PAY-AS-YOU-DRIVE (PAYD) AUTO INSURANCE MODELING REPORT

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1 Introduction

1.1 What is PAYD?

Is the implementation of Pay-As-You-Drive (PAYD) auto insurance beneficial to society and the economy? PAYD auto insurance closely mirrors current insurance practices but introduces mileage driven as an additional variable in determining premium rates for automobile owners and users. Traditional auto insurance premiums are based on various factors, including age, gender, ethnicity, location, and driving records. These variables are analyzed by actuaries, analysts, and other professionals to calculate premium rates that are equitable for both consumers and insurance providers—a process known as risk assessment.

The goal of incorporating mileage into premium calculations is to determine whether PAYD can create more equitable and fair insurance rates. The underlying assumption is that PAYD could yield environmental benefits by incentivizing reduced vehicle miles traveled (VMT). Under PAYD, additional mileage would likely increase an individual's risk exposure, thereby raising premium rates. This potential increase in cost could motivate drivers to reduce their VMT, leading to lower fuel consumption and a reduction in greenhouse gas emissions.

1.2 Research Goals

In conducting the Pay-as-you-drive Auto Insurance Modeling project, our objective was to build upon the foundational work of MIT professors Joseph Ferreira, Jr. and Eric Minikel, as presented in their paper, "*Pay-As-You-Drive Auto Insurance in Massachusetts: A Risk Assessment and Report on Consumer, Industry, and Environmental Benefits*." Utilizing their paper as a model and employing the same dataset, we aimed to evaluate the characteristic of this insurance model under various conditions, particularly focusing on the interplay between driver classes, territories, and mileage in determining individual insurance pricing.

Drawing on data from Massachusetts insurance policies spanning 2004 to 2008, we concentrated on the 2006 policy year, mirroring the original study, to delve deeper into how mileage impacts losses across different class-territory combinations. Our research was driven by several key questions:

- Are there significant differences in predicted losses based on annual mileage across different class-territory groupings?

- How do these differences compare to the original estimates presented in the MIT paper?
- Which policies among the identified differences would be both realistic and feasible for implementation?

1.3 Introductory Reading

Before initiating our research, we thoroughly reviewed the work of Ferreira Jr. and Minikel, along with other relevant studies that could assist us in developing a pricing scheme or understanding how similar PAYD policies function in other contexts. The key papers we consulted include Aaron S. Edlin's *"Per-Mile Premiums for Auto Insurance*," Guensler et al.'s "*Current State Regulatory Support for Pay-As-You-Drive Automobile Insurance Options*," and Todd Litman's "*Understanding Transport Demands and Elasticities."*

The studies by Litman and Edlin were particularly useful for informing our approach to pricing schemes, as they allowed us to connect per-mile price calculations to the elasticities of demand for gasoline—a comparable good that is directly related to driving behavior. Work done by Guensler et al. provided valuable insights into existing policies similar to PAYD, helping us to understand the regulatory framework that would be necessary for implementing such a system across different states.

These resources, alongside the primary paper by Ferreira Jr. and Minikel, were instrumental in shaping our research questions and had the potential to influence our work, especially if we progressed to the stage of developing detailed pricing models.

2 Methodology

2.1 Dataset Summaries

Our data consisted of several CSV files or data tables, specifically "all06clms," "expo06_amile," "terrgroups," "classgroups," and "fuel_economy_summary." The "all06clms" dataset contained our claims data, including crucial details such as identification dimensions for specific vehicles and policies, as well as the losses required for our regression models. This dataset comprised over 680,000 records and was used in conjunction with "expo06_amile."

The "expo06_amile" dataset, with just under four million records, provided vital information for our analysis, including individual identification data such as territory and class, policy start and end dates with adjustment factors, and annual mileage. Territories were represented by 3-digit codes corresponding to 360 towns and neighborhoods in Massachusetts, with the associated values detailed in the "terrgroups" dataset. Class distinctions were represented by 4-digit codes, which were mapped to our five distinct class groupings in the "classgroups" dataset.

2.2 Important Variable Descriptions

Distinguishing between distinct classes and territories is crucial for our analysis, as they define the type of driver for whom we are examining losses. The classes categorize drivers based on experience and driving type, with our groups including adults, business drivers, those with less than three years of experience, those with three-to-six years of experience, and senior citizens. The territories are ordered zones that reflect the level of risk associated with operating a vehicle within a specific town. These territories are numbered from 1 to 6, representing a spectrum from very low to very high risk, respectively.

Using these variables, we created specific class-territory groupings, resulting in thirty claims tables—one for each combination of the five classes and six territories. This allowed us to investigate any differences that might emerge between these groups, as well as within the same class, across different territories. With the class-territory groupings established, we followed the methodology of Ferreira Jr. and Minikel for calculating losses by summing each policy's loss paid and loss reserve amounts to obtain a total loss figure. With this and the annual mileage data, we were nearly ready to develop regression models for our analysis.

2.3 Data Cleaning

Before we could begin our analysis, it was necessary to clean the dataset, as many entries lacked the essential information required for model creation. A significant portion of the data was missing mileage information and, therefore, had to be excluded from the study. Additionally, we followed the precedent set by the MIT paper by excluding policies with total losses below $50.

Once these initial steps were completed, we created subsets of data specific to each class and territory to begin constructing our models. To closely follow the methodology of Ferreira Jr. and Minikel, we adjusted our loss totals based on the duration of the policy. However, during this process, we discovered that many of our preliminary models were skewed by policies with very short durations. Since our per-car-year adjustment involved dividing the total loss by the exposure period, this led to inflated adjusted loss totals for policies with extremely short terms. To address this issue, we decided to exclude policies with durations shorter than one month from our analysis.

2.4 Data Processes

In our data processing, we performed several steps previously described. First, we calculated the total loss for each individual in our dataset and adjusted this value using a factor of 0.67, as outlined in the MIT paper, to approximate a pure premium figure. Although this multiplier was later found to be inaccurate, we retained it in our subsequent analyses with the intent of transforming our regression coefficients for comparison purposes. This approach was necessary because our total loss figure differed from the pure premium figure described in the MIT paper.

Following this, we created 500-mile bins to group the data, consistent with the methodology used in the MIT paper, specifically in their analysis of adults in Territory 3. Within each bin, we averaged the total loss to facilitate a comparison of mileage. Additionally, we calculated claim frequencies within these mile bins to allow for comparison with the linear and Poisson models presented in the MIT study. We limited our analysis to miles between 2,000 and 30,000 to align with the original paper, but we extended our regression analysis to include up to 60,000 miles for Territory 1. This extension was necessary due to the higher driving distances typically associated with rural areas in that region.

We conducted a more detailed analysis using our own linear regression models with the same 2006 policy data from the state of Massachusetts. Our approach involved constructing individualized linear regression models for each selected class within each individual territory.

2.5 Transformation Experimentation

Ferreira Jr. and Minikel incorporated nonlinear transformations and regression techniques in their paper, prompting us to investigate whether our individualized models would exhibit the nonlinear characteristics they predicted would diminish within our class-territory subsets of claims. We experimented with transforming our total loss figure using the natural logarithm and found mixed results. This transformation effectively reduced the outliers and scatter, particularly at higher annual mileages, by mitigating the effects of heteroscedasticity. However, our models already exhibited a strong linear relationship prior to this transformation. The R-squared values remained largely unchanged, with most showing a slight decrease, as detailed in *Appendix A*. Based on these findings, we decided not to pursue this approach further, as the separation of the initial aggregated, nonlinear model into class and territory subsets had already resulted in linear models.

3 Results

3.1 Previous Research Results

Previous research has demonstrated that mileage is a significant exponential factor in enhancing auto-insurance practices. In the paper, "*Pay-As-You-Drive Auto Insurance in Massachusetts: A Risk Assessment and Report on Consumer, Industry, and Environmental Benefits,*" presents linear regression models that highlight the statistical correlations when incorporating mileage with territory and class variables. The data analyzed in this MIT study was sourced from insurance policies and claims from the 2006 policy year in Massachusetts.

Three linear regression models illustrate the statistical impact of mileage on premium rates, defined as the sum of loss paid and loss reserved. The first model, which includes only the mileage variable, is represented by the equation:

$$Premium = 0.0055 \times annual\_mileage + 111.70$$

This model yields a correlation coefficient R-squared of 9%, indicating that mileage alone is not a sufficiently strong predictor of insurance premiums. The second model excludes mileage and focuses solely on class and territory, represented by the equation:

$$Premium = class\_adjustment + territory\_adjustment + 96.50$$

This model achieves a significantly higher correlation coefficient of R-squared of 57%, demonstrating that class and territory alone have a stronger statistical significance in determining premium rates.

The third model integrates all three variables—class, territory, and mileage—resulting in the following equation:

$$Premium = 40.12 + class\_adjustment + territory\_adjustment + ((0.0043 + class\_rate + territory\_rate) \times annual\_mileage))$$

This combined model yields the highest correlation coefficient, R-squared of 72%, indicating that the inclusion of mileage, alongside class and territory, significantly enhances the accuracy of insurance premium calculations. This finding supports the conclusion that mileage is a crucial and exponential factor in determining insurance premiums.

3.2 Result Overview

Our findings contradict the conclusions of the MIT study, which suggested that premium rates should increase with additional mileage. Specifically, we observed that for certain classes in specific risk environments, premium rates can actually decrease with increased mileage. For example, in the 'adult' class within 'territory 1,' we observed a negative slope between mileage and premiums. This indicates that, under certain conditions, the experience of driving in a low-risk environment can outweigh the risk associated with additional mileage. In this case, 'territory 1' generally corresponds to rural environments, and the adult class exhibited a slope of -0.00113 cents per additional mile driven.

This result challenges the assumption that implementing PAYD would universally lead to environmental benefits by reducing vehicle miles traveled (VMT). Our findings suggest that further analysis is needed to refine premium rate calculations by considering not only linear regression models but also other statistical techniques. These could include Poisson regression models that account for car frequency and the number of claims, transformations within linear regression, and the application of alternative regression models and techniques to enhance the current analysis.

3.3 Adults-Territory 3

The adult-territory 3 group served as the primary basis for our comparison with the findings of Ferreira Jr. and Minikel. Like us, they separated this group from the rest of the data and applied several adaptations of a linear regression model, including a pure PAYD (Pay-As-You-Drive) plan where mileage was the sole factor, a traditional plan, a model using aggregate data, and a model that included mileage within the class-territory group with either a $0 base rate or a flat rate for the first 2,000 miles. This approach provided us with multiple points of comparison for this specific class-territory grouping.

For our regression model, presented without any transformations and detailed in *Appendix A* along with the other models we developed, the equation is as follows:

$$\textit{Loss Total (\$)} = \$2788 + \$1.316 \times 10^{-2} \times \textit{(Annual Mileage)}$$

This model produced significant p-values for both the slope and intercept $(p < 2 \times 10^{-16})$, with a multiple R-squared value of *0.06263.* When comparing our results with the MIT paper, we needed to transform our loss total figure into a pure premium figure. Lacking a clear method from the authors, we opted to use their calculations for the average driver—specifically, the price for an adult driving *13,031* miles—and matched it to the closest mile bin in our dataset. We then derived a multiplier that allowed us to equate our slope to the value provided in their study. We found that a *0.21* multiplier was necessary to align our loss total with their pure premium figure.

We applied this multiplier across our other class-territory groupings to scale our loss total to the pure premium, which was essential for making equitable comparisons between models, especially given the ambiguities in their calculations and pricing. Additionally, we adjusted for full coverage premium, as described by the authors, by using their provided multiplier of *5.5* to convert the pure premium to a full-priced premium.

Using these multipliers, our regression model on the MIT premium scale is:

$$\textit{Ours: Loss Total (\$) (on MIT premium scale)} = \$585.31 + \$1.316 \times 10^{-2} \times \textit{(Annual Mileage)}$$

For comparison, the MIT models are as follows:

$$\textit{MIT Adult T3 exclusive: Full Premium (\$)} = \$345.46 + \$2.915 \times 10^{-2} \times \textit{(Annual Mileage)}$$

$$\textit{MIT Aggregate model: Full Premium (\$)} = \$299.97 + \$3.19 \times 10^{-2} \times \textit{(Annual Mileage)}$$

From this comparison, it appears that our pricing scheme suggests that the cost per additional mile is lower than what the MIT models indicate. Additionally, our initial price, approximately *\$585*, suggests that the base price for individuals in this group should be higher than predicted by the MIT models.

