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DA401

PACE Equity: Predictive Analytics for Expansion & Investment Success

Abstract:

One of the hardest issues when combating climate change is finding the necessary balance between financial stability and green efficacy (Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., ... & Zhou, B, 2021). One solution to this problem in the business world is PACE financing. PACE Financing enables property owners to obtain financing for energy efficiency, renewable energy, and water conservation projects, with repayment structured through property tax bills (Rose & Wei, 2020). In this data analysis project, I delved into the financial landscape navigated by PACE Equity, a leading company in the PACE financing scene. The primary focus of the study is to identify the critical variables from a few that I was specifically asked to investigate by PACE Equity. The project also aims to cast a predictive lens towards untapped urban landscapes, identifying which cities hold the most potential for expansion opportunities that PACE Equity has yet to explore. These two goals make up the dual main research questions that I will be focusing on answering with this analysis. To determine what variables impact the total amount invested (TAF) the most I just did some simple regression analysis. This showed that

the term of the loan was the best predictor of a profitable investment. And in order to predict what cities are the best targets for expansion I used a RandomForest model to predict the total investment in every city in the United States with a population greater than 10,000. I then looked at the top 10 cities with the highest predicted total amount invested, and determined that the 10 best cities to consider focusing on are Houston, Los Angeles, New York, Chicago, Philadelphia, Washington D.C., Atlanta, Miami, Phoenix, and Brooklyn.

<u>Introduction:</u>

The overarching research questions guiding this study are: What are the predominant factors that determine the success of construction projects financed by PACE Equity, and which potential markets offer the best opportunities for the company's growth? This inquiry is anchored on two hypotheses: first, that project success is influenced by many different factors; second, that untapped urban markets, identifiable through a data-driven lens, present ripe opportunities for PACE Equity's strategic expansion.

Climate change has been a problem that has continued to snowball for the past few decades, and there is a need for action before everything tumbles out of control (Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., ... & Zhou, B, 2021). One of the most promising potential areas of impact is focusing on sustainable or renewable energy. However, there are many people who do not think that the benefits of renewable energy outweigh the costs (Sovacool, 2009). This has spurred a few financial innovations aimed at encouraging environmentally friendly practices.

One of these financial mechanisms is Property Assessed Clean Energy (PACE) financing. PACE financing enables property owners to obtain financing for energy efficiency, renewable energy, and water conservation projects, with repayment structured through property tax bills (Rose & Wei, 2020). PACE Equity is one of the leading firms in the world of PACE financing. As most financial institutions, PACE Equity is interested in expanding the U.S. Cities they are financing projects in and increasing revenue. PACE Equity operates in a complex landscape characterized by regulatory dynamics, market competition, and varying levels of awareness and acceptance among stakeholders. Expanding its operations to more U.S. cities could significantly enhance the adoption of sustainable practices, consequently contributing to broader climate goals. A necessary portion of this project is to understand the origin of PACE loans and PACE programs as a whole, and what the determinants of a city's outlook on green energy are.

Property Assessed Clean Energy (PACE) programs are the result of state and the federal government's attempts to promote renewable or "clean" energy in order to reduce dependence on foreign energy sources, reducing pollution of both greenhouse gasses and conventional pollutants (Kirkpatrick & Bennear, 2014). PACE loans are loans given if a project meets certain efficient energy guidelines. These programs aim to remove the financial barriers that typically hinder the adoption of sustainability measures by allowing property owners to undertake improvements without any initial capital outlay. The first PACE program was set up in California, and was a massive success (Hoops, 2011). The PACE program in California was created with two main goals in mind: the idea that each improvement should eventually pay for itself and that financing should be limited to investments with a high return in terms of energy efficiency (Headen & Bloomfield & Warnock & Bell, 2011). The financing provided through PACE programs is repaid over time through an additional assessment on the property's tax bill, typically over a period of 10 to 20 years. This repayment structure ensures that the loan stays with the property even if the property is sold (Rose & Wei, 2020). This provides a compelling incentive for property owners to invest in long-term sustainability projects. PACE loans, facilitated through PACE programs, are a critical tool in promoting environmental responsibility and advancing a community's sustainability goals. By offering a secure and effective method for financing green projects, PACE programs play a crucial role in reducing greenhouse gas emissions, promoting energy conservation, and encouraging the uptake of renewable energy technologies (Oliphant & Culhane & Haldar, 2020).

