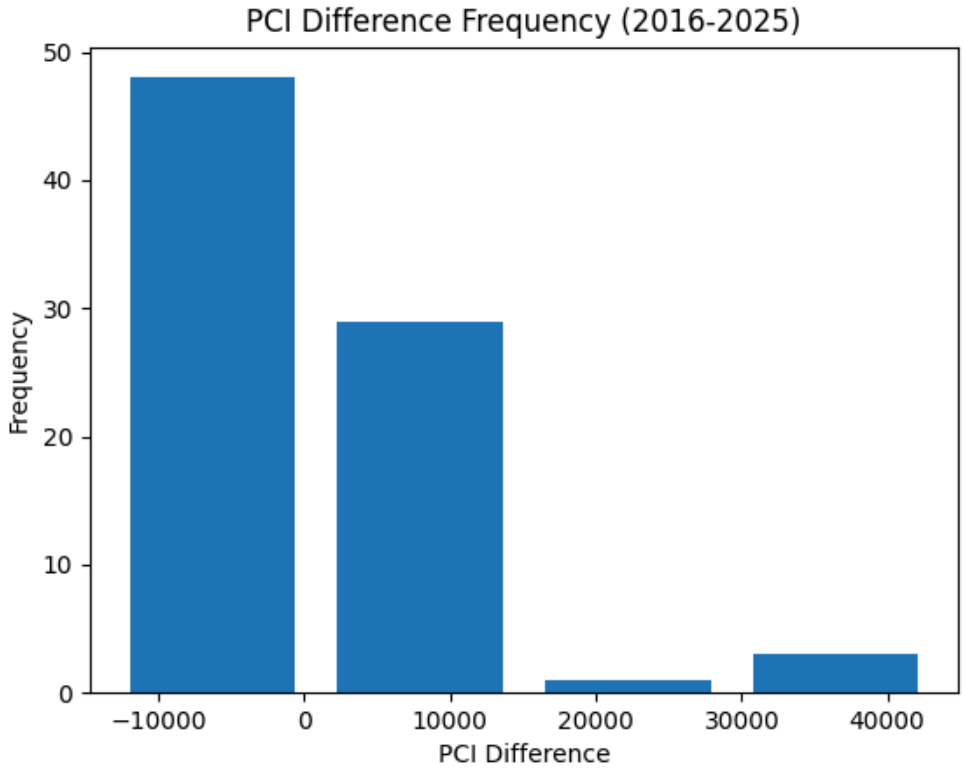

New City Average PCI Frequency (2000-2015)
Frequency
0
5
10
15
20
25
30000
35000
40000
45000
50000
55000
60000
Average PCI


New City Average PCI Frequency (2016-2025)
Frequency
0
10
20
30
40
50
50000
60000
70000
80000
90000
Average PCI


PCI Difference Frequency (1940-1980)
Frequency
PCI Difference
0
5
10
15
20
25
−2000
−1000
0
1000
2000


PCI Difference Frequency (1981-1999)
Frequency
PCI Difference
0
5
10
15
20
25
30
−5000
0
5000
10000
15000
20000
25000

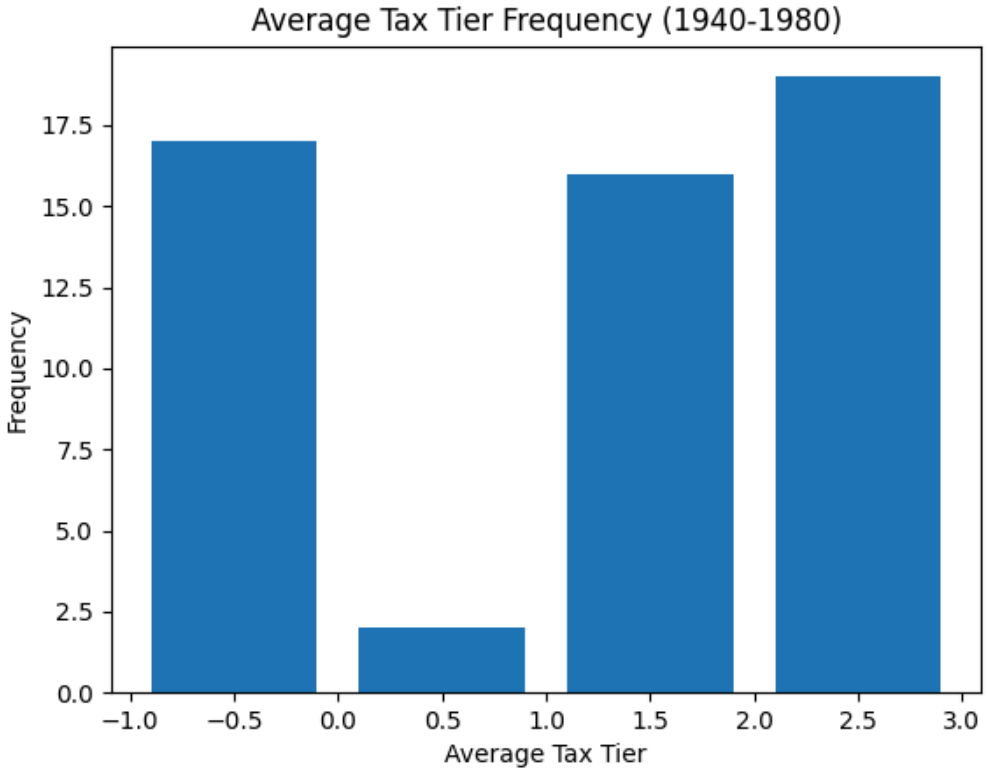

PCI Difference Frequency (2000-2015)
Frequency
PCI Difference
0
5
10
15
20
25
30
−30000
−20000
−10000
0
10000
20000

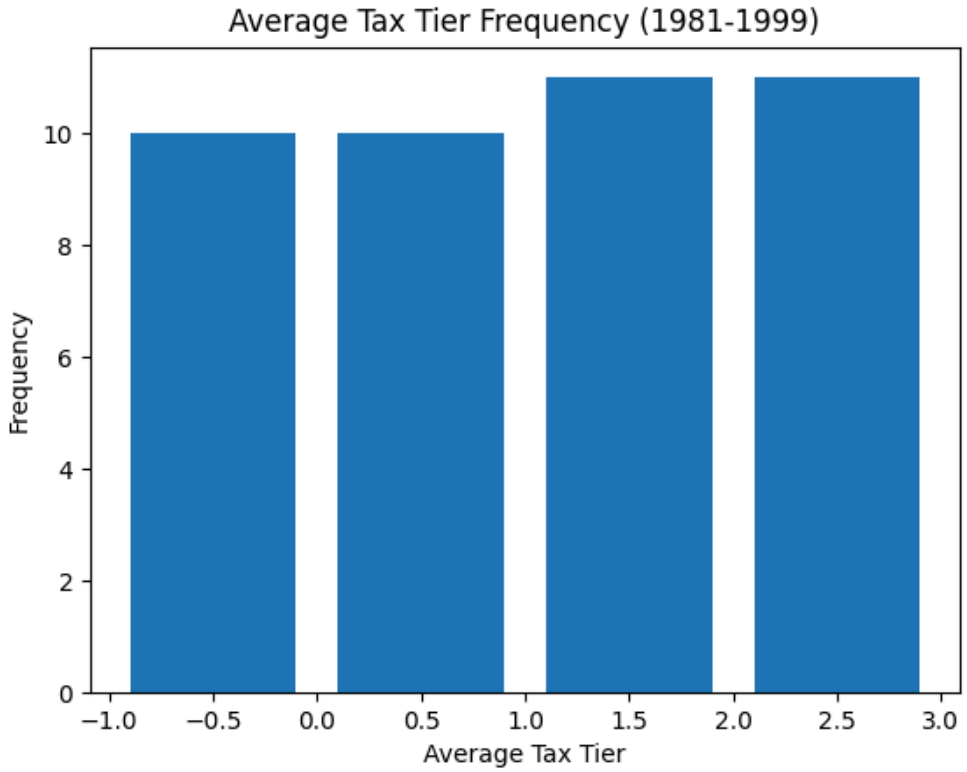

PCI Difference Frequency (2016-2025)
Frequency
PCI Difference
0
10
20
30
40
50
−10000
0
10000
20000
30000
40000

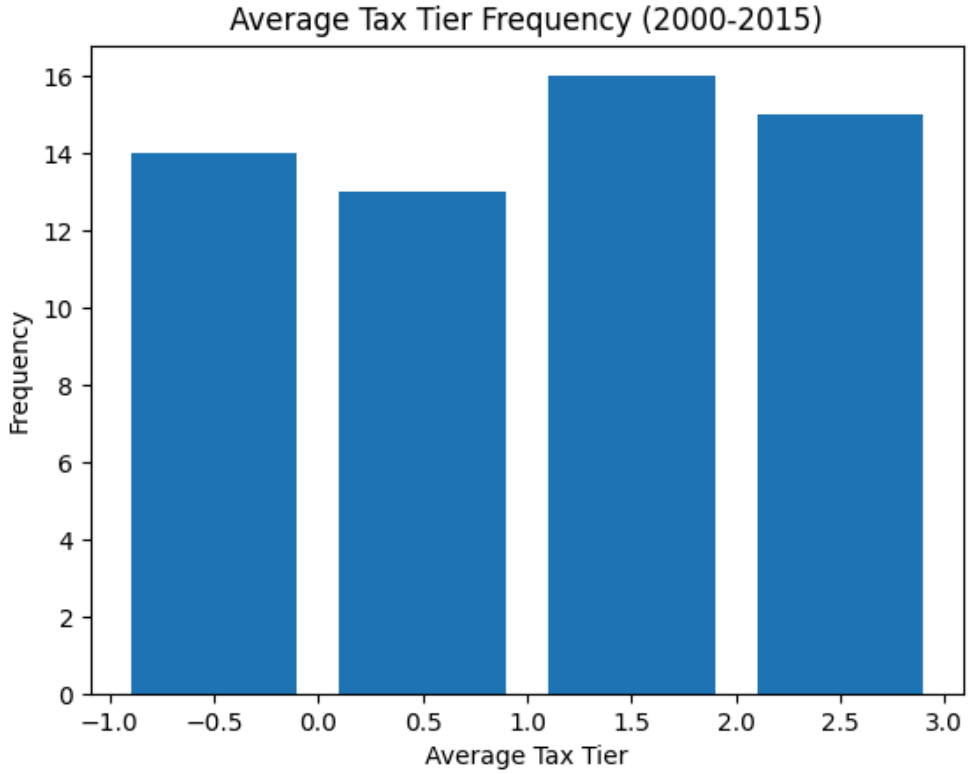
Trend Mapping for Tax Tiers for States and Provinces