3.4 Adults

Our results for the adult groups showed a mix of satisfactory and unsatisfactory outcomes. Among the groups, two had R-squared values below *10%*, with one at *0.06%* for Territory 1, while the best-performing model, for Territory 5, had an R-squared of *46%.* All of our slopes and intercepts were significant at the same level as described for the adult-territory 3 group. Notably, Territory 1 exhibited a negative slope. This suggests that increased experience and time spent driving may reduce the total loss, and therefore the risk on the road, as experience with the roads and continued practice may contribute to safer driving. All other linear models we generated for adults had positive slopes. Further details on the adult groups can be found in *Appendix A.*

3.5 Seniors

Our results for the senior groups represent our best-performing class overall. The R-squared values ranged from a low of *18%* to a high of *40%.* All slopes were positive, and when examining the differences between the various territories, we observed that they were quite similar in several respects. Additionally, the intercepts showed linear increases corresponding to the incremental rise in risk associated with higher territory classifications. This class also exhibited p-values for both slope and intercept that were identical to those observed in the adult-territory 3 group. Further details on the senior groups can be found in *Appendix A*.

3.6 Business

This group yielded some of our poorest regression results, primarily due to the limited number of policies within this class. Ideally, these procedures would be performed on a larger sample of individuals identified as "business" under our dataset criteria. The p-values for slope ranged from significant values, comparable to those observed in the adult-territory 3 group, to as high as *0.7698*. This class had the fewest territory groupings with slope p-values low enough to be considered significant at the *5%* level ($\alpha = 0.05$). The unsatisfactory linear regression results are likely attributable to the substantial difference in sample size between the business group and all other groups. Further details on the business group can be found in *Appendix A*.

3.7 Inexperienced Drivers (<3 yrs)

For drivers with less than three years of experience, the initial results revealed some unexpected patterns. Each territory group within this class appeared to behave independently. For example, in territory 3, there was a negative correlation between miles driven and total loss. While many of the slope p-values were significant at the *0.1%* confidence level ($\alpha = 0.001$), some were not, with territory 3 and 6 showing p-values of *0.499* and *0.103*, respectively. Notably, similar to the adults in territory 1, the inexperienced drivers in territory 1 also showed a decrease in total loss with increased mileage. This suggests that as inexperienced drivers in territory 1 towns drive more, they improve their driving skills, offsetting the increased risk typically associated with higher mileage. Further details on the inexperienced drivers can be found in *Appendix A*.

3.8 Low Experience Drivers (3-6 yrs)

Our analysis of the low-experience driver group revealed that only one territory had a p-value worth noting—territory 1, with a p-value of *0.0106.* While this is statistically significant, it is not as strong as the p-values observed in other territories. Interestingly, territory 4 indicated that, according to our model, the more miles driven, the lower the expected loss totals. However, it is important to mention the low R-squared values for this group, suggesting that the model would benefit from a larger sample size, similar to the business and inexperienced driver groups. Further details on low-experience or occasional drivers can be found in *Appendix A*.

3.9 Poisson Regression

In our Poisson regression analysis, we examined claim frequency by dividing mileage into bins and calculating the number of claims per one hundred car years within each bin. This approach allowed us to assess whether claim frequency increased with higher mileage. Our Poisson regression was applied only to our two best-performing and highest-population classes: adults and seniors. Across all class-territory groups, we found that increased mileage was generally associated with a higher number of claims. The notable exception was adults in territory 1, where our loss regression models indicated a decrease in total loss with increased mileage. While these findings are informative, it's important to note that a claim is a broad metric, and the occurrence of a claim does not necessarily reflect the severity or quality of the claims relative to any standard. Consequently, these results were not deemed highly significant to our overall project. Further details on the Poisson regression output can be found in *Appendix A*.

4 Conclusion

4.1 Our Conclusions

In our study, we found that there are differences among classes and territories for how loss totals are associated with the number of miles driven. We believe this to mean that there should be class-territory specific policies put in place for a sustainable and profitable pay-as-you-drive auto insurance plan.

4.2 Future Direction

This study was conducted over a single summer term, and despite our efforts to closely replicate the referenced study, we encountered several obstacles during the duplication process. Time constraints limited our ability to achieve everything we intended. For instance, we were unable to incorporate a pricing scheme into our data and could only emulate this aspect by scaling our results to align with the MIT paper. Additionally, it would have been valuable to analyze how vehicle miles traveled (VMT) might be reduced over time as the PAYD concept gradually becomes incorporated, possibly only for certain classes or class-territory groupings. We also would have liked to explore the expected impact on greenhouse gas emissions over time. Unfortunately, we were unable to fully develop these aspects within the time frame of the study.

5 Acknowledgements

5.1 Research Department

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5.2 Bibliography

Edlin, A. S. (2003). Per-Mile Premiums for Auto Insurance. In R. Arnott, B. Greenwald, R. Kanbur, & B. Nalebuff (Eds.), *Economics for an Imperfect World: Essays in Honor of Joseph E. Stiglitz* (pp. 53-82). MIT Press.

Litman, T. (2024). *Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior*.

Ferreira, J., Jr., & Minikel, E. (2010). *Pay-As-You-Drive Auto Insurance in Massachusetts: A Risk Assessment and Report on Consumer, Industry and Environmental Benefits*

Guensler, R., Amekudzi, A., Williams, J., Mergelsberg, S., & Ogle, J. *Current State Regulatory Support For Pay-As-You-Drive Automobile Insurance Options*.

Appendix A

A.1 Logarithmic Transform

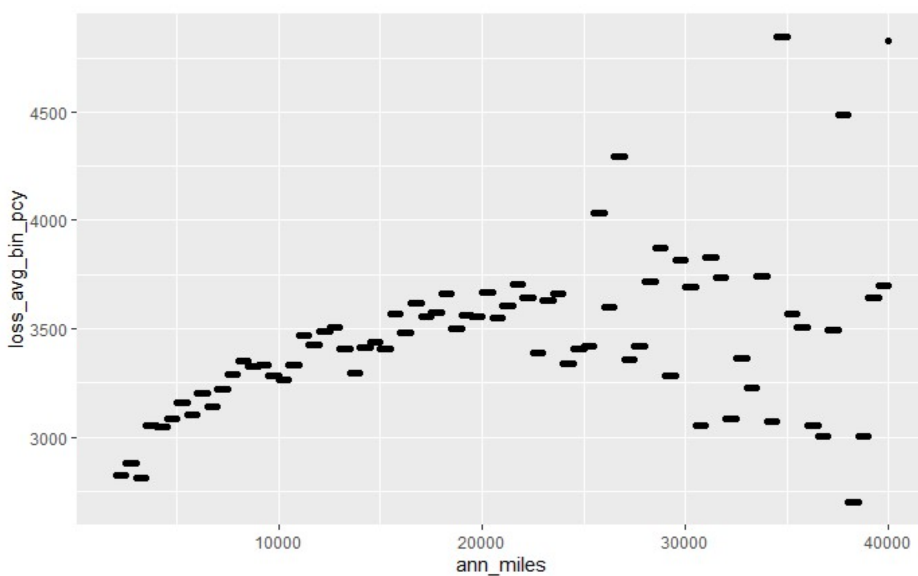
Linear Regression

R^2 Table	T1	T2	T3	T4	T5	T6
Adults	0.0006073	0.1239	0.06263	0.254	0.4609	0.3241
Business	0.0009359	0.005	0.1157	6.049e-05	0.0007947	0.0069
Seniors	0.2097	0.3742	0.1852	0.1808	0.4045	0.1962
Inexperienced	0.00581	0.001095	0.0001577	0.05177	0.04109	0.0004392
Low Experience	0.001763	0.058	0.04153	0.02763	0.02026	0.01879

Log Transformation

R^2 Table	T1	T2	T3	T4	T5	T6
Adults	0.008329	0.1251	0.05373	0.2517	0.4685	0.3168
Business	1.9e-05	0.009281	0.08986	7.525e-04	0.001474	0.01533
Seniors	0.1946	0.3867	0.1264	0.1416	0.3648	0.1515
Inexperienced	0.0348	0.004396	0.01962	0.04363	0.02457	0.002987
Low Experience	0.00214	0.07465	0.03414	0.02804	0.01625	0.006629

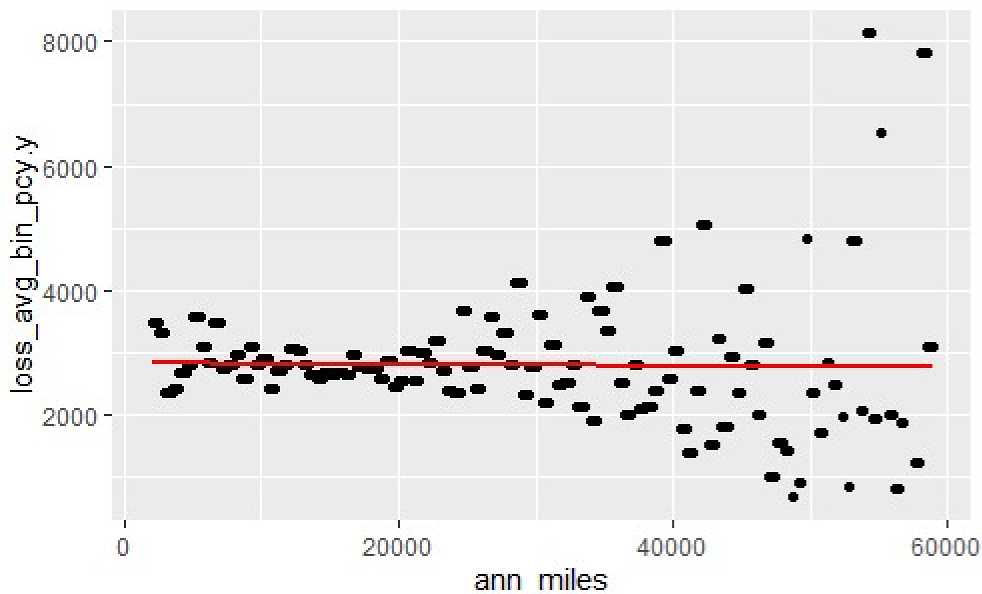
Graph



(All Losses, No <1 Month Policies)

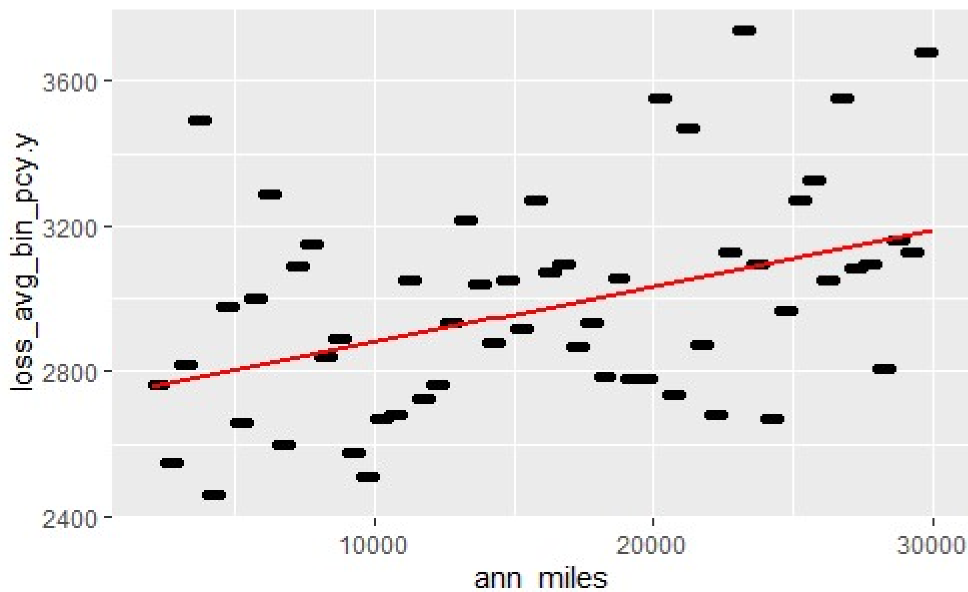
A.2 Linear Regression Output

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_adultT1Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2101.7  -158.2   -35.7   163.3  5360.5