The creation of PACE programs has proven to be incredibly beneficial in multiple different states. In California, the home of the very first PACE program, these programs have enjoyed considerable success, aiding in the broad adoption of renewable energy and energy efficiency measures in both residential and commercial sectors. PACE programs have proven instrumental in unlocking private capital to finance sustainability projects, thus reducing the financial burden on individual property owners and promoting wider community engagement in environmental sustainability. By providing accessible financing, the Ygrene PACE program has financed green property improvements with an average annual increase of $134.7 millions and created 1,305 jobs (Rose & Wei, 2020). Another state that has invested in PACE financing is Florida, where due to the introduction of PACE financing, there have been reductions in energy use, water use, pollutants, and vulnerability to natural disasters like hurricanes (Oliphant & Culhane & Haldar, 2020). The investments into this sector have also created major economic benefits, such as increases in local job growth, economic growth, and tax revenue (Oliphant & Culhane & Haldar, 2020). PACE Equity has very similar success in the Midwest, particularly in Wisconsin, where they are headquartered. They have proven that the PACE financing mechanism has proven to be a pivotal tool for property owners in Wisconsin, enabling them to overcome the financial hurdles of investing in energy-efficient projects. The accessibility and long-term repayment structure of PACE loans provided by PACE Equity have been well-received by both commercial and residential property owners, contributing to a broader adoption of sustainable practices in the region.

The perception of renewable energy among individuals and communities significantly influences the pace and extent of its adoption (Sovacool, 2009). People's understanding and acceptance of renewable energy technologies play a pivotal role in shaping policy frameworks, investment decisions, and consumer behaviors towards greener alternatives, such as if PACE programs even exist in a city or not. A positive perception can foster a conducive environment for the implementation of PACE programs and other supportive regulatory frameworks (Bayulgen & Benegal, 2019). On the other hand, negative perceptions can hinder the transition to renewable energy, can create resistance to necessary policy measures, and discourage stakeholders from engaging in sustainable practices (Bang & Ellinger & Hadjimarcou & Traichal, 2000). The perception of renewable energy often intertwines with broader socio-political contexts, which can either enhance or impede the momentum towards achieving sustainability goals (Sovacool, 2009). This is why understanding and addressing public perception, through effective communication and education is necessary for the successful implementation of programs like PACE. One of the best ways to increase peoples' willingness to support green programs is through successful marketing. In order to be successful, marketing efforts should focus on building the consumers' knowledge on the product or program (Bang & Ellinger & Hadjimarcou & Traichal, 2000). Another technique that has proved to be fruitful are promotional campaigns that focus on the identification of local renewable energy suppliers (Bang & Ellinger & Hadjimarcou & Traichal, 2000).

After an exploration of the inception, evolution, and current impact of PACE financing has unveiled a compelling narrative on promoting and privately funding sustainable development. The journey of PACE loans from their beginning to their implementation across various regions, and their proven success in locales like California and Florida, presents a persuasive framework of a viable financial solution to sustainability challenges in the United States. PACE Equity has had a notable impact in the Midwest, showcasing the program's adaptability and effectiveness across diverse economic and cultural landscapes. The understanding that positive public perception, nurtured through effective communication and engagement, accelerates the adoption and acceptance of renewable energy technologies, underscores the importance of concerted efforts in educating and involving the community in sustainability initiatives. The case of PACE Equity further exemplifies how well-structured financial mechanisms can not only alleviate financial barriers but also act as catalysts in fostering a culture of environmental responsibility and sustainability.

One of the final important aspects to address before diving into analysis is addressing potential issues of conflict of interest. My engagement with this project is solely for research purposes and not under any monetary influence or obligation from PACE Equity. I have an interest in arriving at a particular conclusion that provides actionable insights to PACE Equity. This study is independent of any other coursework, research venture, or professional commitment I am involved in. By dissecting the elements that sway the performance of individual PACE loans and spotlighting cities with untapped potential, this study aims to forge a path for informed decision-making and sustainable urban development.

Methods:

Due to the nature of the central research questions of this analysis, several statistical tests might be considered. Firstly, to understand the relationship between various city attributes and PACE's success, I will use simple linear regressions to analyze the relationships between individual variables and the total amount financed. And for determining which cities that PACE could potentially expand into, predictive modeling or even machine learning algorithms, I will use RandomForest Regression to predict the total amount financed in cities that PACE Equity has not expanded into yet.

The data being employed for this research originates from two primary sources. The first dataset is extracted from the PACE Equity database, accessed through Postgresql. I've gotten permission from PACE Equity to utilize their data, ensuring there will be no breach in ethical concerns. This dataset from PACE Equity is centered around detailing projects, specifically variables that describe the nature of the projects and the amount of investment funneled into them. The categorical variables from this dataset are:Stage, ID, Asset Name, Closing Date, Maturity Date, Amortization Start Date, Cap-I End Date, City, State, Property Type, Project Type, PACE Program, and Closing Year. The numeric variables from this dataset are: Coupon, PACE Asset Balance, Term (Years), Payments per Year, Current Total Debt MGT + PACE, Mortgage Balance, Total Project Budget, as-is Property Value, as-complete Property Value, as-stabilized property value, as-stabilized PACE LTV, as-stabilized Mortgage LTV, as-stabilized combined LTV, and Underwritten DSVR.