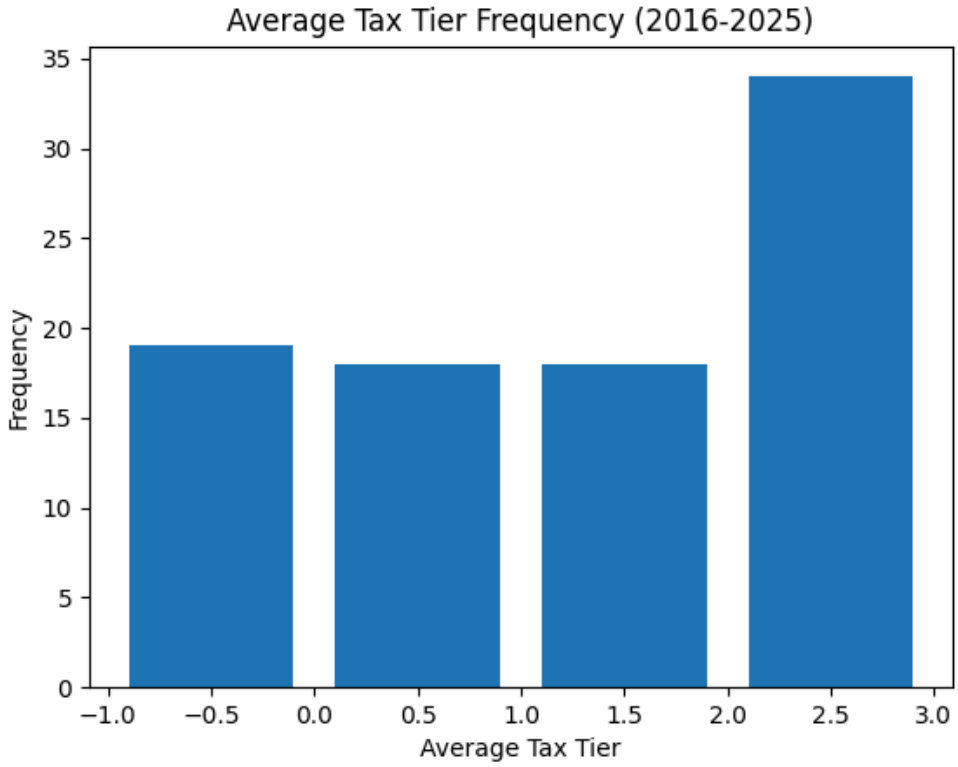
Tax tiers are as follows:

- 0: None
- 1: Low
- 2: Moderate
- 3: High

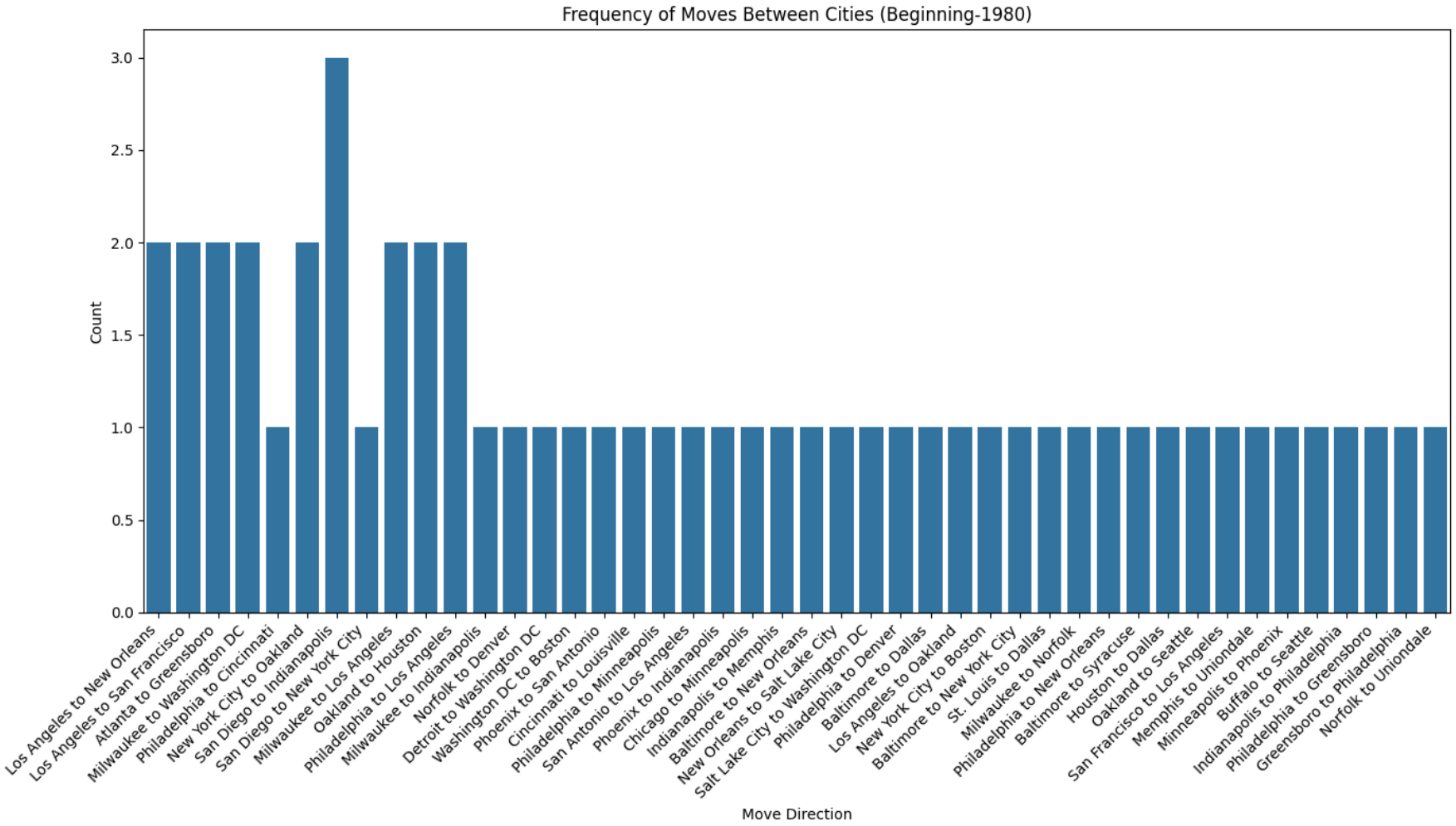

Average Tax Tier Frequency (1940-1980)
Frequency
Average Tax Tier
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0

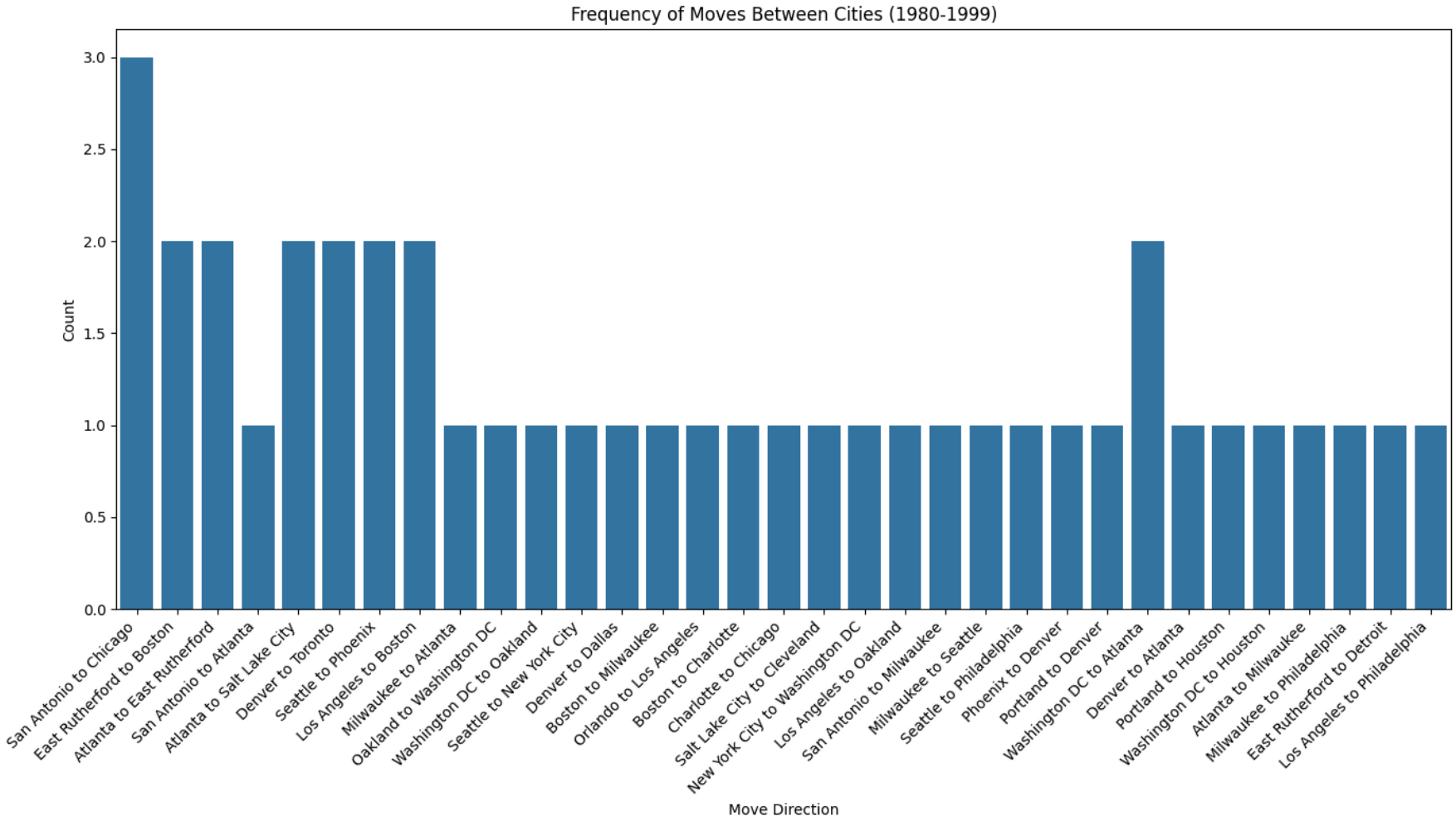

Average Tax Tier Frequency (1981-1999)
Frequency
Average Tax Tier
0
2
4
6
8
10
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0

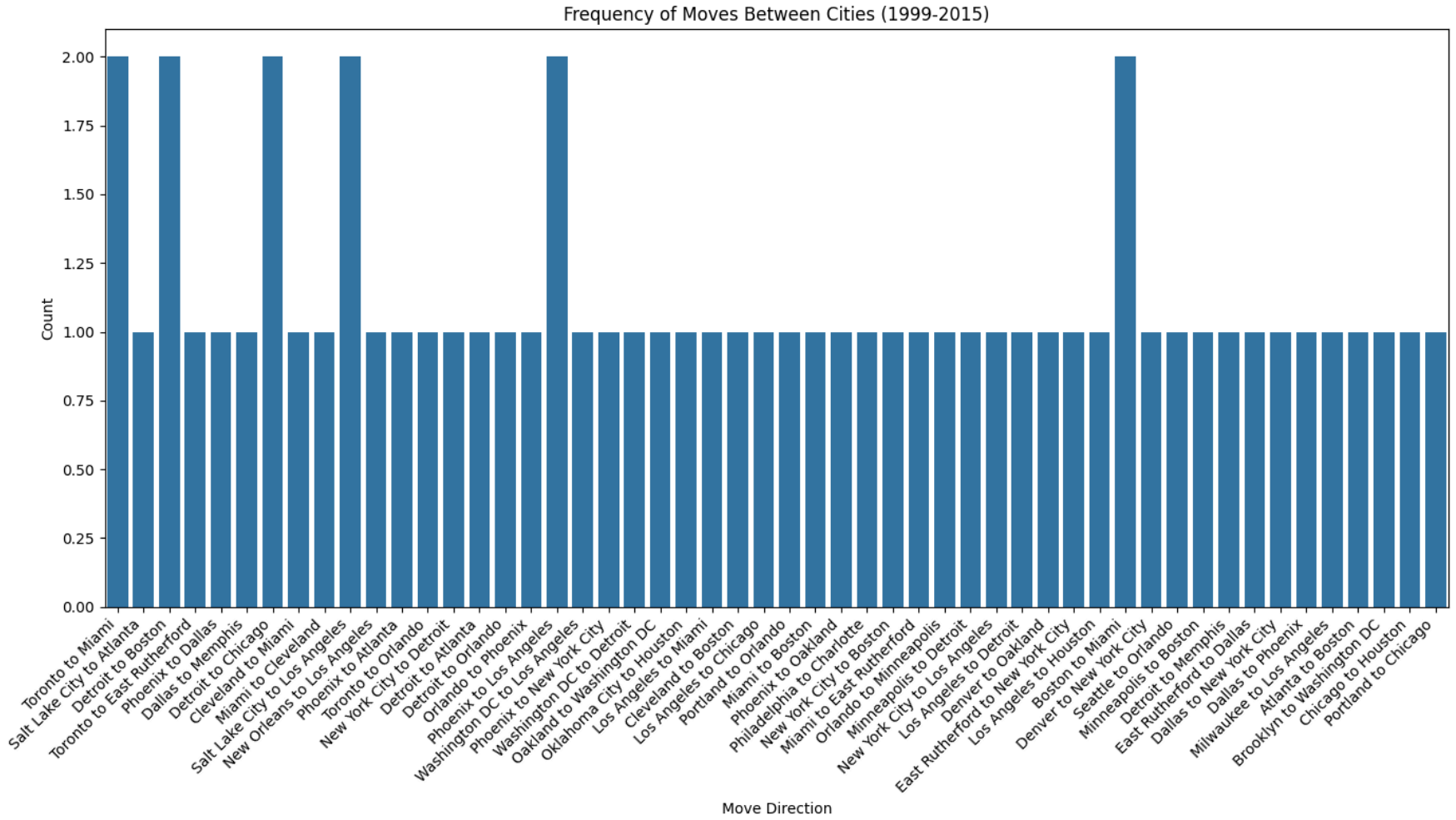

Average Tax Tier Frequency (2000-2015)
Frequency
Average Tax Tier
0
2
4
6
8
10
12
14
16
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0