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.832e+03  3.429e+00 825.869  < 2e-16 ***
ann_miles   -1.131e-03  2.053e-04  -5.507 3.66e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 324 on 49912 degrees of freedom
Multiple R-squared:  0.0006073, Adjusted R-squared:  0.0005873
F-statistic: 30.33 on 1 and 49912 DF,  p-value: 3.66e-08
```



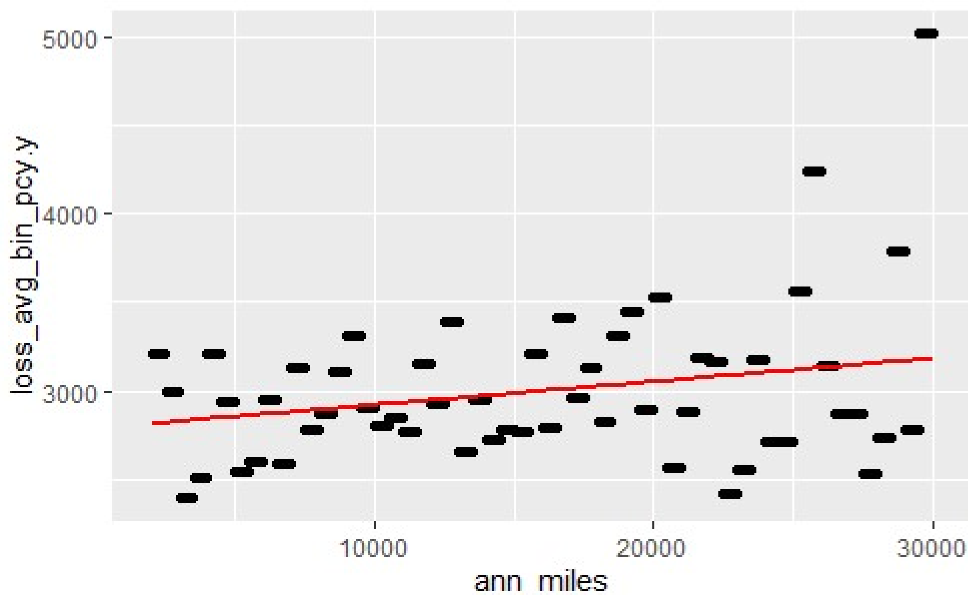
(Adults-Territory 1, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_adultT2Claims)

Residuals:
   Min      1Q Median      3Q     Max 
-435.8 -210.3  -13.8  149.2  709.1 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.727e+03  2.598e+00 1049.97   <2e-16 ***
ann_miles   1.531e-02  1.723e-04   88.85   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 240 on 55806 degrees of freedom
Multiple R-squared:  0.1239,    Adjusted R-squared:  0.1239 
F-statistic:  7895 on 1 and 55806 DF,  p-value: < 2.2e-16
```



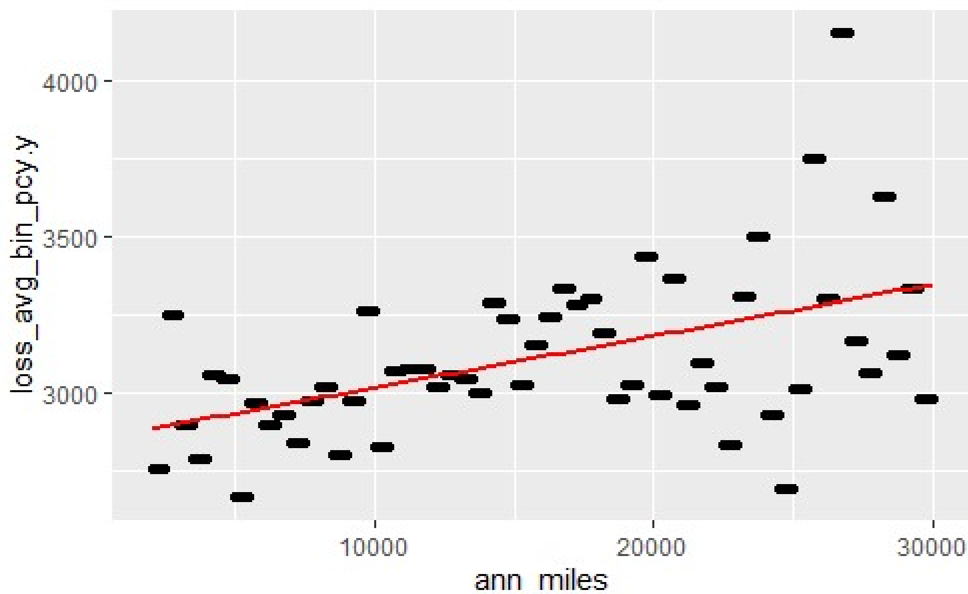
(Adults-Territory 2, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_adultT3Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-670.03 -208.88  -21.77  213.46 1844.38 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.788e+03  4.117e+00  677.04   <2e-16 ***
ann_miles   1.316e-02  2.693e-04   48.88   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 305.2 on 35767 degrees of freedom
Multiple R-squared:  0.06263,   Adjusted R-squared:  0.0626 
F-statistic:  2390 on 1 and 35767 DF,  p-value: < 2.2e-16
```



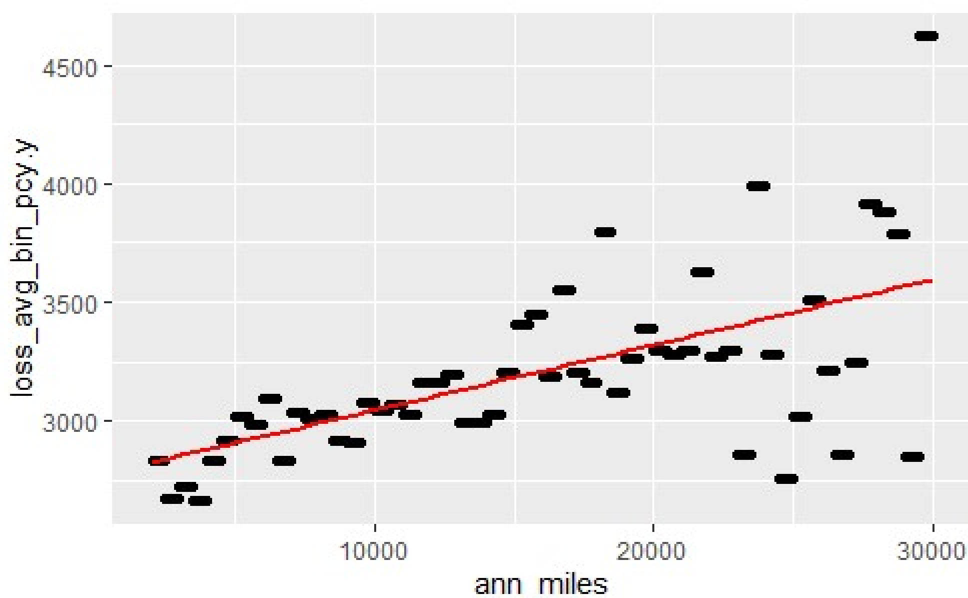
(Adults-Territory 3, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_adultT4Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-570.57  -81.71   -3.06  118.93  861.51 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.853e+03  1.549e+00  1841.8   <2e-16 ***
ann_miles   1.650e-02  1.059e-04   155.9   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 167.3 on 71390 degrees of freedom
Multiple R-squared:  0.254,	Adjusted R-squared:  0.2539 
F-statistic: 2.43e+04 on 1 and 71390 DF,  p-value: < 2.2e-16
```



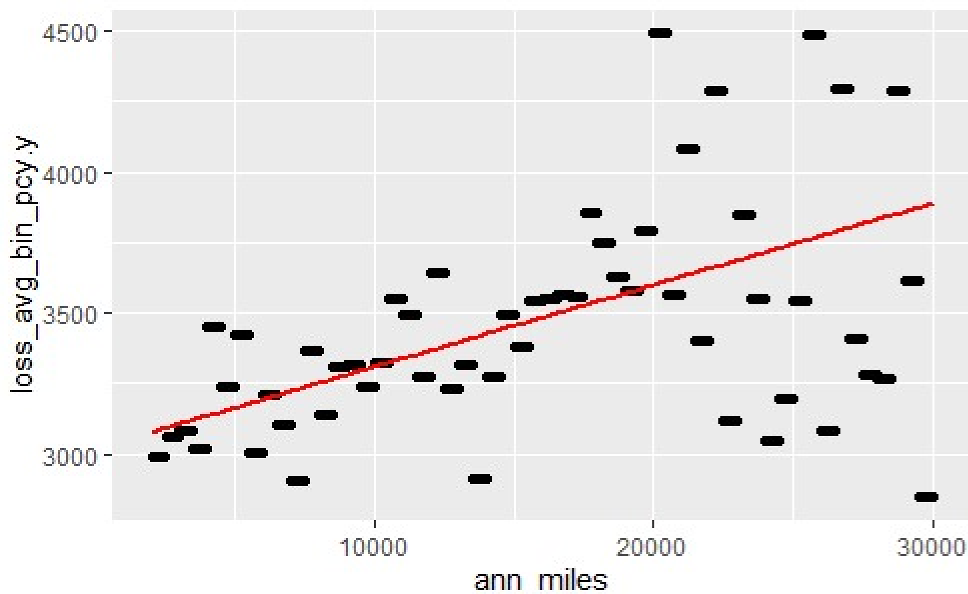
(Adults-Territory 4, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_adultT5Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-728.04  -98.35    1.46   61.69 1037.40 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.772e+03  1.409e+00  1968.0   <2e-16 ***
ann_miles   2.746e-02  1.041e-04   263.9   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 169.1 on 81451 degrees of freedom
Multiple R-squared:  0.4609,	Adjusted R-squared:  0.4609 
F-statistic: 6.964e+04 on 1 and 81451 DF,  p-value: < 2.2e-16
```



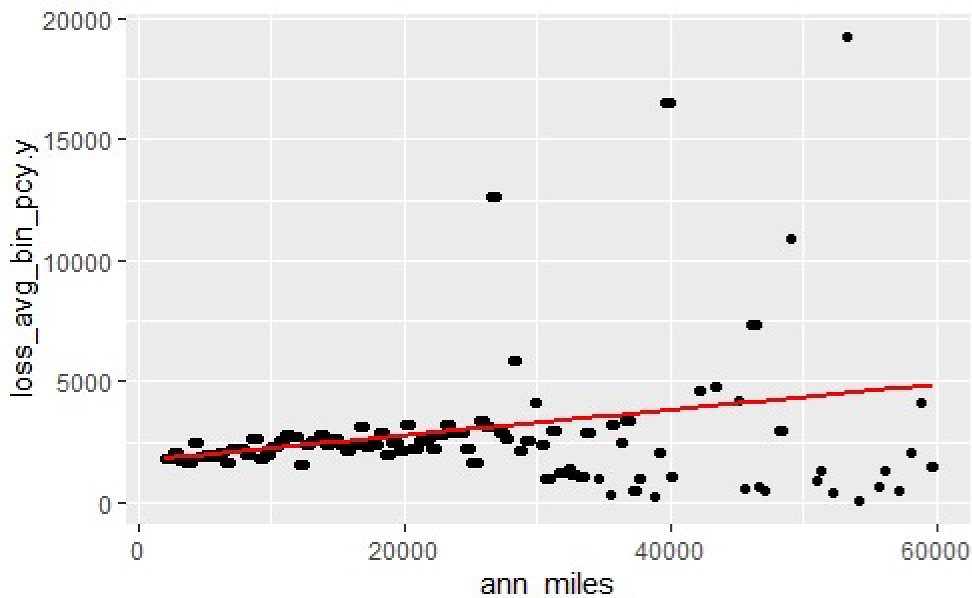
(Adults-Territory 5, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_adultT6Claims)

Residuals:
     Min       1Q   Median       3Q      Max
-1044.11  -111.74    12.05   121.71   891.11

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.019e+03  2.095e+00  1441.3   <2e-16 ***
ann_miles   2.900e-02  1.596e-04   181.7   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 232.3 on 68874 degrees of freedom
Multiple R-squared:  0.3241,    Adjusted R-squared:  0.3241
F-statistic: 3.303e+04 on 1 and 68874 DF,  p-value: < 2.2e-16
```



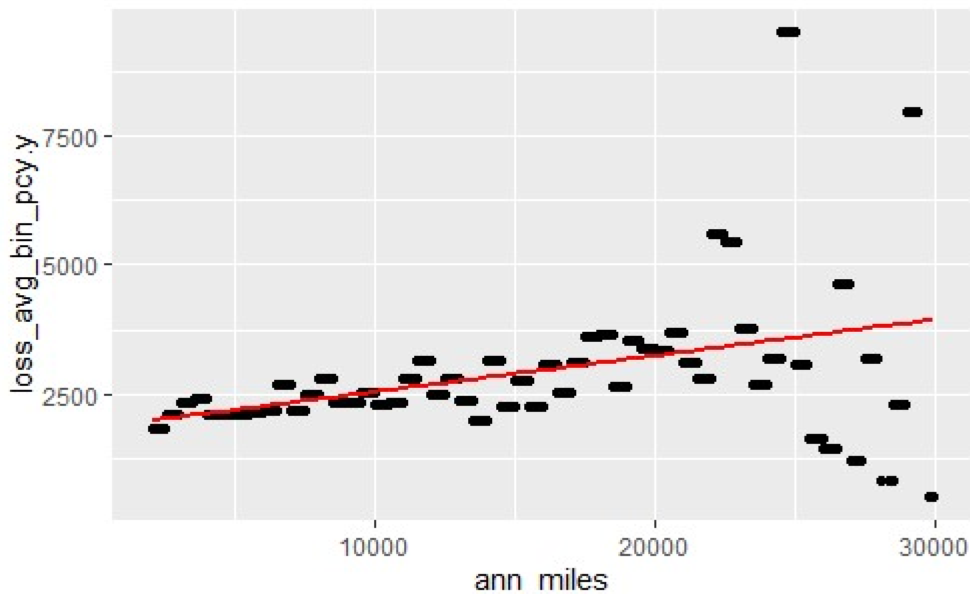
(Adults-Territory 6, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_seniorT1Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-4516.5  -238.0   -23.4   212.7 14697.0