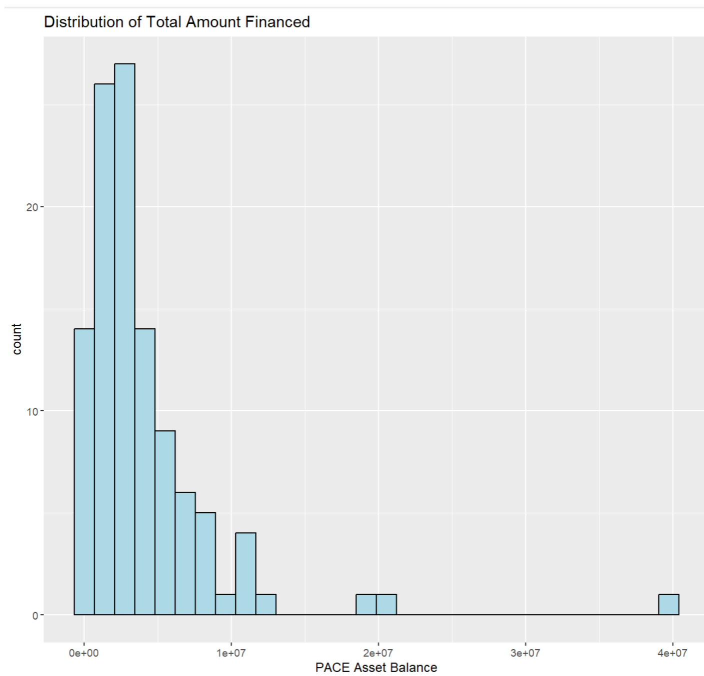

Figure 1: Distribution of Total Amount Invested

The secondary dataset contains quantitative data describing every city in the United States. The variables in this dataset are: City, city_ascii, state_id, state_name, county_fips, county_name, lat, lng, population, population_proper, density, source, military, incorporated, timezone, ranking, id, age_median, male, female, married, family_size, income_household_median, income_household_six_figure, home_ownership, home_value, rent_median, education_college_or_above, labor_force_participation, unemployment_rate, race_white, race_black, race_asian, race_native, race_pacific, race_other, race_multiple. This dataset is publicly accessible, and will be cited at the end of this paper.

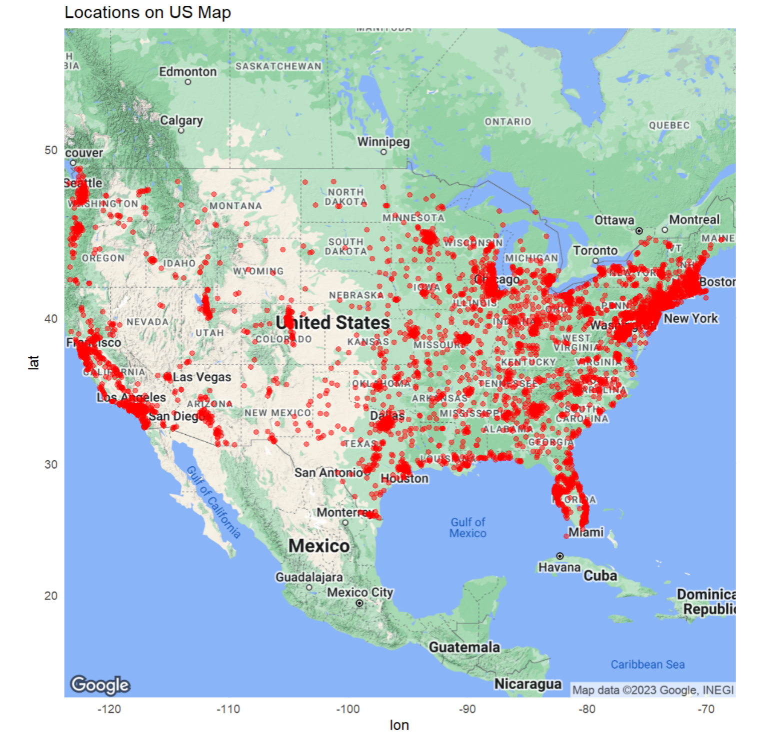

Figure 2: Location of all Cities with Pop > 10,000

Analysis of Variance (ANOVA) is a statistical method used to compare means among three or more groups to ascertain if at least one group mean is statistically different from the others (Faraw). It is particularly useful when analyzing the impact of one or more nominal predictor variables on a single, continuous outcome variable, making it useful in studies seeking to understand the influence of categorical factors. In regression analysis, ANOVA is extended to test the significance of the model as a whole and the contribution of individual predictors or groups of predictors in explaining the variance in the dependent variable (Faraw). For this study on PACE Equity's financing, ANOVA is being utilized to assess the impact of Property Type on the total amount financed by the company's PACE loans. Property Type is a categorical variable that includes various classifications of properties, such as residential, commercial, etc. I hypothesize that the kind of property could influence the financing amount due to factors inherent to the property classification, which may affect the total amount investment.