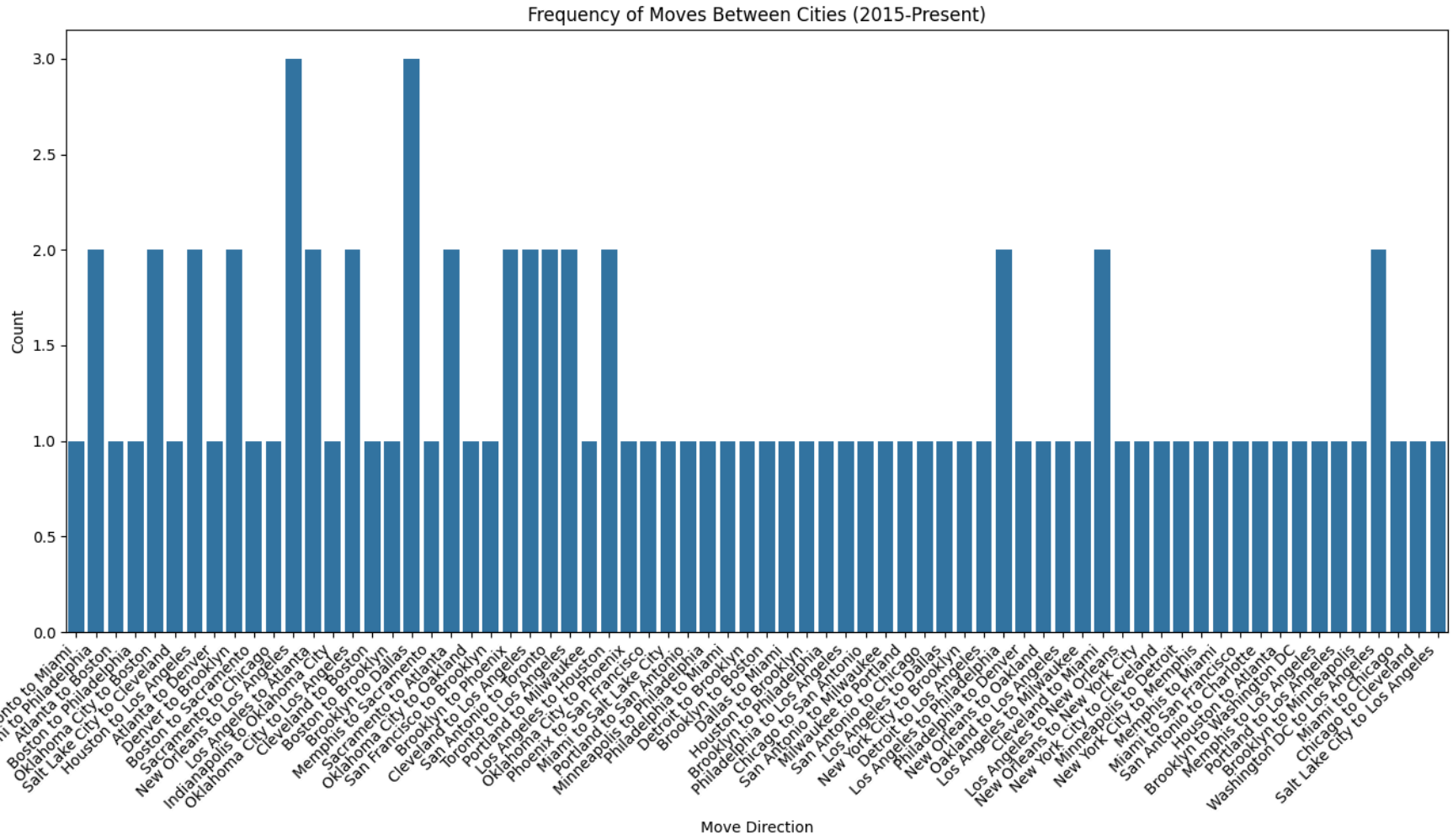

Average Tax Tier Frequency (2016-2025)
Frequency
Average Tax Tier
0
5
10
15
20
25
30
35
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0

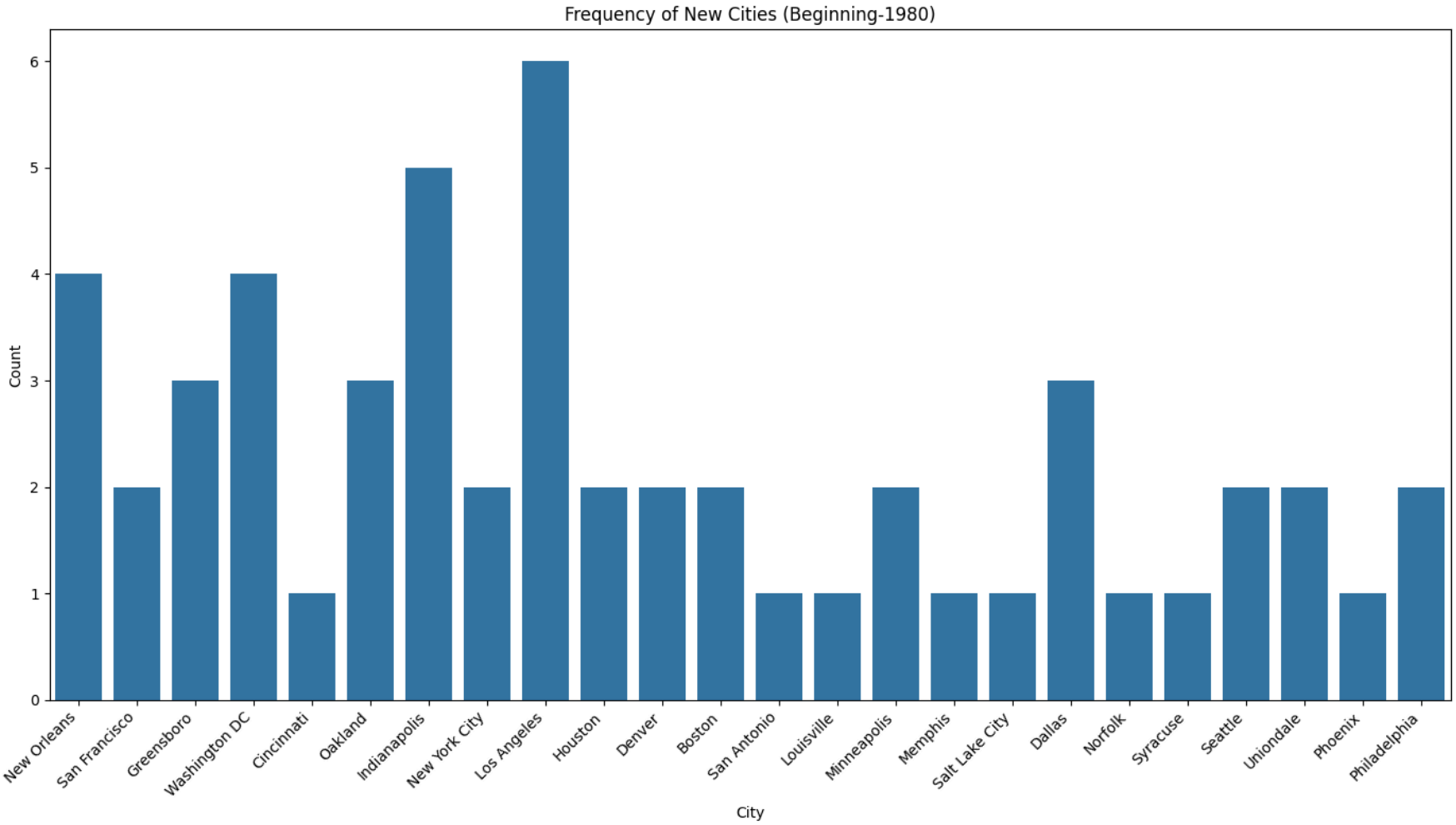
Frequency Bar Charts in Binned Years from ‘plotbinnedfreq.ipynb’