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.709e+03  1.208e+01  141.44   <2e-16 ***
ann_miles   5.259e-02  1.018e-03   51.64   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 658.1 on 10047 degrees of freedom
Multiple R-squared:  0.2097,    Adjusted R-squared:  0.2097
F-statistic:  2666 on 1 and 10047 DF,  p-value: < 2.2e-16
```



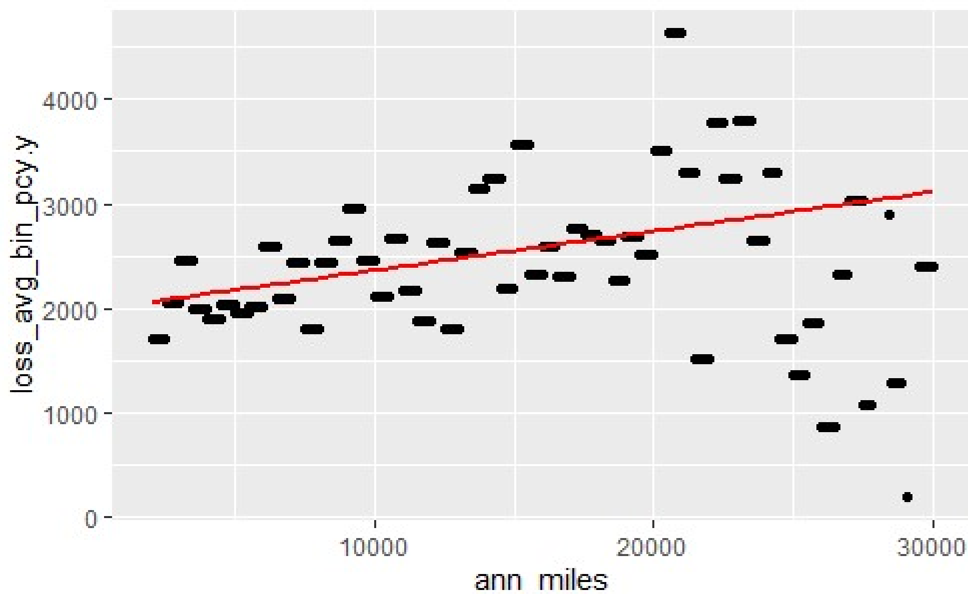
(Seniors-Territory 1, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_seniorT2Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-3446.2  -162.3   -74.8   175.1  5943.5

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.847e+03  8.923e+00   207.0   <2e-16 ***
ann_miles   7.007e-02  8.412e-04    83.3   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 489.2 on 11603 degrees of freedom
Multiple R-squared:  0.3742,    Adjusted R-squared:  0.3742
F-statistic:  6939 on 1 and 11603 DF,  p-value: < 2.2e-16
```



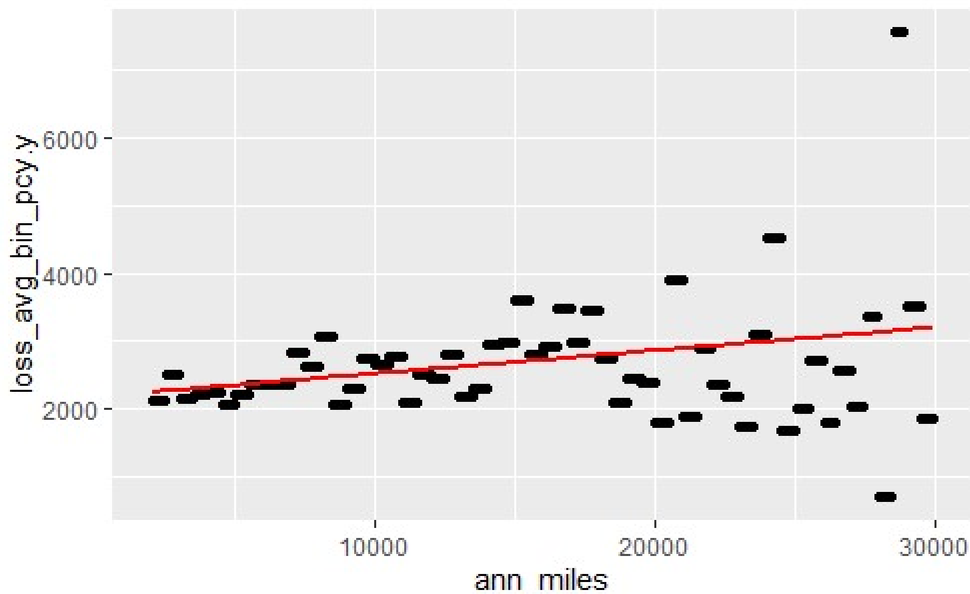
(Seniors-Territory 2, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_seniorT3Claims)

Residuals:
     Min       1Q   Median       3Q      Max 
-2884.09  -238.57   -44.27   276.21  1872.85 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 1.987e+03  1.048e+01   189.6   <2e-16 ***
ann_miles   3.750e-02  9.664e-04    38.8   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 432.8 on 6623 degrees of freedom
Multiple R-squared:  0.1852,	Adjusted R-squared:  0.1851 
F-statistic:  1505 on 1 and 6623 DF,  p-value: < 2.2e-16
```



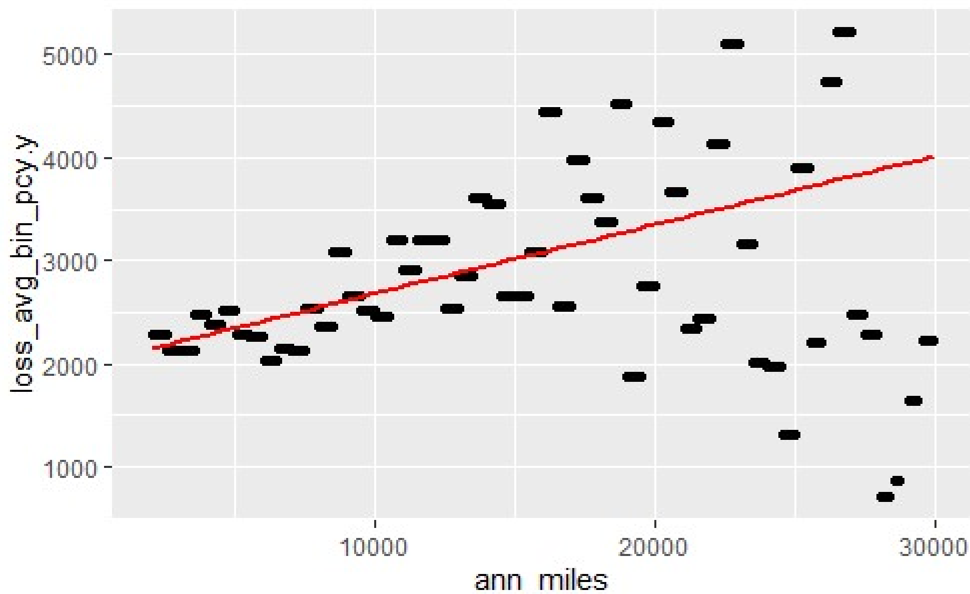
(Seniors-Territory 3, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_seniorT4Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2456.1  -148.7   -64.2   225.7  4400.9 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.182e+03  6.340e+00  344.23   <2e-16 ***
ann_miles   3.405e-02  6.241e-04   54.55   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 377.9 on 13479 degrees of freedom
Multiple R-squared:  0.1808,	Adjusted R-squared:  0.1808 
F-statistic:  2976 on 1 and 13479 DF,  p-value: < 2.2e-16
```



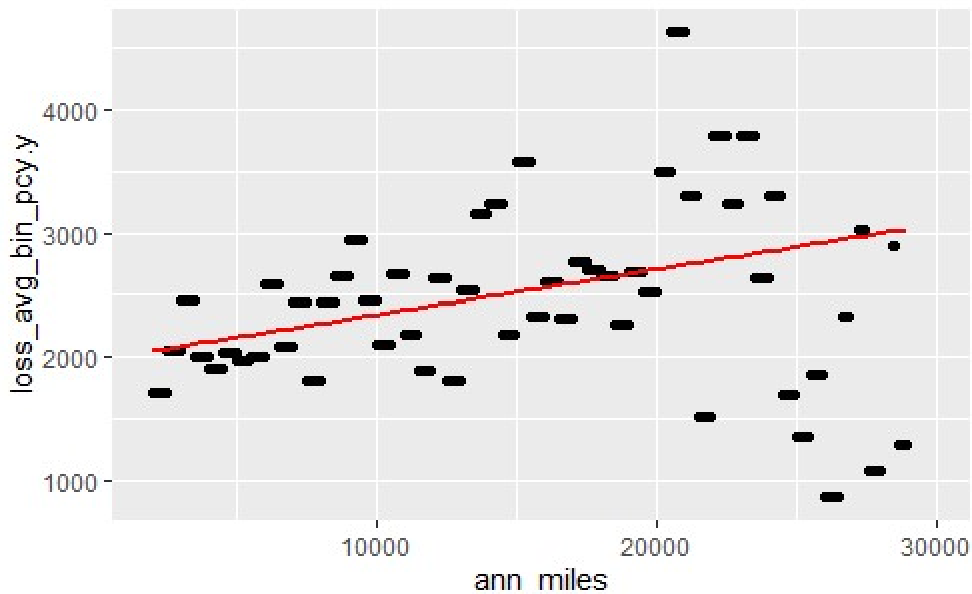
(Seniors-Territory 4, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_seniorT5Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-3203.6  -199.5   -57.7   184.2  1579.8

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.018e+03  6.543e+00  308.44   <2e-16 ***
ann_miles   6.659e-02  6.831e-04   97.48   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 410.4 on 13993 degrees of freedom
Multiple R-squared:  0.4045,    Adjusted R-squared:  0.4044
F-statistic:  9503 on 1 and 13993 DF,  p-value: < 2.2e-16
```



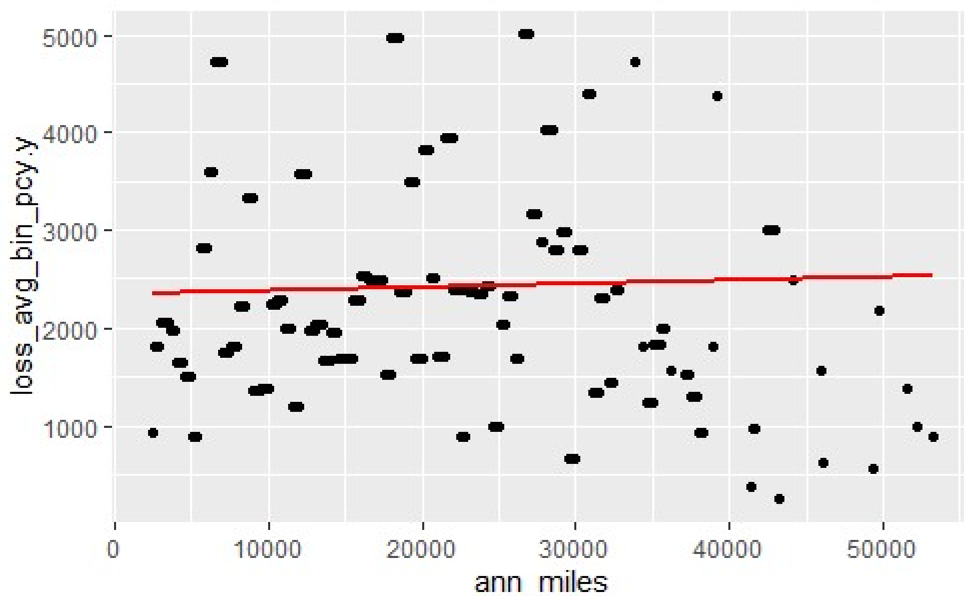
(Seniors-Territory 5, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_seniorT6Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2082.0  -212.0  -102.8   292.0  1905.1

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.974e+03  7.673e+00   257.3   <2e-16 ***
ann_miles   3.652e-02  7.992e-04    45.7   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 372.2 on 8554 degrees of freedom
  (12 observations deleted due to missingness)
Multiple R-squared:  0.1962,    Adjusted R-squared:  0.1961
F-statistic:  2088 on 1 and 8554 DF,  p-value: < 2.2e-16
```