Multiple linear regression is an extension of simple linear regression that allows for the examination of the influence of two or more independent variables on a single continuous dependent variable. This statistical technique is invaluable when exploring complex relationships where several factors may concurrently impact the outcome variable (Kelley & Bolin). It is particularly adept at untangling the individual effect of each predictor while controlling for the influence of others, providing a comprehensive understanding of the roles played by each variable. In the study of PACE Equity's financial practices, multiple linear regression will be used to unravel the multifaceted nature of factors influencing the total amount financed. The dependent variable, total amount financed, is predicted by a series of independent variables.

Random Forest is a powerful model that operates by constructing a multitude of decision trees during training and outputting the mean prediction of the individual trees to form a comprehensive, more accurate final prediction (Liaw & Weiner). This method is particularly beneficial for its robustness and its ability to handle a large number of input variables without overfitting, making it highly suitable for complex predictive modeling tasks where the relationship between the predictors and the outcome is not linear or easily discernible (Liaw & Weiner). The decision tree foundation of the Random Forest model is advantageous for this study because decision trees are non-parametric, meaning they are flexible in the face of large and potentially complicated datasets. They inherently perform feature selection, which can be invaluable when considering the numerous factors that could influence the total amount financed in new cities. Additionally, the Random Forest algorithm improves upon the simplicity of decision trees by adding randomness to the model, thus increasing accuracy and reducing the risk of overfitting. In applying Random Forest to predict the total amount financed in cities not yet ventured into by PACE Equity, the model can utilize its multitude of trees to evaluate the importance of various predictors, such as demographic trends and economic indicators across these new geographies. The output will provide a ranking of cities based on the predicted financing amount, offering strategic insights into where PACE Equity could potentially focus its expansion efforts.

I will use R-studio as the primary analytical tool for this project. R has an extensive array of packages and is an incredibly flexible programming language, and I will make use of many of these packages for my analysis. Central to R's capability in data analysis is the tidyverse suite of packages, a collection designed for data science that makes it easier to import, tidy, transform, and visualize data (Averick, Bryan, Chang, McGowna, François, & Yutani). Tidyverse also contains the package dplyr. dplyr is utilized for data manipulation, providing data transformation that is both intuitive and powerful, enabling the efficient preparation of datasets for my analysis (Averick, Bryan, Chang, McGowna, François, & Yutani). Visualization is a critical component of my data analysis, and ggplot2 stands as a cornerstone for creating sophisticated and informative graphics in R (Wickham). This package makes it possible to produce clear and attractive visual representations of the underlying patterns and relationships in the data.

For spatial data visualization, ggmap integrates mapping capabilities, enhancing the analysis by allowing for the incorporation of geographical context, a vital aspect when assessing potential new markets for PACE Equity (Kahle & Wickham). Correlation structures within the data are examined using the corrplot package, which provides a graphical display of the correlation matrix, aiding in the identification of multicollinearity or potential predictors for the regression models (Wei, Simko, Levy, Xie, Jin, & Zemla). The randomForest package enables the deployment of the Random Forest algorithm, a decision-tree-based ensemble method used to predict the total amount financed across new cities, forming the basis for market expansion recommendations (Liaw & Weiner). Together, these packages form a toolkit that allowed me to complete my analysis for PACE Equity.

Ensuring the transparency and trustworthiness of this research is incredibly important to me. I will ensure to validate my choice of models. The goal of this research is to provide strategic insights for PACE Equity's potential expansion. As such, the findings can be beneficial for the company in understanding potential areas of growth and investment. I will attempt to ensure that insights derived are equitable and avoid perpetuating any biases.

Results:

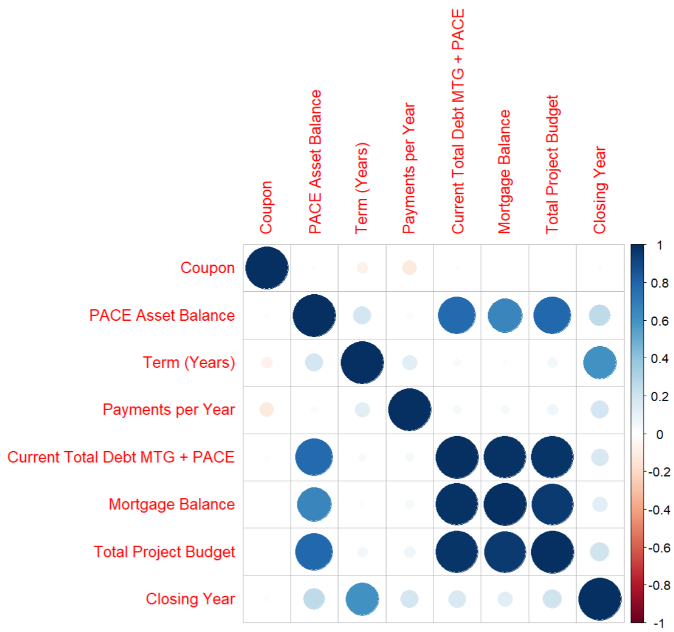

Figure 3: High Levels of Correlation Throughout PACE Equity Dataset

The dataset analysis reveals key financial relationships within PACE Equity's projects: larger project budgets are associated with higher PACE loan balances, suggesting a strategy of supporting more significant ventures. Longer loan terms correlate with more frequent annual payments, possibly reflecting a tailored approach to managing long-term financing. A strong positive correlation exists between total debt management plus PACE and mortgage balances, indicating that higher leveraged properties typically carry more significant combined debt. However, the Closing Year's weak correlation with financial variables implies that the project completion timing has little impact on financial structuring or investment size. These insights are vital to understand patterns in the data before completing the more complex analysis.

The ANOVA test conducted on the dataset yielded insightful results regarding the impact of different factors on Total Amount Financed. The analysis revealed that Property Type had a significant effect on the Total Amount Financed. The test statistics, ($F(9, 100) = 1.837$, $p = .0707$) pointed to a statistically significant effect of Property Type on the Total Amount Financed at the 10% significance level. This evidence suggests a pattern where the type of the property, whether it is commercial, residential, or industrial, may dictate the investment confidence and financial commitment extended by PACE Equity. Overall, the ANOVA test has identified Property Value as a critical variable affecting Total Amount Financed.

The use of multiple linear regression with the PACE Equity dataset provides an understanding of the variables influencing the Total Amount Financed. The regression model, with an exceptional F-statistic of 3.18e+30 on 5 and 104 degrees of freedom and a p-value of less than 2.2e-16, indicates an overwhelmingly significant predictive capability. The Multiple R-squared value is 1, and the Adjusted R-squared is also 1, which are both perfect fits to the data. However, these values typically suggest overfitting. In examining the coefficients, the variable 'Current Total Debt MGT + PACE' stands out with an estimate of 1.000e+00 and a strikingly significant t-value, suggesting that for every unit increase in this predictor, there is a one-unit increase in the Total Amount Financed. Conversely, 'Mortgage Balance' has a coefficient of -1.000e+00, implying an inversely proportional effect on the Total Amount Financed. The 'Coupon' and 'Term (Years)' variables, with p-values of 0.215 and 0.780, did not show a statistically significant impact on the financing amount. The 'Total Project Budget' also did not prove to be a significant predictor in this model.

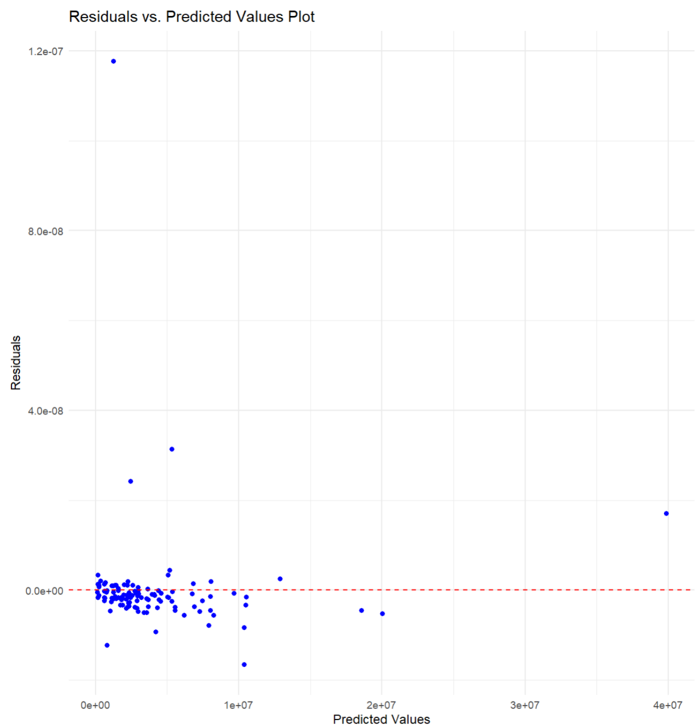

Figure 4 - Residual Plot for Multiple Linear Regression

The residuals versus predicted values plot for the regression model presents several important features indicative of the model's performance. The residuals predominantly cluster around the zero line, which suggests that the model does not systematically overestimate or underestimate the Total Amount Financed. This indicates an unbiased model.