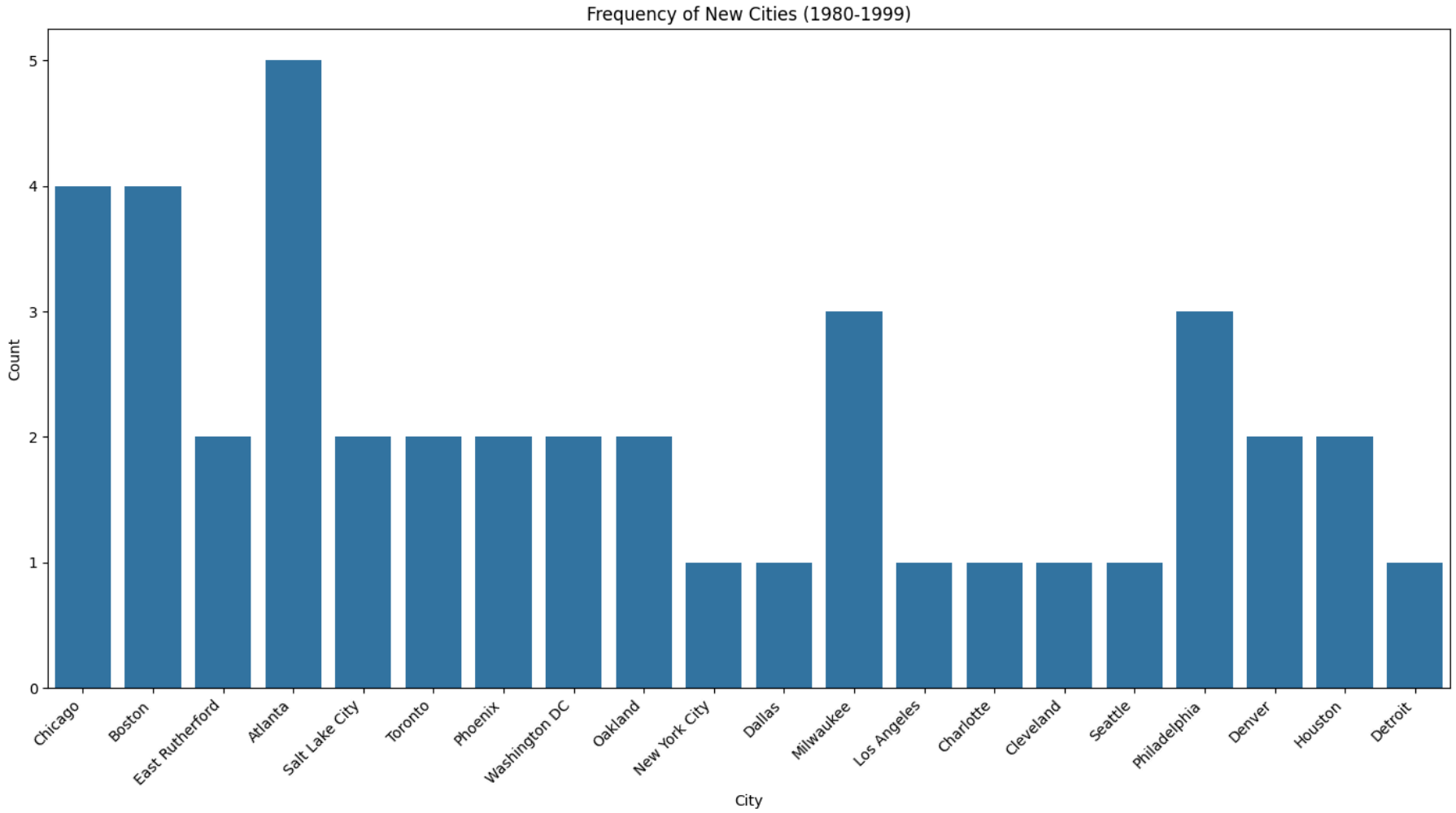

Frequency of Moves Between Cities (Beginning-1980)
Count
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Move Direction
Los Angeles to New Orleans
Los Angeles to San Francisco
Atlanta to Greensboro
Milwaukee to Washington DC
Philadelphia to Cincinnati
New York City to Oakland
San Diego to Indianapolis
San Diego to New York City
Milwaukee to Los Angeles
Oakland to Houston
Philadelphia to Los Angeles
Milwaukee to Indianapolis
Norfolk to Denver
Detroit to Washington DC
Washington DC to Boston
Phoenix to San Antonio
Cincinnati to Louisville
Philadelphia to Minneapolis
San Antonio to Los Angeles
Phoenix to Indianapolis
Chicago to Minneapolis
Indianapolis to Memphis
Baltimore to New Orleans
New Orleans to Salt Lake City
Salt Lake City to Washington DC
Philadelphia to Denver
Baltimore to Dallas
Los Angeles to Oakland
New York City to Boston
Baltimore to New York City
St. Louis to Dallas
Milwaukee to Norfolk
Philadelphia to New Orleans
Baltimore to Syracuse
Houston to Dallas
Oakland to Seattle
San Francisco to Los Angeles
Memphis to Uniondale
Minneapolis to Phoenix
Buffalo to Seattle
Indianapolis to Philadelphia
Philadelphia to Greensboro
Greensboro to Philadelphia
Norfolk to Uniondale

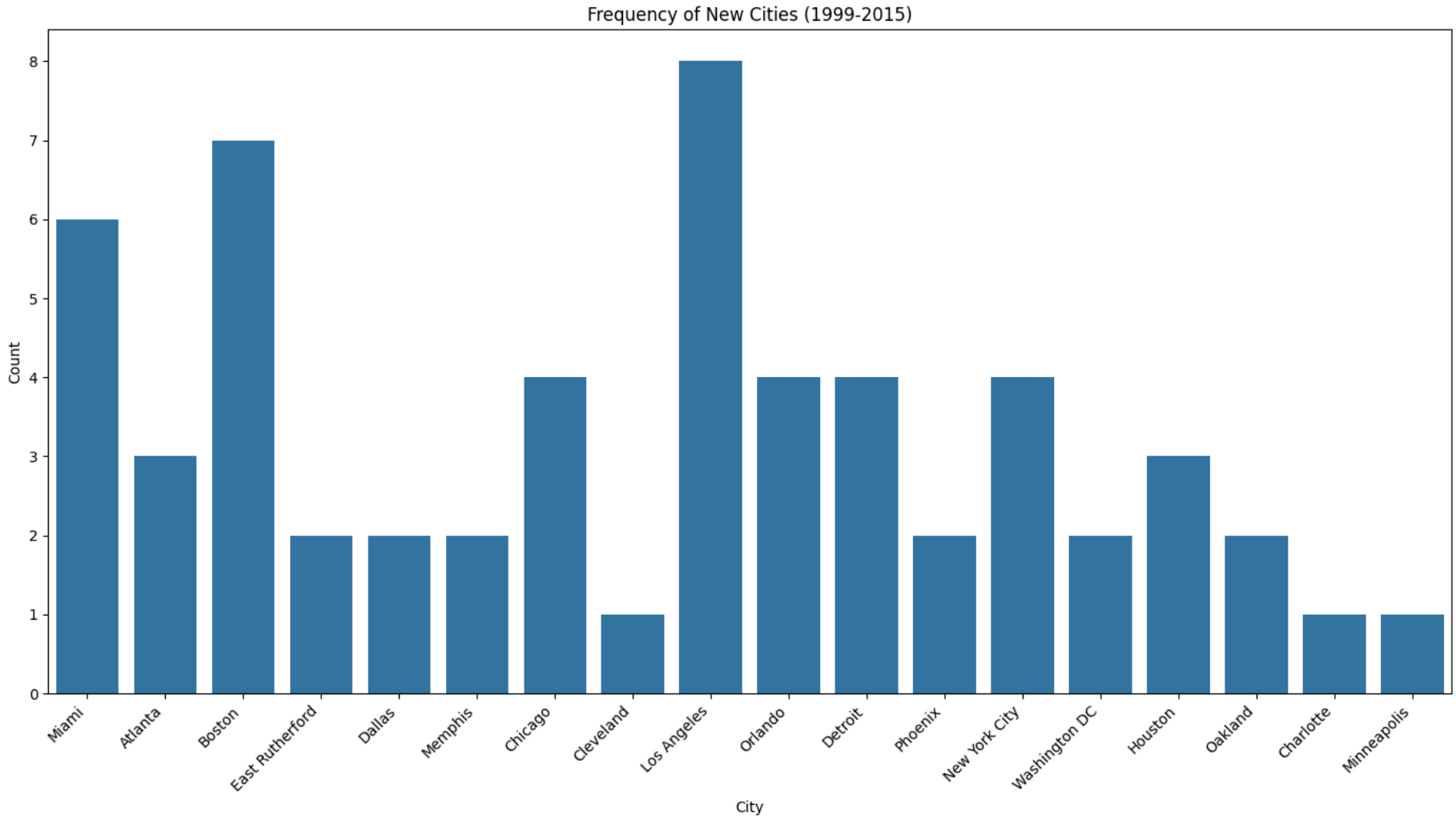

Frequency of Moves Between Cities (1980-1999)
Count
Move Direction
0.0
0.5
1.0
1.5
2.0
2.5
3.0
San Antonio to Chicago
East Rutherford to Boston
Atlanta to East Rutherford
San Antonio to Atlanta
Atlanta to Salt Lake City
Denver to Toronto
Seattle to Phoenix
Los Angeles to Boston
Milwaukee to Atlanta
Oakland to Washington DC
Washington DC to Oakland
Seattle to New York City
Denver to Dallas
Boston to Milwaukee
Orlando to Los Angeles
Boston to Charlotte
Charlotte to Chicago
Salt Lake City to Cleveland
New York City to Washington DC
Los Angeles to Oakland
San Antonio to Milwaukee
Milwaukee to Seattle
Seattle to Philadelphia
Phoenix to Denver
Portland to Denver
Washington DC to Atlanta
Denver to Atlanta
Portland to Houston
Washington DC to Houston
Atlanta to Milwaukee
Milwaukee to Philadelphia
East Rutherford to Detroit
Los Angeles to Philadelphia

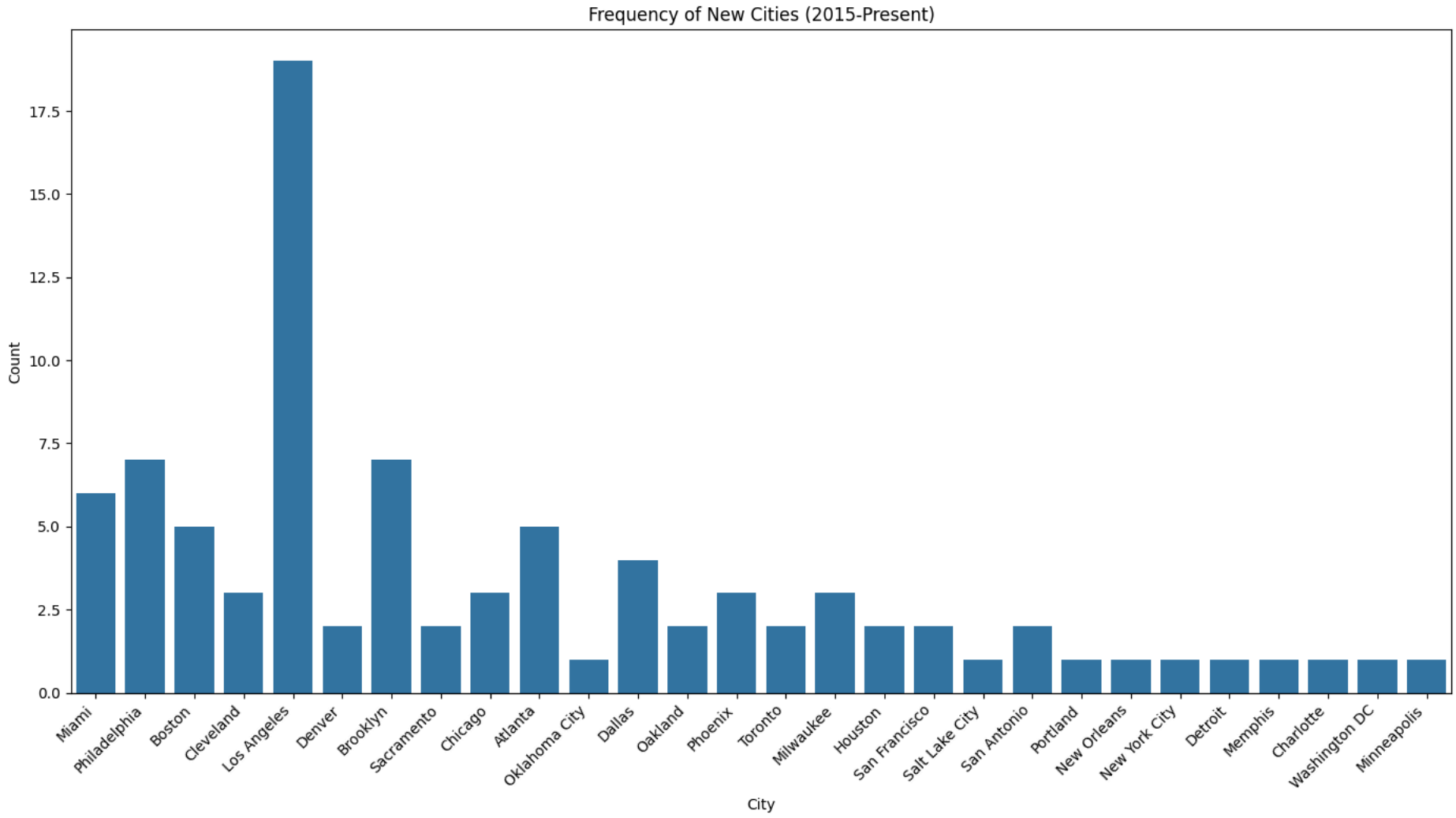

Frequency of Moves Between Cities (1999-2015)
Count
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Move Direction
Toronto to Miami
Salt Lake City to Atlanta
Detroit to Boston
Toronto to East Rutherford
Phoenix to Dallas
Dallas to Memphis
Detroit to Chicago
Cleveland to Miami
Miami to Cleveland
Salt Lake City to Los Angeles
New Orleans to Los Angeles
Phoenix to Atlanta
Toronto to Orlando
New York City to Detroit
Detroit to Atlanta
Detroit to Orlando
Orlando to Phoenix
Phoenix to Los Angeles
Washington DC to Los Angeles
Phoenix to New York City
Washington DC to Detroit
Oakland to Washington DC
Oklahoma City to Houston
Los Angeles to Miami
Cleveland to Boston
Los Angeles to Chicago
Portland to Orlando
Miami to Boston
Phoenix to Oakland
Philadelphia to Charlotte
New York City to Boston
Miami to East Rutherford
Orlando to Minneapolis
Minneapolis to Detroit
New York City to Los Angeles
Los Angeles to Detroit
Denver to Oakland
East Rutherford to New York City
Los Angeles to Houston
Denver to Miami
Boston to New York City
Seattle to Orlando
Minneapolis to Boston
Detroit to Memphis
East Rutherford to Dallas
Dallas to New York City
Dallas to Phoenix
Milwaukee to Los Angeles
Atlanta to Boston
Brooklyn to Washington DC
Chicago to Houston
Portland to Chicago