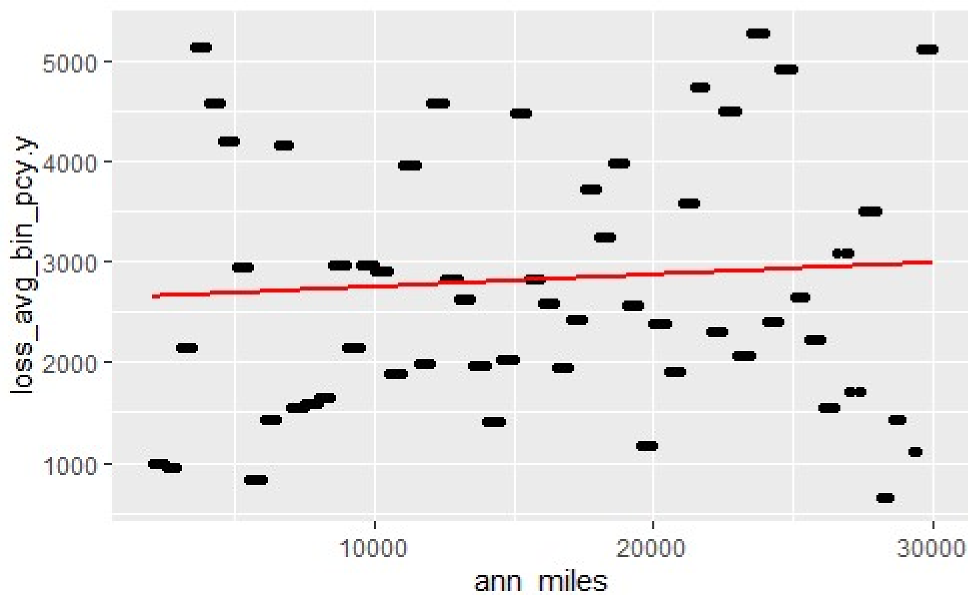
(Seniors-Territory 6, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_businessT1Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2248.7  -707.8  -138.7   362.7  2571.6

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.341e+03  6.290e+01  37.220   <2e-16 ***
ann_miles   3.556e-03  3.330e-03   1.068    0.286
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 998 on 1217 degrees of freedom
Multiple R-squared:  0.0009359, Adjusted R-squared:  0.000115
F-statistic:  1.14 on 1 and 1217 DF,  p-value: 0.2859
```



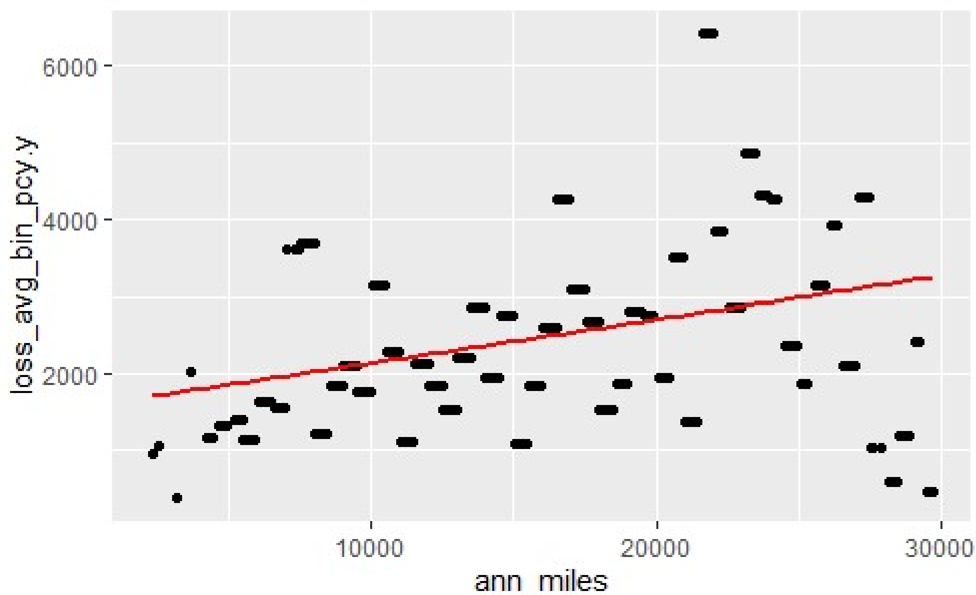
(Business-Territory 1, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_businessT2Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2323.6  -829.5  -173.3   700.8  2461.0 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.625e+03  7.763e+01  33.821   <2e-16 ***
ann_miles   1.213e-02  4.898e-03   2.477   0.0134 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1091 on 1221 degrees of freedom
Multiple R-squared:  0.005,	Adjusted R-squared:  0.004185 
F-statistic: 6.136 on 1 and 1221 DF,  p-value: 0.01338
```



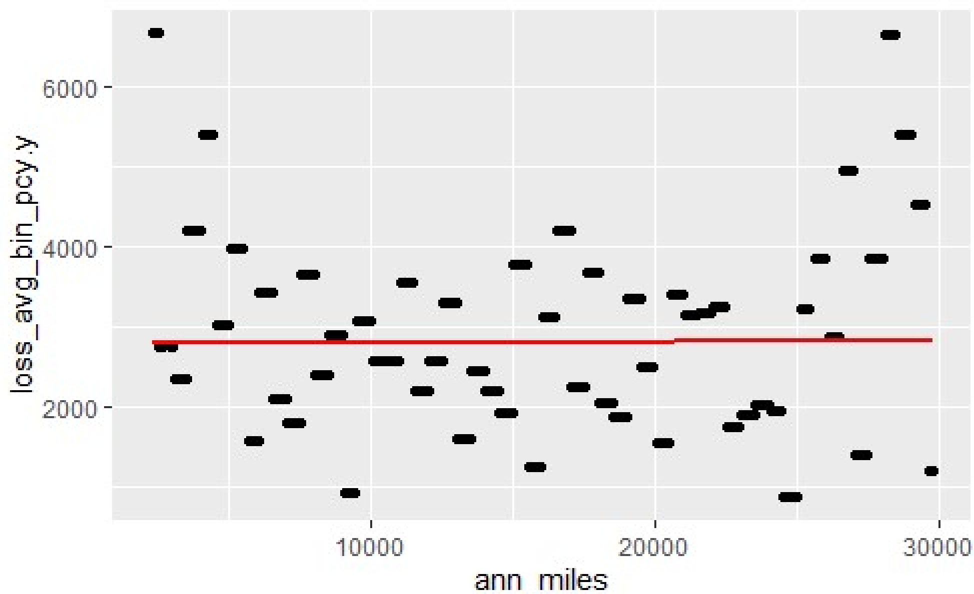
(Business-Territory 2, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_businessT3Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2774.2  -619.6    -3.4   501.8  3612.6 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 1.578e+03  9.680e+01  16.304   <2e-16 ***
ann_miles   5.623e-02  5.635e-03   9.977   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 957 on 761 degrees of freedom
Multiple R-squared:  0.1157,	Adjusted R-squared:  0.1145 
F-statistic: 99.55 on 1 and 761 DF,  p-value: < 2.2e-16
```



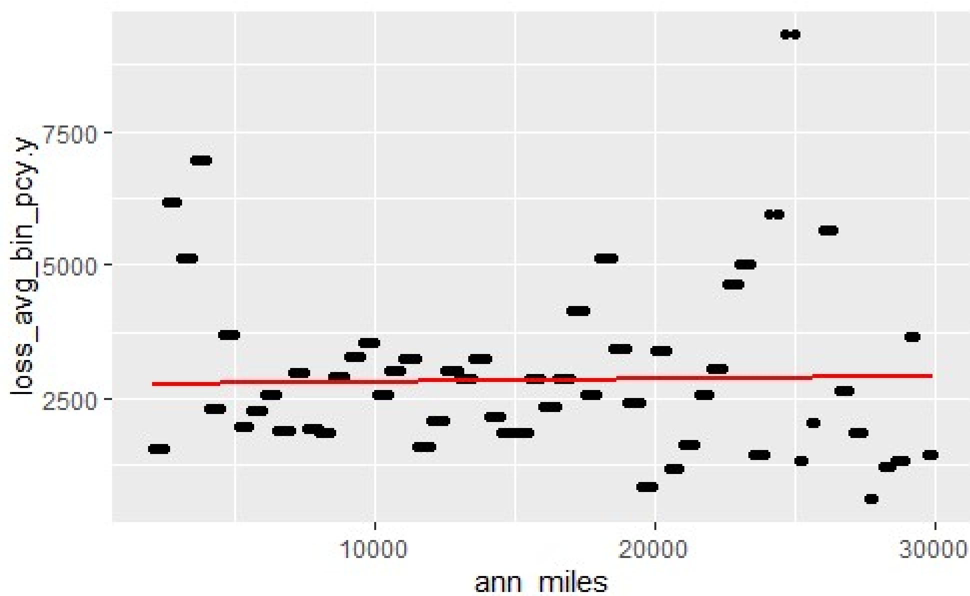
(Business-Territory 3, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_businessT4Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-1951.2  -753.5  -223.7   578.5  3873.4 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.797e+03  6.911e+01  40.477   <2e-16 ***
ann_miles   1.265e-03  4.321e-03   0.293     0.77    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1049 on 1416 degrees of freedom
Multiple R-squared:  6.049e-05, Adjusted R-squared:  -0.0006457 
F-statistic: 0.08567 on 1 and 1416 DF,  p-value: 0.7698
```



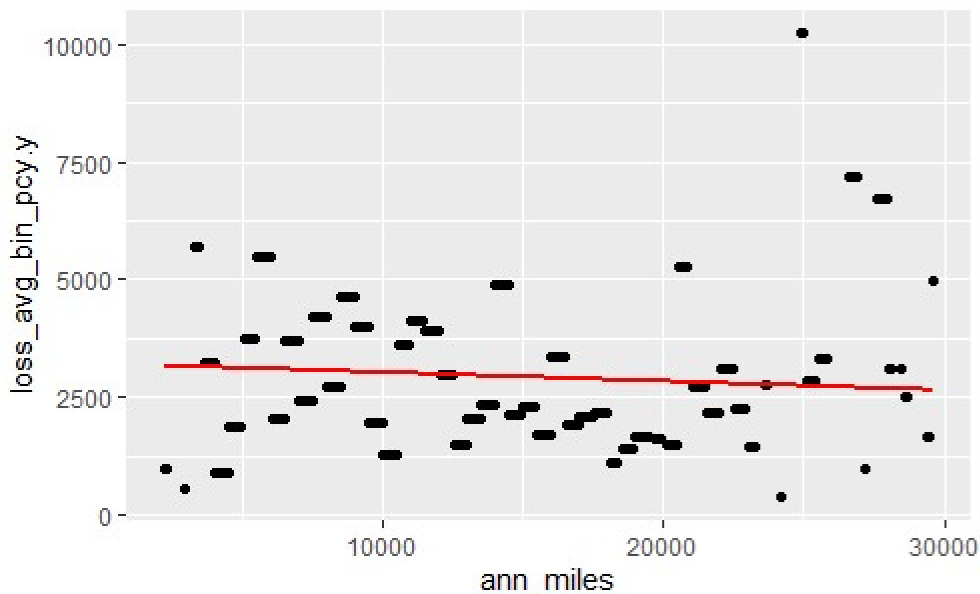
(Business-Territory 4, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_businessT5Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2292.3  -829.4    16.2   438.2  6411.4 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.763e+03  7.964e+01  34.699   <2e-16 ***
ann_miles   5.287e-03  5.385e-03   0.982    0.326    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1142 on 1212 degrees of freedom
Multiple R-squared:  0.0007947, Adjusted R-squared:  -2.971e-05 
F-statistic: 0.964 on 1 and 1212 DF,  p-value: 0.3264
```



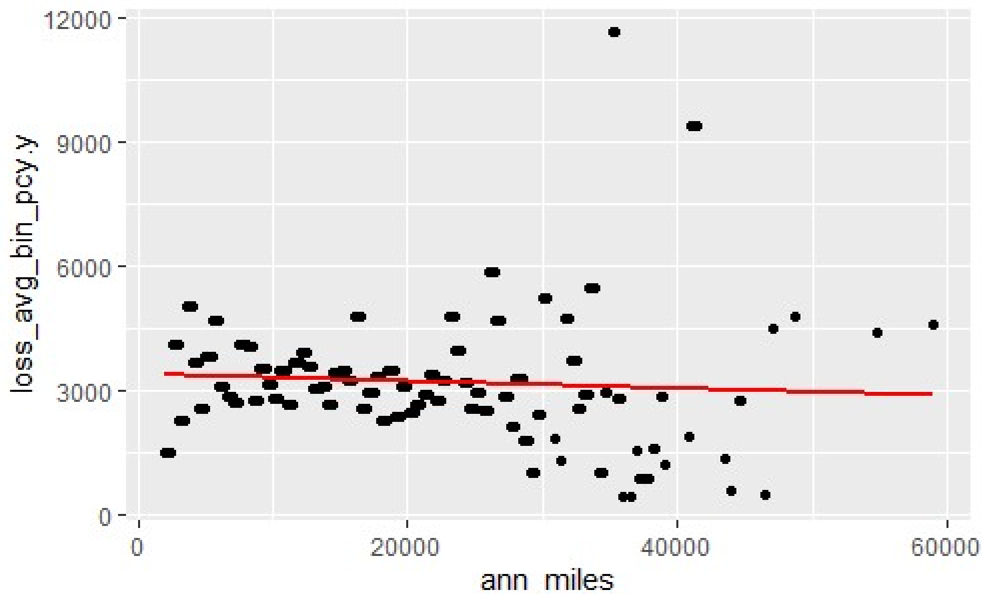
(Business-Territory 5, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_businessT6Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2591.3  -926.9  -357.8   935.7  7487.2 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.214e+03  1.153e+02  27.876   <2e-16 ***
ann_miles   -1.881e-02  7.894e-03  -2.383   0.0174 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1334 on 817 degrees of freedom
Multiple R-squared:  0.0069,	Adjusted R-squared:  0.005685 
F-statistic: 5.677 on 1 and 817 DF,  p-value: 0.01742
```