The Random Forest decision tree model was applied to forecast the Total Amount Financed by PACE Equity in various cities. The output of the model, represented by the top 10 cities with the highest predicted Total Amount Financed, highlights potential urban centers where PACE Equity could strategically focus its expansion efforts. Los Angeles, California, emerges as the city with the highest predicted financing. The nine other predicted cities are Houston, New York, Chicago, Philadelphia, Washington D.C., Miami, Atlanta, Phoenix, and Brooklyn.

<u>**Discussion**</u>

The results of this study provide a comprehensive analysis of PACE Equity's investment patterns, revealing significant correlations that could inform future financing strategies. A clear linkage between project scale and loan allocation is identified, suggesting a strategic focus on larger ventures. I also learned how important the property type is on financing amounts. Though the multiple linear regression indicates potential overfitting, it also highlights key financial indicators such as 'Current Total Debt MGT + PACE' as influential on loan amounts, whereas other variables like 'Coupon' and 'Term (Years)' appear less impactful. The Random Forest model's forecasts for expansion opportunities further enrich these findings. Collectively, these results provide insights into the fiscal trends and operational focus areas that could guide PACE Equity’s future initiatives.

Interpreting the correlations within the PACE Equity dataset is necessary to understanding the data I was working with and the company’s financing dynamics and focus areas. The high level of correlation between larger project budgets and higher PACE loan balances points towards a deliberate investment strategy that suggests that PACE Equity may prioritize substantial projects, potentially due to their greater impact on portfolio performance. Such a strategy could also reflect PACE Equity’s confidence in the scalability of larger projects and their ability to yield significant energy savings and operational efficiencies, which are often the cornerstones of PACE financing.

The relationship between loan terms and payment frequency is another area that the correlation analysis brings to light. The positive correlation here indicates that loans with extended terms tend to have more frequent payments within a year. This could be a strategic choice to mitigate the risk associated with longer loan periods. By structuring the repayment in this manner, PACE Equity could be aiming to maintain a steady cash flow and minimize credit risk, while also providing flexibility to borrowers to manage their debt obligations without undue financial strain.

The correlations between data within the PACE Equity dataset are indicative of a strategic approach to project financing that favors significant, potentially more profitable projects, and demonstrates a careful balance of risk management with borrower accommodation in loan structuring. These insights show PACE Equity's current operational strategies and also provide valuable benchmarks for industry best practices in construction project financing.

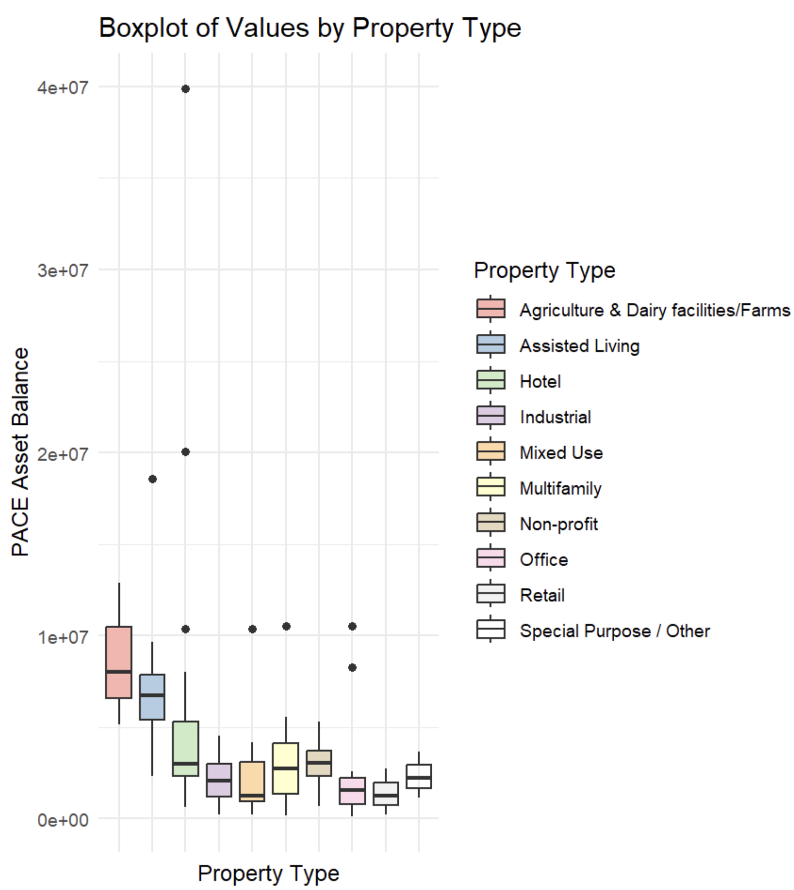

Figure 5: Boxplot of Values

Property Type's substantial impact on the Total Amount Financed shows the importance of this variable in shaping PACE Equity's investment strategies. The type of property plays a defining role in dictating the magnitude of investment commitment. For example, agricultural buildings and dairy farms may demand larger financing to support energy-efficient upgrades that enhance operational efficiency and reduce operating costs. On the other hand, retail spaces might involve smaller-scale renovations, leading to lower financing amounts.