Frequency of Moves Between Cities (2015-Present)
Count
Move Direction
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Toronto to Miami
Miami to Philadelphia
Atlanta to Boston
Boston to Philadelphia
Oklahoma City to Boston
Salt Lake City to Cleveland
Houston to Los Angeles
Atlanta to Denver
Denver to Brooklyn
Boston to Sacramento
Sacramento to Chicago
New Orleans to Los Angeles
Los Angeles to Atlanta
Indianapolis to Oklahoma City
Oklahoma City to Los Angeles
Cleveland to Oklahoma City
Boston to Brooklyn
Brooklyn to Dallas
Memphis to Sacramento
Sacramento to Atlanta
Oklahoma City to Oakland
San Francisco to Brooklyn
Brooklyn to Phoenix
Cleveland to Los Angeles
San Antonio to Toronto
Toronto to Los Angeles
Portland to Milwaukee
Los Angeles to Houston
Oklahoma City to Phoenix
Phoenix to San Francisco
Miami to Salt Lake City
Portland to San Antonio
Minneapolis to Philadelphia
Philadelphia to Miami
Detroit to Brooklyn
Brooklyn to Boston
Houston to Miami
Dallas to Brooklyn
Brooklyn to Philadelphia
Philadelphia to Los Angeles
Chicago to San Antonio
San Antonio to Milwaukee
Milwaukee to Portland
San Antonio to Chicago
Los Angeles to Dallas
New York City to Brooklyn
Detroit to Los Angeles
Los Angeles to Philadelphia
Philadelphia to Denver
New Orleans to Oakland
Oakland to Los Angeles
Los Angeles to Milwaukee
Cleveland to Miami
Los Angeles to New Orleans
New Orleans to New York City
New York City to Cleveland
Minneapolis to Detroit
Memphis to Miami
Miami to San Francisco
San Antonio to Charlotte
Houston to Atlanta
Brooklyn to Washington DC
Memphis to Los Angeles
Portland to Minneapolis
Brooklyn to Los Angeles
Washington DC to Los Angeles
Miami to Chicago
Chicago to Cleveland
Salt Lake City to Los Angeles


Frequency of New Cities (Beginning-1980)
Count
0
1
2
3
4
5
6
City
New Orleans
San Francisco
Greensboro
Washington DC
Cincinnati
Oakland
Indianapolis
New York City
Los Angeles
Houston
Denver
Boston
San Antonio
Louisville
Minneapolis
Memphis
Salt Lake City
Dallas
Norfolk
Syracuse
Seattle
Uniondale
Phoenix
Philadelphia

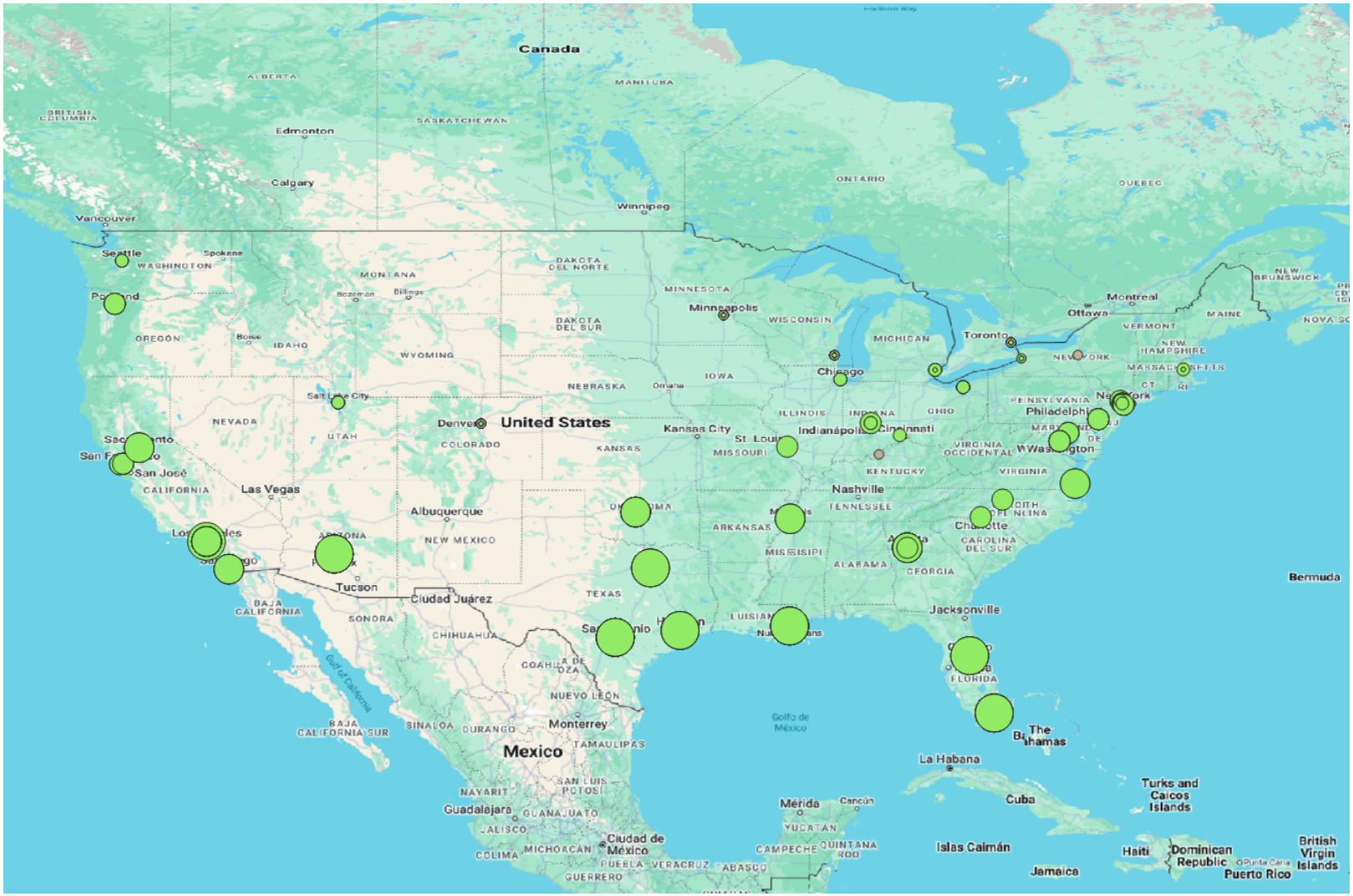

Frequency of New Cities (1980-1999)
Count
0
1
2
3
4
5
Chicago
Boston
East Rutherford
Atlanta
Salt Lake City
Toronto
Phoenix
Washington DC
Oakland
New York City
Dallas
Milwaukee
Los Angeles
Charlotte
Cleveland
Seattle
Philadelphia
Denver
Houston
Detroit
City


Frequency of New Cities (1999-2015)
Count
0
1
2
3
4
5
6
7
8
Miami
Atlanta
Boston
East Rutherford
Dallas
Memphis
Chicago
Cleveland
Los Angeles
Orlando
Detroit
Phoenix
New York City
Washington DC
Houston
Oakland
Charlotte
Minneapolis
City