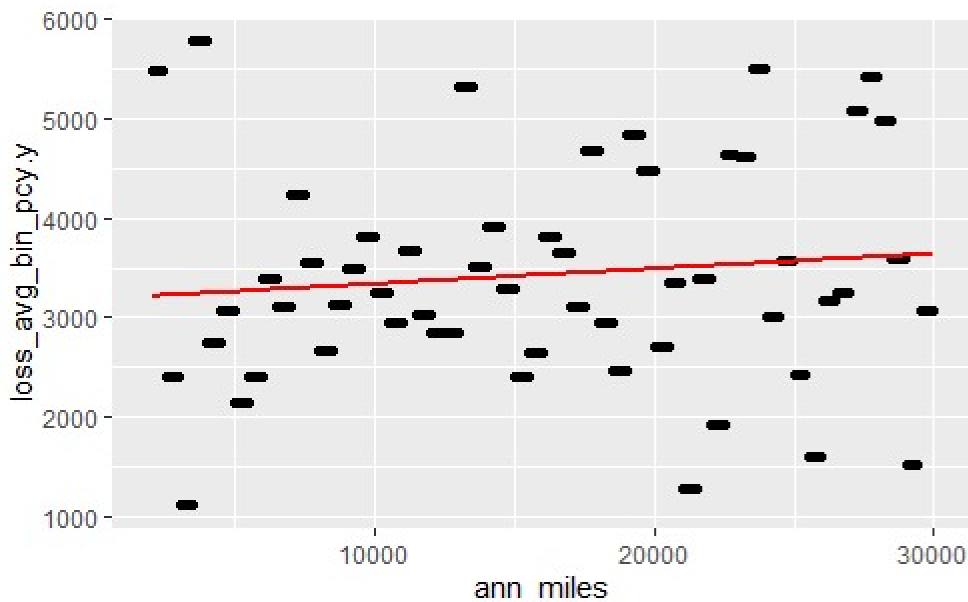
(Business-Territory 6, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_inexperiencedT1Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2665.0  -562.6  -158.4   285.4  8551.7

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.384e+03  2.573e+01 131.490  < 2e-16 ***
ann_miles   -8.699e-03  1.671e-03  -5.205 2.03e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 763.6 on 4635 degrees of freedom
Multiple R-squared:  0.00581,   Adjusted R-squared:  0.005596
F-statistic: 27.09 on 1 and 4635 DF,  p-value: 2.028e-07
```



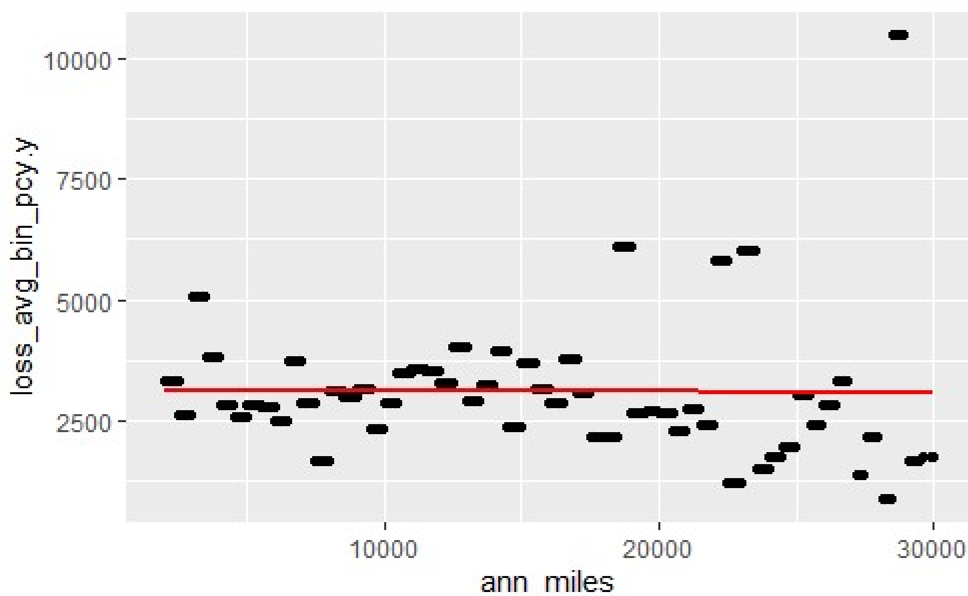
(Inexperienced-Territory 1, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_inexperiencedT2Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2236.1  -519.9  -118.0   314.7  2535.5

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.187e+03  3.003e+01 106.146  < 2e-16 ***
ann_miles   1.520e-02  2.058e-03   7.387 1.76e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 840 on 4930 degrees of freedom
Multiple R-squared:  0.01095,   Adjusted R-squared:  0.01075
F-statistic: 54.57 on 1 and 4930 DF,  p-value: 1.756e-13
```



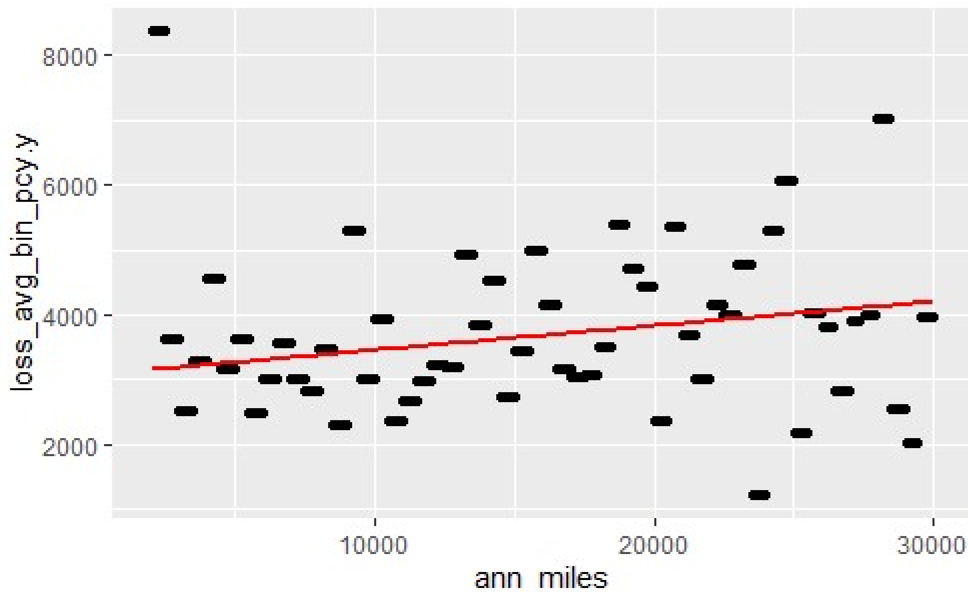
(Inexperienced-Territory 2, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_inexperiencedT3Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2217.6  -426.8   -57.0   421.5  7390.2

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.143e+03  4.284e+01  73.367   <2e-16 ***
ann_miles   -1.992e-03  2.947e-03  -0.676    0.499
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 925.3 on 2895 degrees of freedom
Multiple R-squared:  0.0001577, Adjusted R-squared:  -0.0001877
F-statistic: 0.4566 on 1 and 2895 DF,  p-value: 0.4993
```



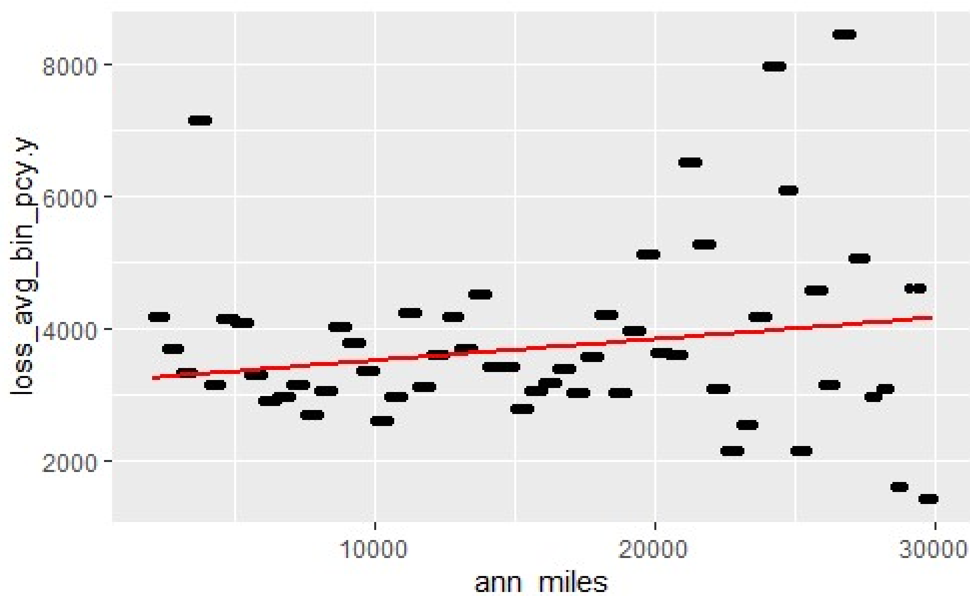
(Inexperienced-Territory 3, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_inexperiencedT4Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2764.9  -672.9  -260.7   463.2  5212.8 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.080e+03  3.116e+01   98.87   <2e-16 ***
ann_miles   3.740e-02  2.156e-03   17.35   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 943.2 on 5511 degrees of freedom
Multiple R-squared:  0.05177,	Adjusted R-squared:  0.0516 
F-statistic: 300.9 on 1 and 5511 DF,  p-value: < 2.2e-16
```