Understanding the significance of Property Type empowers PACE Equity to fine-tune its investment strategies and allows them to optimize their portfolio composition. For instance, recognizing that farming properties typically attract higher financing amounts could lead to tailored marketing for this sector. Conversely, understanding the financing nuances of residential properties might allow PACE Equity to penetrate new markets or refine existing offerings.

In terms of practical implications, the ANOVA findings support the idea of portfolio diversification for PACE Equity. By recognizing the influence of Property Type on financing amounts, PACE Equity can strategically balance its portfolio with a mix of property types, reducing concentration risk and enhancing overall resilience to market fluctuations while still pursuing the projects that will most likely yield a high total amount invested. This diversification strategy aligns with prudent financial management practices, ensuring stability and sustainability in the face of varying market conditions.

The multiple linear regression analysis conducted with the PACE Equity dataset has provided profound insights into the determinants of financing amounts. The model revealed that certain expected significant variables, such as 'Coupon' and 'Term

(Years)', did not have a statistically significant impact on the Total Amount Financed. There are several potential reasons for this. It could be that these factors are less influential in the context of PACE Equity's projects, or that their effects are mediated through other variables not included in the model. I would love to explore the effects of other variables, but these were the specific ones I was asked to investigate.

The residual plot for the model showed an indication of an unbiased model, with residuals mostly scattered randomly around the zero line. This suggests that the model's predictions are neither systematically too high nor too low. However, the presence of outliers, particularly those with large residuals, raises questions about potential anomalies in the data or exceptional cases that the model does not adequately address. The findings from the multiple linear regression offer a valuable exploration of the factors influencing PACE Equity's financing amounts. While the one-to-one relationship of 'Current Total Debt MGT + PACE' stands out as a key finding, the potential overfitting indicated by the perfect R-squared values and the non-significant impact of variables like 'Coupon' and 'Term (Years)' require careful consideration. These factors make it hard to draw concrete conclusions with this model.

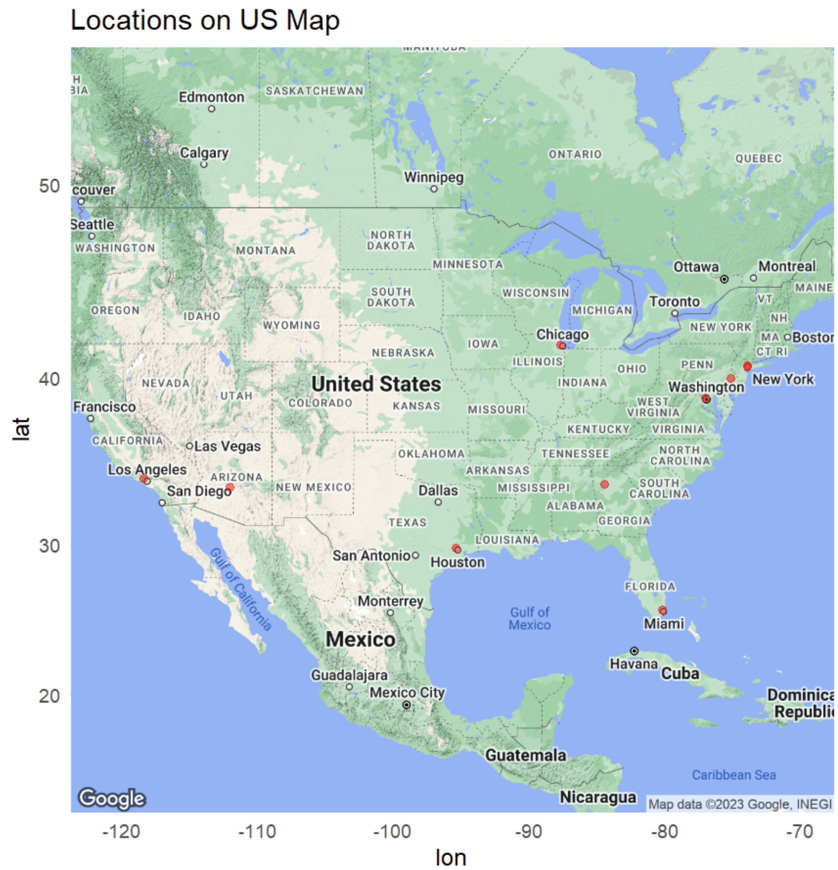

Figure 6: Location of Predicted Cities

The predictions from the Random Forest model reveal a strategic map for PACE Equity's potential expansion into new urban markets. The model has identified ten cities as prime candidates. Los Angeles, Houston, and New York, among others, are predicted to have the highest Total Amount Financed, suggesting that PACE Equity could prioritize these locations for future investment and development. The selection of these cities by the Random Forest model is likely not coincidental. These urban centers are typically characterized by robust economic activity, substantial construction and development sectors, and significant energy efficiency needs, all factors that align well with the objectives of PACE financing. Economic growth trends in these cities could also be driving the model's predictions. A thriving economy can lead to increased commercial and residential development, which in turn could heighten the demand for PACE financing to support energy-efficient improvements.