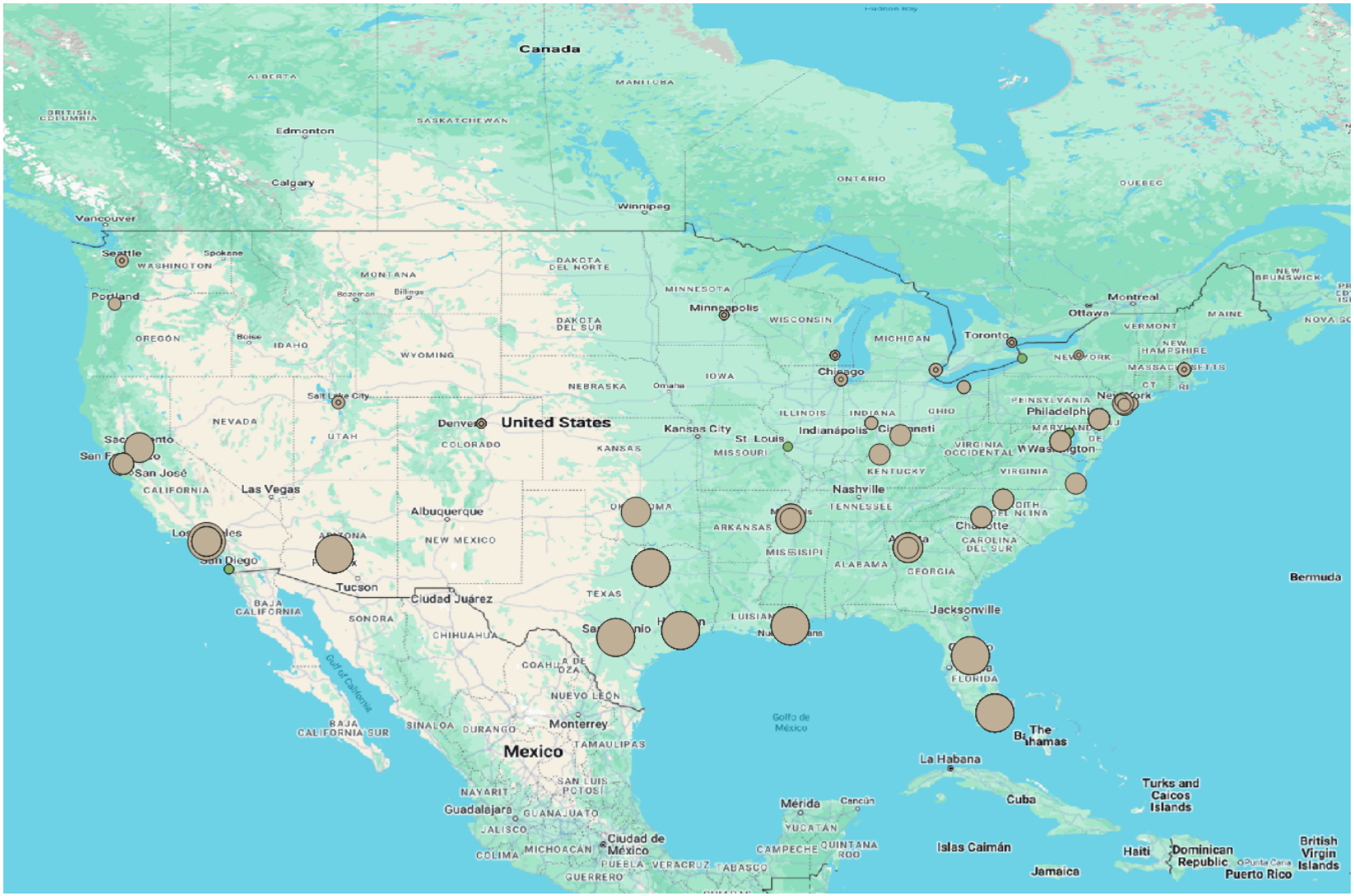


Maps Created using QGIS

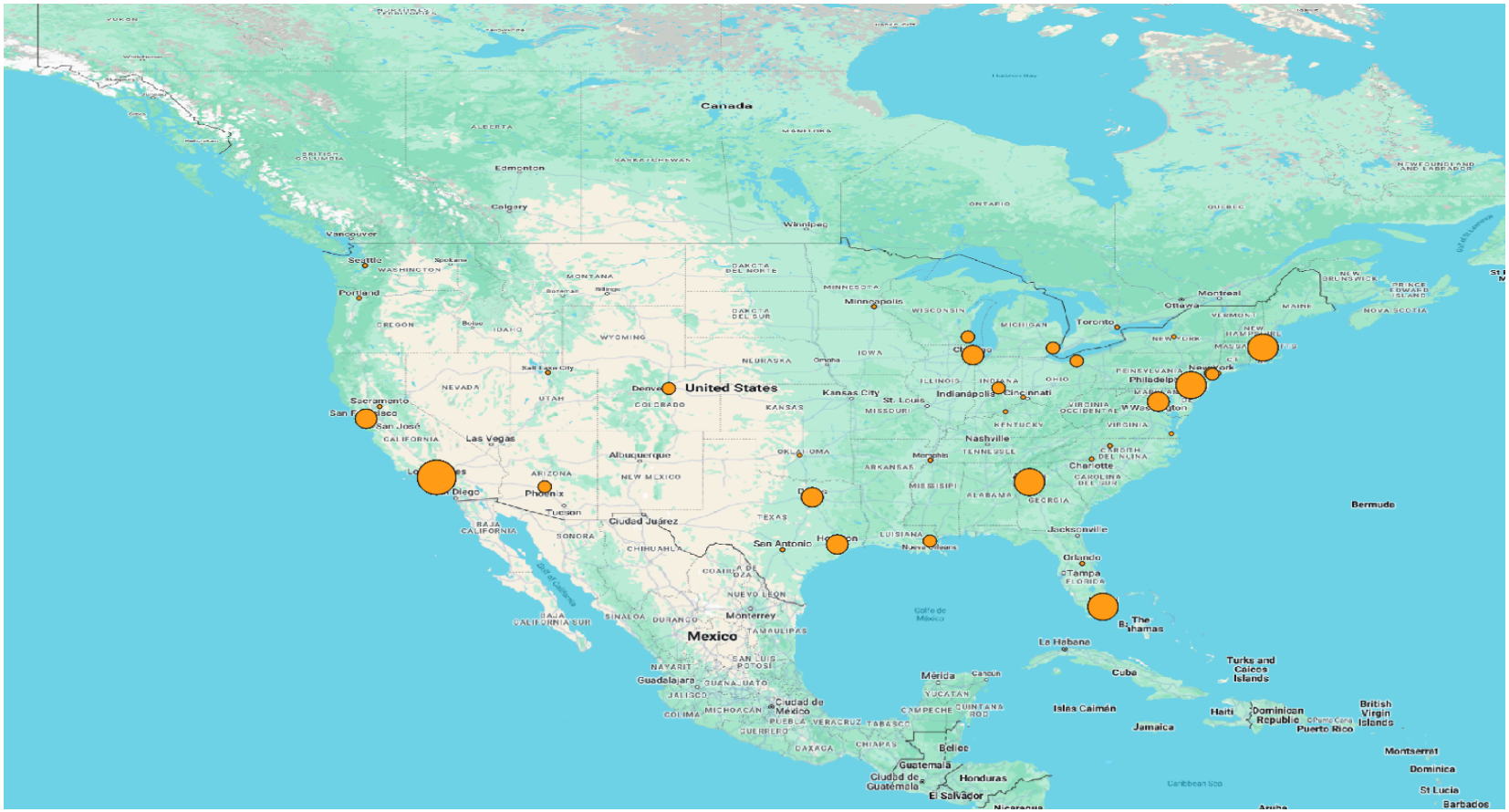
Previous City Temperature Bubble Map, larger bubble indicates higher annual average temperature



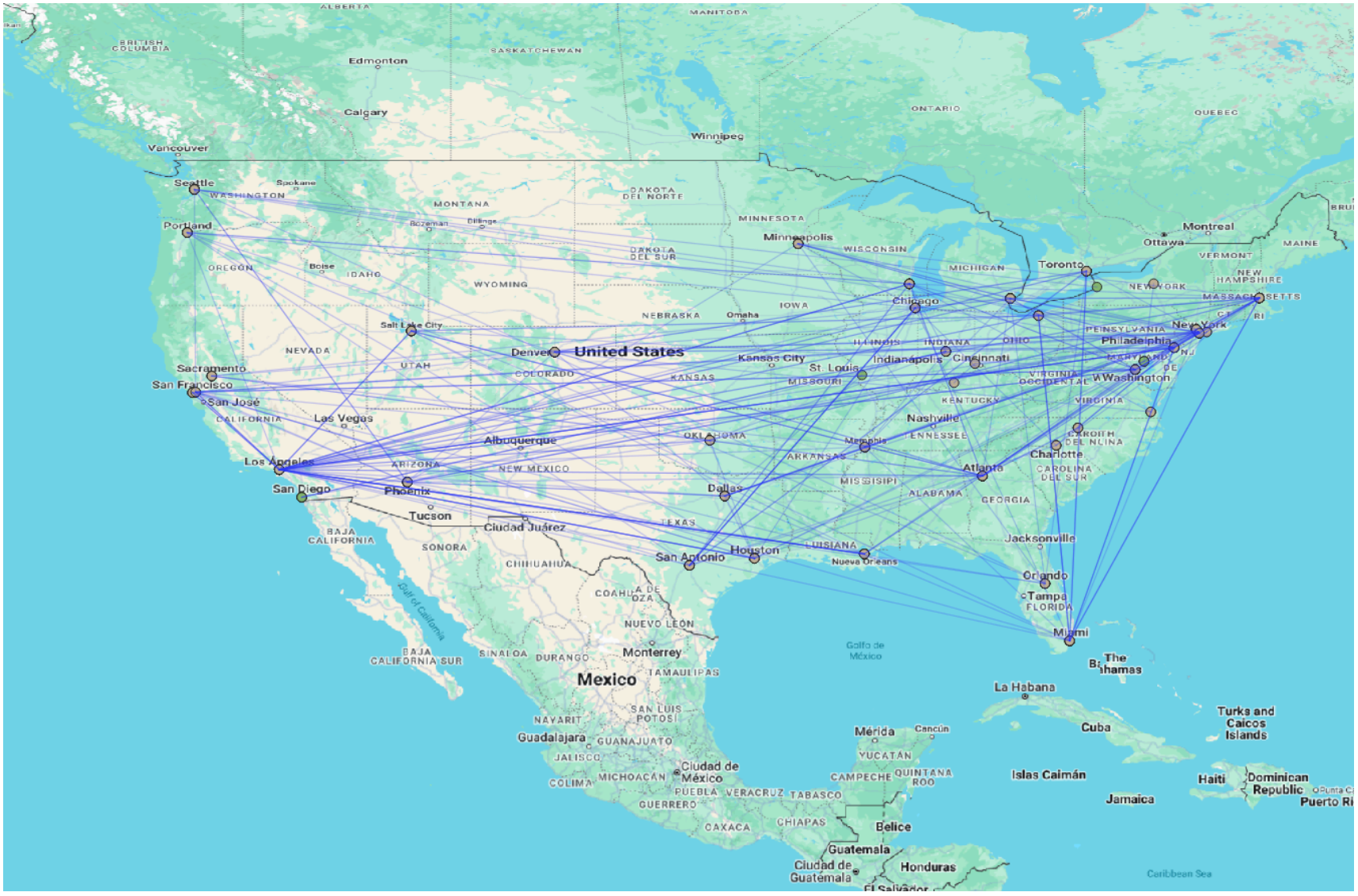
New City Temperature Bubble Map, larger bubble indicates higher annual average temperature



New City Frequency Bubble Map, larger bubble indicates larger amount of player moves to that city



Maps showing player movement paths



Discussion

Regression Analysis

Regression shows none of the three quantifiable criteria chosen, per capita income, average temperature, state tax tier, make a significant difference in a player choosing a new team when at the 5% significance and event at the 10% level.

Given these results, we can conclude that:

1. **Temperature Differences**: There is no significant difference in the average temperatures between the previous and new cities for the years analyzed.
2. **PCI Differences**: There is no significant difference in the PCI between the previous and new cities for the years analyzed.
3. **Tax Differences**: There was insufficient data to test for significant differences in tax tiers between the previous and new states.

General Graphs Discussion from 'graphing.ipynb'

The binned graphs for average annual temperature and PCI show an even distribution throughout which makes it difficult to draw any conclusions and are better explained by the following trend graphs. Tax tier shows even distribution but are not adjusted by year which makes analysis not as useful.

Trend Mapping Discussion from 'trend mapping.ipynb'

When looking at the difference in average annual temperature, the graphs follow the regression analysis in that the majority of player movements result in a plus or minus 5 celsius difference. Additionally, previous and current cities are similar in that either the coldest block or 2nd coldest have the highest frequency but do not mirror each other when going from previous to current cities. This can be explained by colder cities such as Philadelphia, Boston, Chicago, and San Francisco being historically popular destinations which will be explored in the QGIS discussion later.

Regarding PCI trends, for some eras, there were modest increases in PCI going from former to new cities but otherwise, the overall difference was negligible which supports the regression analysis conclusion. Something to notice is that PCI increased going from era to era which makes sense due to inflation which lead to the increase of salaries along with costs for everyone. Something that is not within the realms of this analysis but could be explored is if salaries for NBA players kept up with cost of living dissimilar to that of the average person in the United States.

For tax tiers, the tiers were evenly distributed for the first 3 eras but in the most recent one, then skewed towards the higher tiers.

Binned Frequency Discussion from 'plotbinnedfreq.ipynb'

When looking at the trends, understandably, it was difficult to determine why players chose certain teams, as the most common cities were Los Angeles and Indianapolis, although there were only 6 and 5 moves, respectively, as players were not able to choose their teams as much back then. This did not correlate with the most successful teams as the Lakers did have multiple championships while located in Minneapolis, and so did Indianapolis thanks to the Indiana Pacers' success in the 40s, but most of them came before the NBA and ABA merged as the most successful dynasty by far back then was the Boston Celtics who famously won 11 championships in 13 years led by franchise legend Bill Russell.

Players still did not have much power but did choose teams that were generally successful from 1980 to 1999, aside from Atlanta, which had 5 moves with 0 championships to show for it, as the other teams had a bit more success with Chicago, Boston, and Philadelphia proving relatively popular, although with none having more than 4 players aside from Atlanta, it was hard to gauge players' motivations for changing teams. During this era, the Chicago Bulls won 6 championships in 8 years in the 90s led by Michael Jordan and Scottie Pippen, followed by the Los Angeles Lakers winning 4 championships thanks to Magic Johnson and Kareem Abdul-Jabbar, and Larry Bird and Kevin McHale leading the Boston Celtics to 3 championships. Of those players, only Kareem changed teams and had left the Milwaukee Bucks to go to the Lakers.