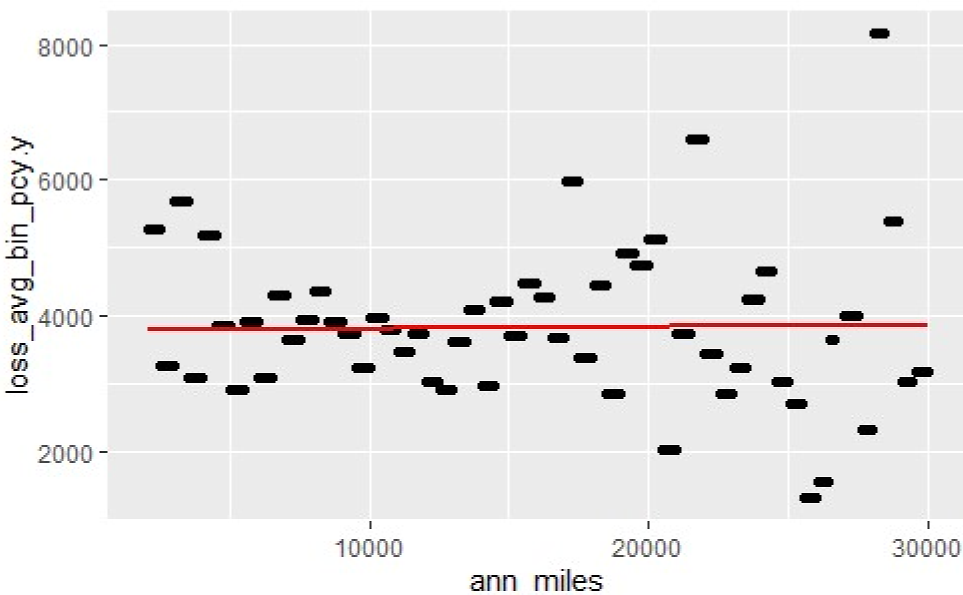
(Inexperienced-Territory 4, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_inexperiencedT5Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2744.9  -491.1  -195.1   470.2  4390.0 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.197e+03  2.827e+01  113.08   <2e-16 ***
ann_miles   3.232e-02  2.057e-03   15.71   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 878.3 on 5761 degrees of freedom
Multiple R-squared:  0.04109,	Adjusted R-squared:  0.04092 
F-statistic: 246.9 on 1 and 5761 DF,  p-value: < 2.2e-16
```



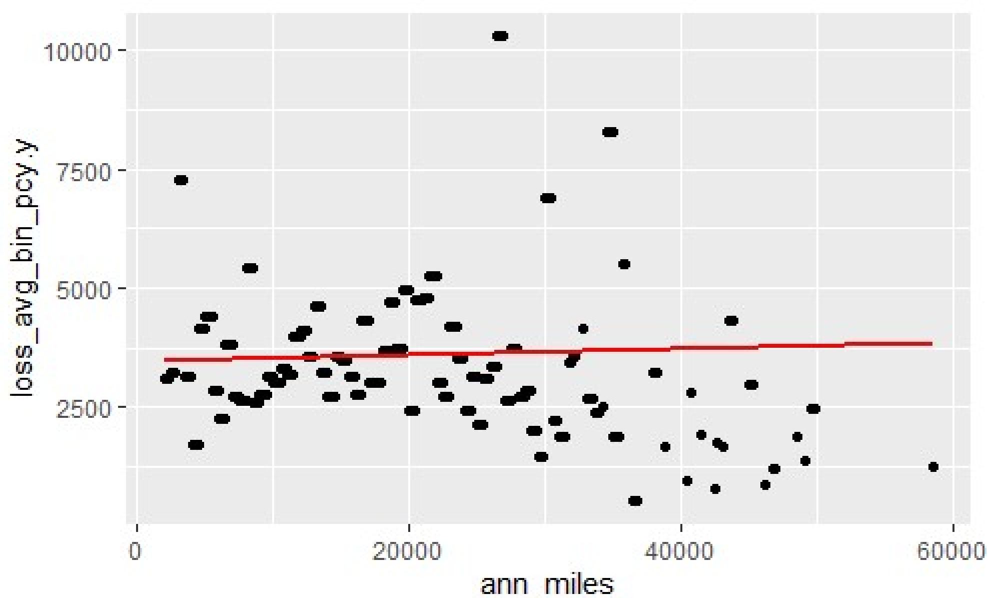
(Inexperienced-Territory 5, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_inexperiencedT6Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2546.0  -578.2   -70.0   378.1  4283.6

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.786e+03  2.455e+01  154.22   <2e-16 ***
ann_miles   2.943e-03  1.806e-03    1.63    0.103
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 776.7 on 6044 degrees of freedom
Multiple R-squared:  0.0004392, Adjusted R-squared:  0.0002738
F-statistic: 2.656 on 1 and 6044 DF,  p-value: 0.1032
```



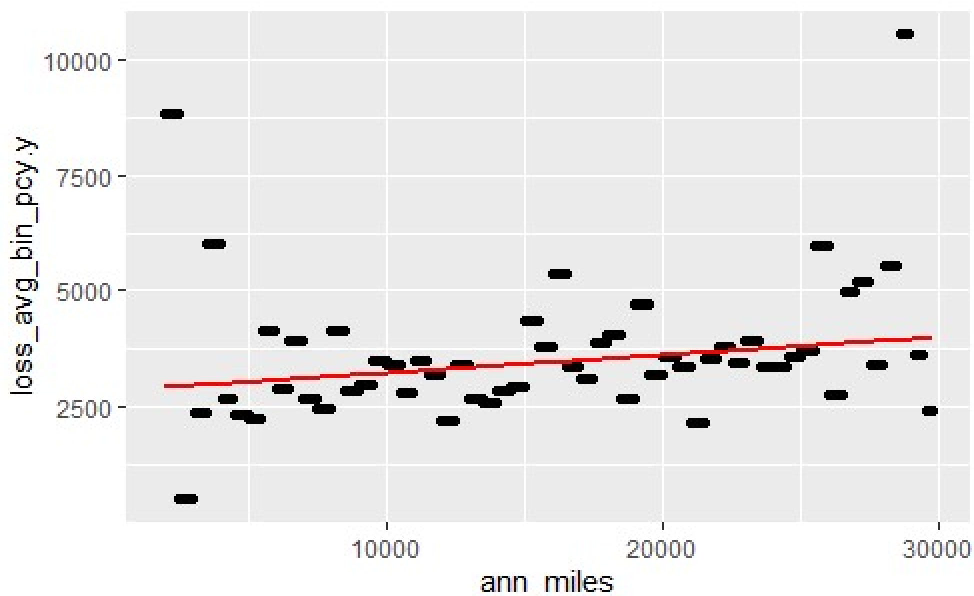
(Inexperienced-Territory 6, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_occasionalT1Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-3182.8  -648.9  -293.7   568.0  6663.5

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.458e+03  4.230e+01  81.750   <2e-16 ***
ann_miles   6.503e-03  2.543e-03   2.557   0.0106 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1068 on 3702 degrees of freedom
Multiple R-squared:  0.001763,  Adjusted R-squared:  0.001493
F-statistic: 6.537 on 1 and 3702 DF,  p-value: 0.0106
```



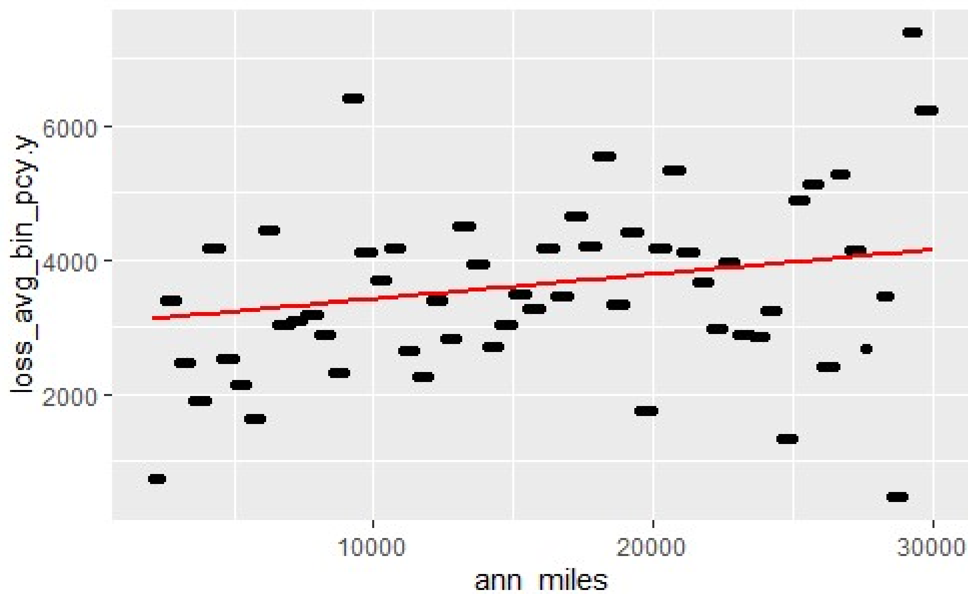
(Low Experience-Territory 1, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_occasionalT2Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2452.4  -487.9  -195.0   255.6  6573.4

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.853e+03  3.645e+01   78.25   <2e-16 ***
ann_miles   3.862e-02  2.356e-03   16.39   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 898.7 on 4363 degrees of freedom
Multiple R-squared:  0.058,	Adjusted R-squared:  0.05779
F-statistic: 268.6 on 1 and 4363 DF,  p-value: < 2.2e-16
```



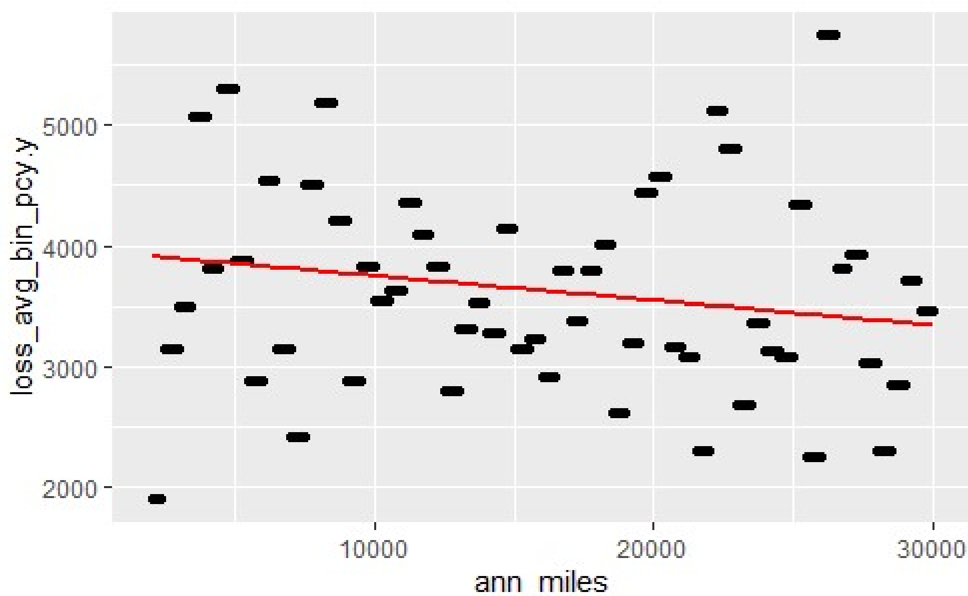
(Low Experience-Territory 2, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_occasionalT3Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-3643.2  -685.9  -138.5   651.0  3266.8

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.050e+03  4.992e+01   61.10   <2e-16 ***
ann_miles   3.649e-02  3.226e-03   11.31   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1012 on 2953 degrees of freedom
Multiple R-squared:  0.04153,	Adjusted R-squared:  0.0412
F-statistic: 127.9 on 1 and 2953 DF,  p-value: < 2.2e-16
```



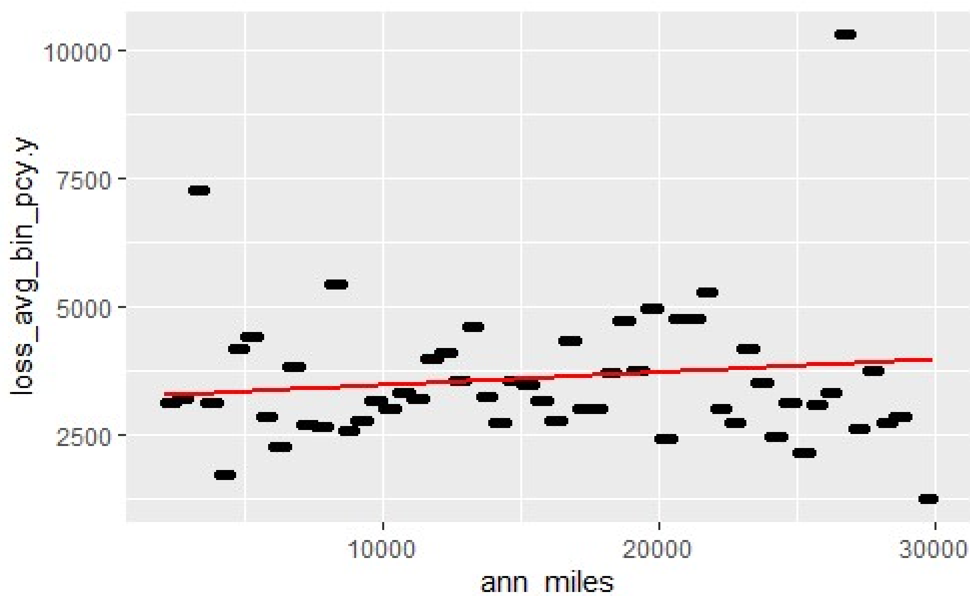
(Low Experience-Territory 3, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_occasionalT4Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2011.1  -400.8  -106.2   436.3  2326.8 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.952e+03  2.463e+01  160.47   <2e-16 ***
ann_miles   -2.029e-02  1.604e-03  -12.65   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 706.6 on 5631 degrees of freedom
Multiple R-squared:  0.02763,	Adjusted R-squared:  0.02746 
F-statistic:   160 on 1 and 5631 DF,  p-value: < 2.2e-16
```