This project focused on using a range of analytical tools to analyze PACE Equity's dataset, and the relationship between their investments and a database on every city in the United States. Correlation analysis has been instrumental in identifying strategic funding patterns, while ANOVA has highlighted the importance of property type. Further, multiple linear regression has provided insights into key financial indicators, and Random Forest modeling has been effective in pinpointing promising markets for expansion.

This analysis has given clear insights into PACE Equity's financing operations, revealing the variables with the greatest influence on loan amounts and identifying new cities for investment expansion. Drawing from these insights, it is recommended that PACE Equity considers including in their strategic planning a focus on property types and market segments that are most conducive to higher financing amounts. For market expansion, the cities identified by the Random Forest should be prioritized, with an eye on local economic indicators and policy environments conducive to PACE financing. Further research could be enriched by incorporating additional variables such as regional economic trends, energy prices, sustainability benchmarks, and political alignment. Another interesting study would be to analyze if PACE Equity is fully succeeding in each city that they are currently present in, and if not what factors could be causing this. New analytical techniques, perhaps encompassing machine learning algorithms beyond Random Forest, could also provide deeper insights, especially in handling the complex interactions of the variables at play. As PACE Equity looks to the future, the potential for data analytics to revolutionize investment strategies is clear..

Works Cited

Bang, H. K., Ellinger, A. E., Hadjimarcou, J., & Traichal, P. A. (2000). Consumer concern, knowledge, belief, and attitude toward renewable energy: An application of the reasoned action theory. Psychology & Marketing, 17(6), 449-468.

Bayulgen, O., & Benegal, S. (2019). Green Priorities: How economic frames affect perceptions of renewable energy in the United States. Energy Research & Social Science, 47, 28-36.

Faraw, J. J. (2015). Practical Regression and ANOVA using R.

Headen, R. C., Bloomfield, S. W., Warnock, M., & Bell, C. (2011). Property assessed clean energy financing: The Ohio story. The Electricity Journal, 24(1), 47-56.

Hoops, J. (2011). Setting the pace for energy efficiency: The rise, fall, and (potential) return of property assessed clean energy. Wash. UL Rev., 89, 901.

Kahle, David J., and Hadley Wickham. "ggmap: spatial visualization with ggplot2." R J. 5.1 (2013): 144.

Kelley, K., & Bolin, J. H. (2013). Multiple regression. In Handbook of quantitative methods for educational research (pp. 69-101). Brill.

Kirkpatrick, A. J., & Bennear, L. S. (2014). Promoting clean energy investment: An empirical analysis of property assessed clean energy. Journal of Environmental Economics and Management, 68(2), 357-375.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. R news, 2(3), 18-22.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., ... & Zhou, B. (2021). Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change, 2.

Oliphant, Z., Culhane, T., & Haldar, P. (2020). Public Impacts of Florida's Property Assessed Clean Energy (PACE) Program. Patel College of Global Sustainability, University of South Florida.

Rose, A., & Wei, D. (2020). Impacts of the Property Assessed Clean Energy (PACE) program on the economy of California. Energy Policy, 137, 111087.

RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.

Simple Maps (2023), Simple Maps: Interactive Maps and Data. https://simplemaps.com/data/us-cities

Sovacool, B. K. (2009). The cultural barriers to renewable energy and energy efficiency in the United States. Technology in Society, 31(4), 365-373.

Uddin, S., Haque, I., Lu, H., Moni, M. A., & Gide, E. (2022). Comparative performance analysis of K-nearest neighbour (KNN) algorithm and its different variants for disease prediction. Scientific Reports, 12(1), 6256

Vap, Brian. (2023). PACE Equity: Predictive Analytics for Expansion & Investment Success. GitHub. https://github.com/Brianvap/DA401-PEQ-Project

Wei, T., Simko, V., Levy, M., Xie, Y., Jin, Y., & Zemla, J. (2017). Package 'corrplot'. Statistician, 56(316), e24.

Wickham, H. (2011). ggplot2. Wiley interdisciplinary reviews: computational statistics, 3(2), 180-185.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D. A., François, R., ... & Yutani, H. (2019). Welcome to the Tidyverse. Journal of open source software, 4(43), 1686.

Zhang, S., Cheng, D., Deng, Z., Zong, M., & Deng, X. (2018). A novel kNN algorithm with data-driven k parameter computation. Pattern Recognition Letters, 109, 44-54.