This was a surprise as beginning with the new millennium until 2015, players started to have much more agency in changing teams as Los Angeles (Lakers and Clippers combined, although the Lakers were and continue to be the much more popular franchise) had 8 movements, followed by Boston with 7 and then Miami with 6, as Boston returned to glory in 2008 led by the first superteam of Paul Pierce, Kevin Garnett, and Ray Allen, as the last chose to join Pierce in Boston from their former teams. The Lakers won 5 championships led by Shaquille O'Neal, Kobe Bryant, and Pau Gasol. The Clippers did not have as much success but still had some players join them in free agency, notably Chris Paul. Miami won 2 championships with 4 consecutive appearances led by the next superteam when LeBron James and Chris Bosh joined Dwyane Wade in 2012.

The most recent bin has Los Angeles as far and away the most popular destination with 19 movements, although the spread between the Lakers and Clippers was much more equal as both teams had superstars join, most notably LeBron James, again, and Anthony Davis for the Lakers, while Kawhi Leonard and Paul George left teams that they had previously joined in free agency to try and bring success to the Clippers. The next most popular were Philadelphia and Brooklyn with 7 each, followed by Miami with 6, which does not coincide with team success as the

Golden State Warriors were the most successful team by far with 4 championships but only had 4 movements with 2 from their time in Oakland and 2 after they moved to San Francisco, although they were very consequential moves, especially in Oakland as them adding Kevin Durant and Andre Iguodala to the team brought them from elite to world-beaters.

Several players were featured multiple times, with some including Kevin Durant, Al Horford, LeBron James, Paul George, James Harden, and Kawhi Leonard. This era came to be known as the "player empowerment era" as players gained the power to even force a trade to a team of their own choosing, which often hamstrung their new team as the previous team could put on heavy requests that the new team would have to meet to be able to acquire those star players. This pendulum swing resulted in a pushback from ownership, especially after Paul George forced a trade to the Los Angeles Clippers to play with Kawhi Leonard only one year after signing a multi-year contract extension with the Oklahoma City Thunder.

QGIS Discussion

The temperature bubble maps show the difference in average annual temperature between regions but without adjusting for years, comparison and analysis are not as useful as just generalizing which regions tend to be warmer and which tend to be cooler. For the frequency map based new city, it shows Los Angeles, Atlanta, Miami, Boston, and New York City as the most popular destinations but are not as useful for comparison as the binned frequency graphs which divide based on era.

Conclusion

The research indicates that star players choose teams based on a combination of basketball-specific factors, such as contract terms, proximity to home, and the opportunity to play with desired teammates or under specific coaches. However, they are also influenced by broader motivations, such as a desire for a change from their previous location—an aspect that mirrors decisions made by people in other professions. These broader motivations are inherently harder to quantify due to limitations like privacy concerns around home locations and the complexity of financial motivations. This highlights the challenges of leveraging data analytics, especially big data, where ethical considerations and data reliability play significant roles. As illustrated by the graphs, the trends align with this analysis, with the changes between previous and new cities (measured by the three chosen components) centering around zero.

One notable insight lies in the frequency distribution of new cities, which reveals patterns across different NBA eras. The eras were defined based on key milestones in league history:

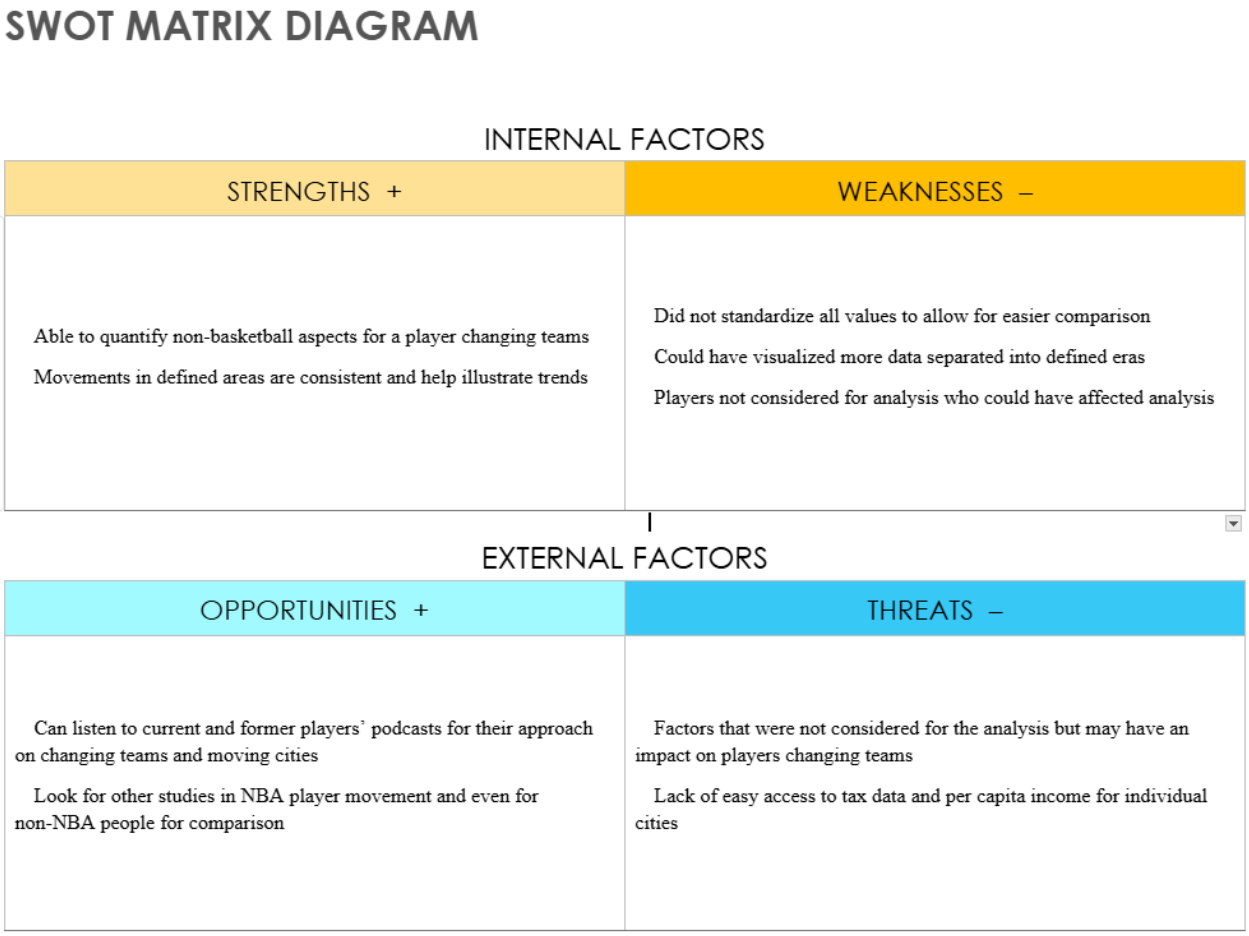
- **Pre-Free Agency Era (before 1980):** This period was marked by limited player movement and restricted player agency. The league saw increased popularity with the arrival of Larry Bird and Magic Johnson in 1980, following their historic college

basketball championship. This era laid the foundation for a league on the verge of bankruptcy to grow its audience and revenue.

- **Globalization Era (1981–2000):** Superstars like Michael Jordan and Shaquille O'Neal helped globalize the NBA brand. This era also included the first NBA lockout in 1999, motivated by monetary disputes, reflecting the growing financial stakes of the league.
- **Player Empowerment Era (2001–2016):** This period saw the rise of "superteams" and increased player control over their careers, epitomized by decisions like Kevin Durant joining the Golden State Warriors in 2016. The Warriors dynasty, alongside legends like Kobe Bryant, Tim Duncan, LeBron James, and Dwyane Wade, defined this era.
- **Modern Global and Post-Empowerment Era (2016–present):** The pendulum of power has swung back toward team management as organizations have grown less accommodating of player demands, particularly after high-profile cases like Paul George's forced trade to the Clippers shortly after signing an extension with the Thunder. Simultaneously, the league's global growth has been evident, with superstars like Giannis Antetokounmpo (Greece), Nikola Jokić (Serbia), Luka Dončić (Slovenia), and Shai Gilgeous-Alexander (Canada) leading the charge. The increase in NBA player participation in the Olympics, from 16 players in 1992 to 81 players in 2024, further reflects the NBA's global impact (NBA.com Paris Olympics).

The era bins were designed not only to reflect historical milestones but also to balance the number of transactions per era, enabling meaningful cross-era comparisons. This structure provided insights into how external and internal motivations have shaped player movement over time.

SWOT Analysis



Strengths for my project were that by using quantifiable aspects, i.e. annual average temperature, per capita income, and tax bracket, it was easier to visualize and draw analysis from those values as numbers are easier to compare than qualitative values. Also, by dividing years into different eras, comparisons can be made across different bins and there is more cleanliness than if each year were analyzed individually. Also, it may be difficult to do each year individually because the amount of movements in each year is not consistent and as shown by previous discussions, increased over time.

A weakness of my project is that the quantifiable aspects could have and should have been standardized to account for inflation. In fact, the website that had the PCI for the United States, Rea Project, had both regular PCI and PCI that was adjusted for inflation. This could have helped when comparing across decades because the PCI, which represents income for people has increased over the years. Also I failed to adjust for United States dollars and Canadian dollars because there were players who went to and left the Toronto Raptors. I created a lot of visuals but some were not as useful such as the heatmaps and destination buble maps because they included all values rather than separating heatmaps by eras. Another weakness and possible

avenue for future improvement is expanding the research to players not considered stars but a possible challenge for that is that it is harder to determine if a player had chosen their next destination if they were traded.

An external opportunity for my project is that thanks to the growth of podcast ran by players such as Paul George, Kevin Garnett, JJ Redick, Jeff Teague, and several others, it is possible to hear a first-person perspective on life in the NBA, what motivates them to change teams, and anything else that can relate to this project. Players have talked about how moving cities is not easy, having to leave teammates and friends who they are around more than their own families, and anything else that helps them relate to regular people. Another opportunity is utilizing the global interest in the NBA to find other studies that look at players changing teams and their motivations along with finding a way to compare those motivations and reasons that people in a different occupation change companies and choose to move.

A threat that affected my project is factors that I did not look at that may have had as strong or stronger of an impact on player movement such as the basketball-related reasons that may have already been analyzed by others such as salary, role on team, desired teammates and coaches, along with more personal information such as desired locations they would want to raise a family. I did not look at the more personal information such as the last one because I believe that is an invasion of privacy along with not following ethical guidelines for Big Data Analytics. Another threat is that information for specific cities was limited, mainly for tax data and per capita income where I had to generalize and use states or provinces, in the case of Ontario. An issue that arises from the assumption of homogeneity is that there is a variety within states, namely the differences between urban, suburban, and rural areas which have different costs of living and other economic situations. Something that may sort of help is the fact that most NBA teams are located within metropolitan cities but even then, for example, Los Angeles and San Francisco are both in California but likely still have different city taxes and cost of living. A more drastic difference would be between those two cities and Sacramento.

Further Research

Future studies should expand the dataset to include more players, not just stars, as this could provide insights that align more closely with general perceptions of why players change teams. The primary challenge lies in determining whether a player had agency in choosing their next destination, especially in trades, whereas free agency movements are more straightforward. Star players typically have greater bargaining power and influence over their career moves, much like highly skilled professionals who can transition between roles with ease, driven by market dynamics of supply and demand.

Another area for improvement involves analyzing cities rather than states or provinces. While this approach could capture greater nuances in local economic and environmental factors, it presents logistical challenges. Historical tax rates for cities are difficult to obtain due to

variations in record-keeping practices. Moreover, many cities scale taxes based on income, necessitating an examination of individual player salaries. While most players likely fall into the highest tax brackets, additional considerations, such as property taxes and other forms of income taxation, add complexity. States and provinces were used in this study for their relative uniformity and the greater availability of data.

To enhance the temporal analysis, future research could segment graphs and maps by eras to facilitate comparisons across different time periods, potentially revealing more trends in player movement.

Addressing Insufficient Data:

- Gather more historical tax data to ensure a robust sample size for tax-related analyses. This includes verifying the completeness and accuracy of the merged dataset.
- Incorporate inflation-adjusted per capita income (real PCI) to improve comparisons, particularly across years with significant time gaps. This adjustment would make economic comparisons more reliable.

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Appendices

1. **Criteria for "star" players and the amount of them that were found when looking them up on basketball-reference.com**

Star Criteria	4 All Star Game Appearances	2 All-NBA	1 MVP	1 FMVP	3 DPOY	NBA 75 Team
Amount of Players	209	190	42 (DR J won both, 6 + Dr J ABA)	34	4	76

2. README output of scripts and notebooks used for analysis

```
## Initial Dataset
 **players_that_fit_query.xlsx**: Excel file containing detailed criteria and the list of players who meet those criteria sourced from basketball-reference.com.
 **players_data.csv**: CSV file with aggregated statistics of players meeting the specified criteria.

## Data Files
 **results/player_movements.json**: JSON file containing player movements data.
 **results/player_movements_tax.json**: JSON file containing player movements with tax data.
 **results/player_movements_pci.json**: JSON file containing player movements with PCI data.
 **results/player_movements_temp.json**: JSON file containing temporary player movements data.

# Python Scripts

## City and State Updates
 **update_city_state.py**: Adds state abbreviations to city data.

## Annual Temperature Data
 **annual_temperature_lookup.py**: Searches Open-Meteo for average temperature of cities and their given years.
 **finish_temperature.py**: Completes temperature data retrieval.

## Cost of Living
 **insert_pci_data.py**: Collects per capita income (PCI) for all US states and adds it to MongoDB.
 **insert_toronto_pci.py**: Collects PCI for Toronto and adds it to MongoDB.
 **update_pci_data.py**: Updates the player_movements collection with PCI for the states in the player documents.

## Tax Rate Data
 **tax_rate.py**: Sets tax rate tiers and years for US states and Ontario, obtained from Tax Foundation.
 **add_tax_player_movement.py**: Fills out documents in player_movements according to the tax_rate.py.

## Data Separation
 **separate_collections.py**: Creates new collections in MongoDB that only contain documents with either annual temperature, cost of living (PCI), or tax rate.

# Jupyter Notebooks

## Regression Analysis
 **regression1.ipynb**: Performs regression analysis on the dataset to determine the impact of different factors on player movements.

## Graphing
 **graphing.ipynb**: Generates various bar charts and visualizations to illustrate the data, including PCI, tax tiers, and temperature differences. PCI graphs are incorrectly titled and should be for states and provinces.
 **trend mapping.ipynb**: Creates trend maps that divides based on time periods.
 **plotbinnedfreq.ipynb**: Creates frequency bar charts for the most popular destinations and city-to-city movements, divided into different periods.
```

3. **Example of basketball-reference.com page used for data collection. Able to copy the box and output came with the player's URL hyperlink to name.**

Awards Index | Season Awards ▾ | Award Voting ▾ | Hall of Fame | More Awards & Honors ▾

Summary

Player	Lg	Count
Kareem Abdul-Jabbar	NBA	6
Michael Jordan	NBA	5
Bill Russell	NBA	5
Wilt Chamberlain	NBA	4
LeBron James	NBA	4
Larry Bird	NBA	3
Julius Erving	ABA	3
Magic Johnson	NBA	3
Nikola Jokić	NBA	3
Moses Malone	NBA	3
Giannis Antetokounmpo	NBA	2
Stephen Curry	NBA	2
Mel Daniels	ABA	2
Tim Duncan	NBA	2
Karl Malone	NBA	2
Steve Nash	NBA	2
Bob Pettit	NBA	2
Charles Barkley	NBA	1
Kobe Bryant	NBA	1
Bob Cousy	NBA	1
Dave Cowens	NBA	1
Billy Cunningham	ABA	1
Kevin Durant	NBA	1
Joel Embiid	NBA	1
Julius Erving	NBA	1
Kevin Garnett	NBA	1
Artis Gilmore	ABA	1
James Harden	NBA	1
Connie Hawkins	ABA	1
Spencer Haywood	ABA	1
Player	**Lg**	**Count**
Allen Iverson	NBA	1
Bob McAdoo	NBA	1
George McGinnis	ABA	1
Dirk Nowitzki	NBA	1

4. **Text file of location history for all NBA and some ABA teams, including former teams.**

NBA Teams and Their Corresponding Cities (Including Historical Teams)

Atlanta Hawks
- Atlanta, Georgia: 1968–Present
- St. Louis, Missouri: 1955–1968
- Milwaukee, Wisconsin: 1951–1955
- Tri-Cities (Moline, Illinois, Rock Island, Illinois, and Davenport, Iowa): 1949–1951

Boston Celtics
- Boston, Massachusetts: 1946–Present

Brooklyn Nets
- Brooklyn, New York: 2012–Present
- East Rutherford, New Jersey (New Jersey Nets): 1977–2012
- Piscataway, New Jersey (New Jersey Nets): 1977–1981
- Uniondale, New York (New York Nets): 1972–1977
- Teaneck, New Jersey (New Jersey Americans): 1967–1968

Charlotte Hornets
- Charlotte, North Carolina: 1988–2002, 2004–Present
- New Orleans, Louisiana (New Orleans Hornets): 2002–2005 (temporarily in 2005-2007 due to Hurricane Katrina)
- New Orleans/Oklahoma City Hornets: 2005–2007 (due to Hurricane Katrina)

Chicago Bulls
- Chicago, Illinois: 1966–Present

Cleveland Cavaliers
- Cleveland, Ohio: 1970–Present

Dallas Mavericks
- Dallas, Texas: 1980–Present

Denver Nuggets
- Denver, Colorado: 1974–Present (NBA)
- Denver, Colorado: 1967–1974 (ABA)

Detroit Pistons
- Detroit, Michigan: 1957–Present
- Fort Wayne, Indiana: 1941–1957 (Fort Wayne Zollner Pistons, Fort Wayne Pistons)

Golden State Warriors
- San Francisco, California: 2019–Present
- Oakland, California: 1971–2019
- San Francisco, California: 1962–1971
- Philadelphia, Pennsylvania: 1946–1962

Houston Rockets
- Houston, Texas: 1971–Present
- San Diego, California: 1967–1971

Indiana Pacers
- Indianapolis, Indiana: 1967–Present (NBA and ABA)

Los Angeles Clippers
- Los Angeles, California: 1984–Present
- San Diego, California: 1978–1984
- Buffalo, New York (Buffalo Braves): 1970–1978

Los Angeles Lakers
- Los Angeles, California: 1960–Present
- Minneapolis, Minnesota: 1947–1960

Memphis Grizzlies
- Memphis, Tennessee: 2001–Present
- Vancouver, British Columbia (Vancouver Grizzlies): 1995–2001

Miami Heat
- Miami, Florida: 1988–Present

Milwaukee Bucks
- Milwaukee, Wisconsin: 1968–Present

Minnesota Timberwolves
- Minneapolis, Minnesota: 1989–Present

New Orleans Pelicans
- New Orleans, Louisiana: 2002–Present
- Temporarily moved to Oklahoma City, Oklahoma (due to Hurricane Katrina): 2005–2007

New York Knicks
- New York City, New York: 1946–Present

Oklahoma City Thunder
- Oklahoma City, Oklahoma: 2008–Present
- Seattle, Washington (Seattle SuperSonics): 1967–2008

Orlando Magic
- Orlando, Florida: 1989–Present

Philadelphia 76ers
- Philadelphia, Pennsylvania: 1963–Present
- Syracuse, New York (Syracuse Nationals): 1946–1963

Phoenix Suns
- Phoenix, Arizona: 1968–Present

Portland Trail Blazers
- Portland, Oregon: 1970–Present

Sacramento Kings
- Sacramento, California: 1985–Present
- Kansas City, Missouri (Kansas City Kings): 1975–1985
- Omaha, Nebraska (Kansas City-Omaha Kings): 1972–1975
- Cincinnati, Ohio (Cincinnati Royals): 1957–1972
- Rochester, New York (Rochester Royals): 1945–1957

San Antonio Spurs
- San Antonio, Texas: 1973–Present (NBA)
- Dallas, Texas (Dallas Chaparrals): 1967–1973 (ABA)

Toronto Raptors
- Toronto, Ontario: 1995–Present

Utah Jazz
- Salt Lake City, Utah: 1979–Present
- New Orleans, Louisiana (New Orleans Jazz): 1974–1979

Washington Wizards
- Washington, D.C.: 1997–Present
- Landover, Maryland (Washington Bullets): 1973–1997
- Baltimore, Maryland (Baltimore Bullets): 1963–1973
- Chicago, Illinois (Chicago Zephyrs): 1962–1963
- Chicago, Illinois (Chicago Packers): 1961–1962

ABA Franchises and Their Moves

Carolina Cougars
- **1969–1974**: Played in various cities across North Carolina, including Greensboro, Charlotte, and Raleigh.
- **1974**: The team was sold and moved to St. Louis, becoming the Spirits of St. Louis.

Spirits of St. Louis
- **1974–1976**: Originally the Carolina Cougars, the team was relocated to St. Louis, Missouri.
- **1976**: The team folded after the ABA-NBA merger, and the franchise did not move to the NBA.

Kentucky Colonels
- **1967–1976**: Based in Louisville, Kentucky.
- **1976**: The team folded after the ABA-NBA merger, and the franchise did not move to the NBA.

New Orleans Buccaneers
- **1967–1970**: Based in New Orleans, Louisiana.
- **1970**: The franchise moved to Memphis, Tennessee, becoming the Memphis Pros.

Memphis Pros / Tams / Sounds
- **1970–1972**: Known as the Memphis Pros, based in Memphis, Tennessee.
- **1972–1974**: Rebranded as the Memphis Tams.
- **1974–1975**: Became the Memphis Sounds.
- **1975**: The franchise was sold and moved to Baltimore, but folded before playing any games as the Baltimore Claws.

Virginia Squires
- **1970–1971**: Originally the Oakland Oaks, the team moved to Washington, D.C., becoming the Washington Caps.
- **1971–1976**: Relocated to Norfolk, Virginia, and rebranded as the Virginia Squires. The team also played games in Hampton, Richmond, and Roanoke, Virginia.
- **1976**: The team folded just before the ABA-NBA merger and did not join the NBA.

Utah Stars
- **1970–1976**: Originally the Los Angeles Stars, the team moved to Salt Lake City, Utah.
- **1976**: The team folded during the ABA's final season and did not join the NBA.

5. References for Literature Review

a. SB Nation. (2024, August 1). *NBA trades and free agency: The rise of player movement in 2018*. Retrieved from https://www.sbnation.com/nba/2018/7/23/17594660/nba-trades-all-stars-free-agency-2018

b. NBA.com. (2024, August 1). *Trade deadline: When friends are dealt*. Retrieved from https://www.nba.com/news/trade-deadline-when-friends-are-dealt

c. Field Insider. (2024, August 1). *The reasons NBA players switch teams*. Retrieved from https://fieldinsider.com/the-reasons-nba-players-switch-teams/

d. Fadeaway World. (2024, August 1). *10 NBA stars who will change teams this summer*. Retrieved from https://fadeawayworld.net/10-nba-stars-who-will-change-teams-this-summer

6. **All files and data are available on GitHub: https://github.com/danceswithme/nba_analysis.**

7. **Project website link is https://danceswithme.github.io/nba_analysis/.**

8. **Video link is at https://www.youtube.com/watch?v=UYdEn0_qdsM.**