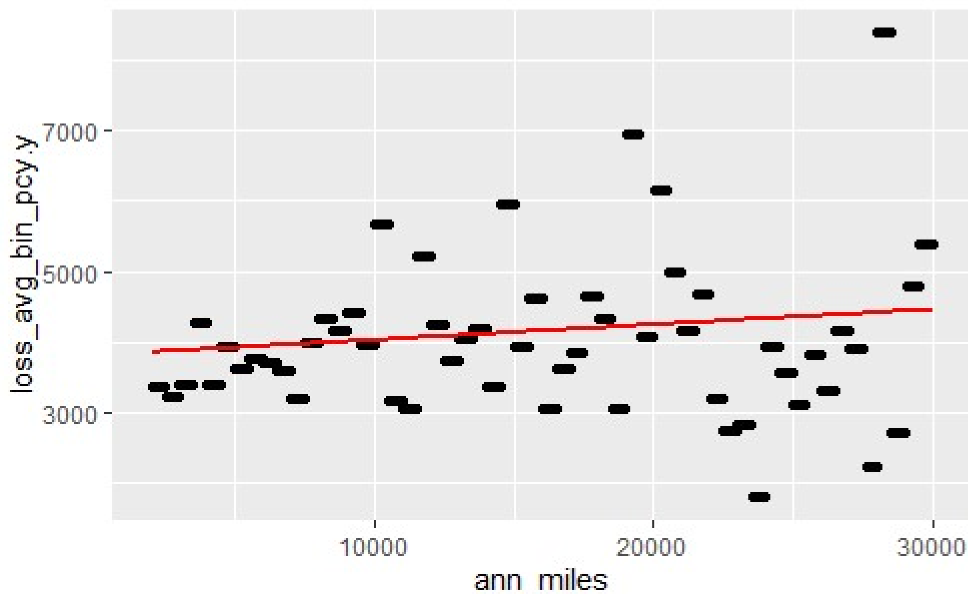
(Low Experience-Territory 4, Linear Regression: No <1 Month Policies)

```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_occasionalT5Claims)

Residuals:
    Min      1Q  Median      3Q     Max 
-2727.0  -674.9  -276.7   498.2  6417.3 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.211e+03  3.062e+01  104.89   <2e-16 ***
ann_miles   2.507e-02  2.118e-03   11.84   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 990.7 on 6777 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.02026,	Adjusted R-squared:  0.02012 
F-statistic: 140.2 on 1 and 6777 DF,  p-value: < 2.2e-16
```



(Low Experience-Territory 5, Linear Regression: No <1 Month Policies)

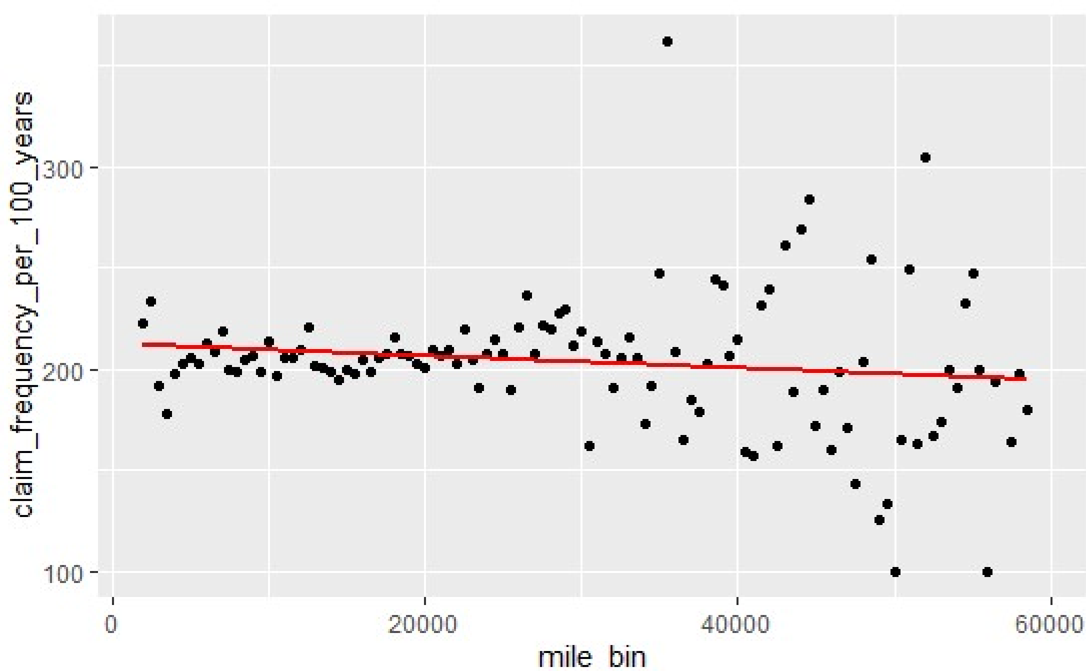
```
Call:
lm(formula = loss_avg_bin_pcy.y ~ ann_miles, data = adjusted_occasionalT6Claims)

Residuals:
    Min      1Q  Median      3Q     Max
-2552.2  -524.2   -47.8   356.1  3980.0

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.809e+03  2.600e+01  146.49   <2e-16 ***
ann_miles   2.183e-02  1.867e-03   11.69   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 872.2 on 7136 degrees of freedom
Multiple R-squared:  0.01879,	Adjusted R-squared:  0.01865
F-statistic: 136.7 on 1 and 7136 DF,  p-value: < 2.2e-16
```



(Low Experience-Territory 6, Linear Regression: No <1 Month Policies)

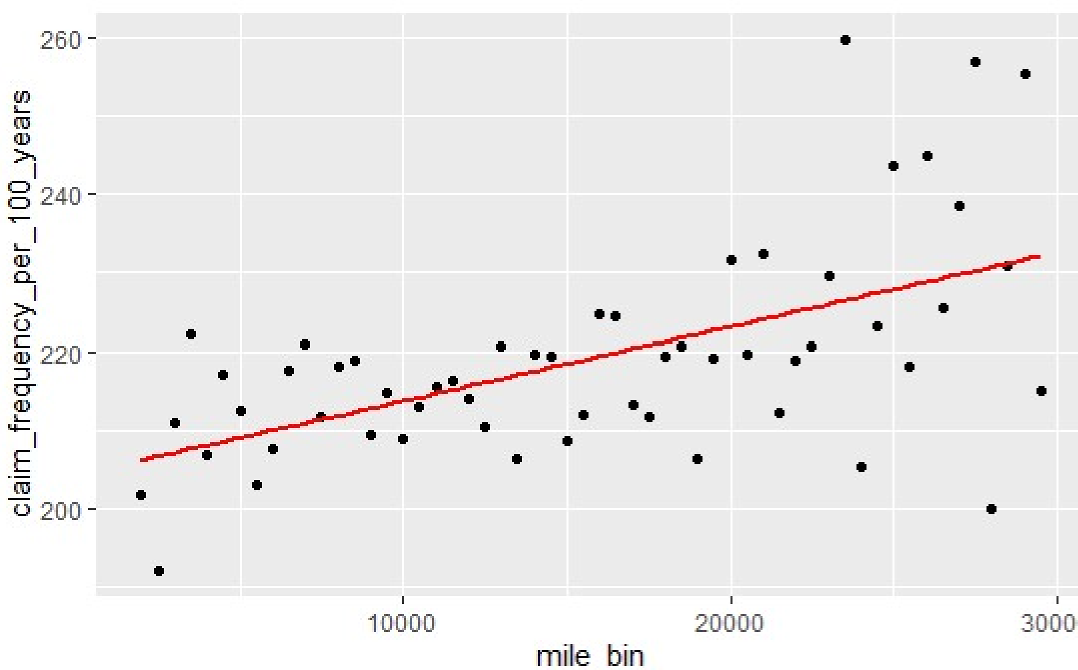
A.3 Poisson Regression Output

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = adultT1Frequency)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-7.6750  -0.8923  -0.1021   0.6928  10.1366

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  5.359e+00  1.366e-02 392.275  < 2e-16 ***
mile_bin    -1.467e-06  4.039e-07  -3.633  0.00028 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 644.06  on 112  degrees of freedom
Residual deviance: 630.85  on 111  degrees of freedom
  (3 observations deleted due to missingness)
AIC: Inf

Number of Fisher Scoring iterations: 4
```



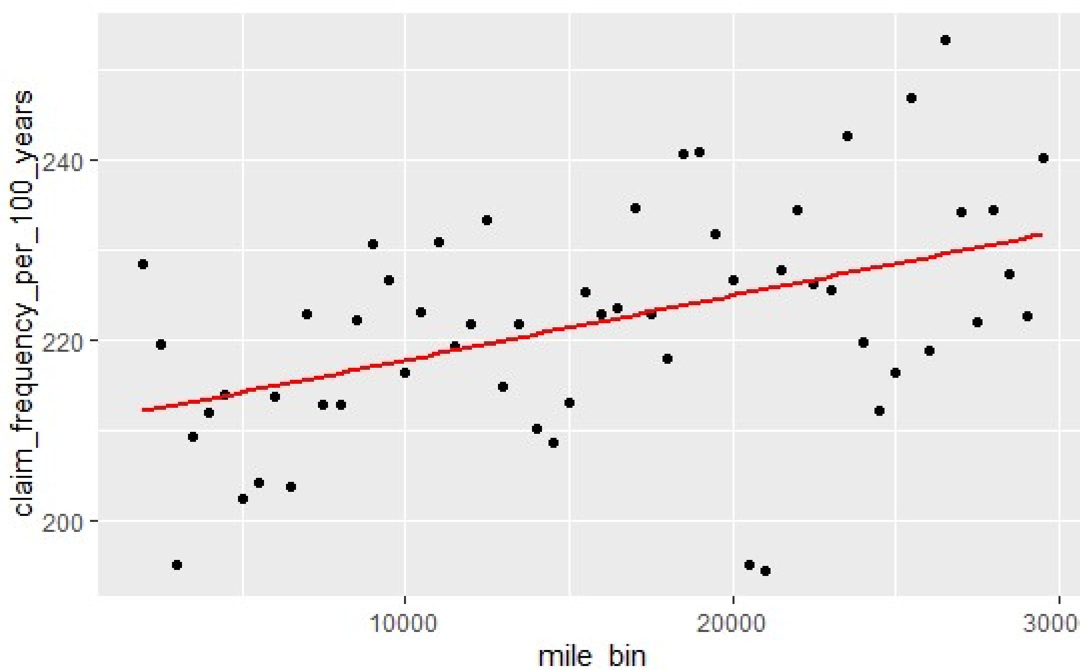
(Adult-Territory 1, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = adultT2Frequency)

Deviance Residuals:
     Min         1Q     Median         3Q        Max
-2.07066  -0.38992  -0.06763   0.38678   2.15733

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.322e+00  2.006e-02  265.35  < 2e-16 ***
mile_bin    4.290e-06  1.117e-06    3.84 0.000123 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 44.797  on 55  degrees of freedom
Residual deviance: 30.048  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 3
```



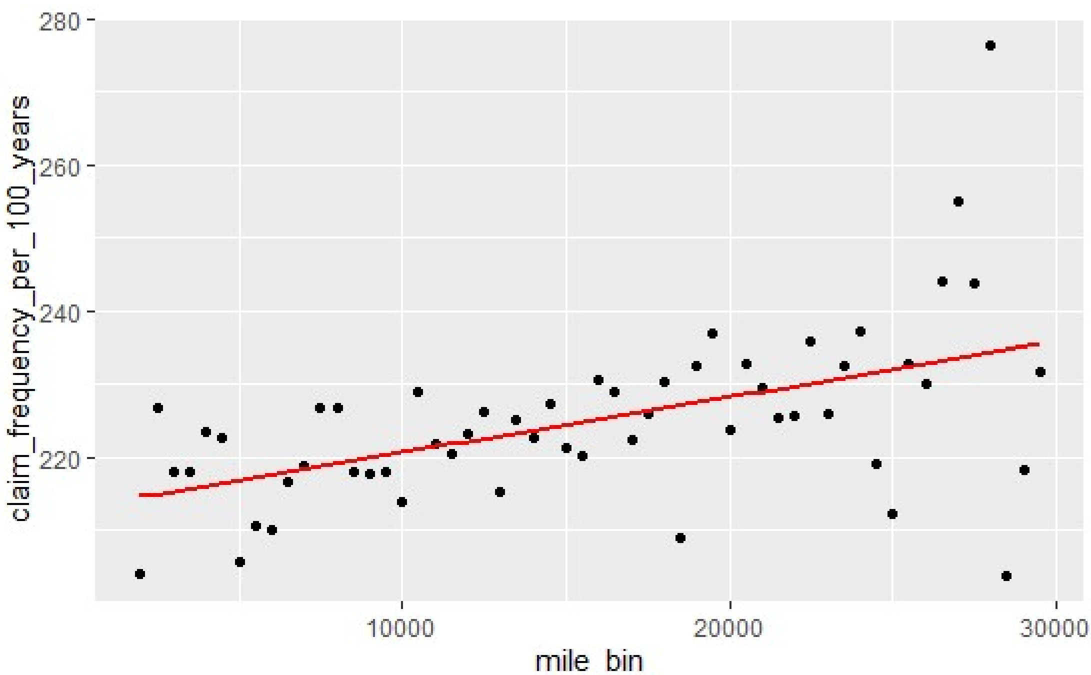
(Adult-Territory 2, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = adultT3Frequency)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.12521  -0.53277   0.01472   0.48136   1.54191

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.351e+00  1.986e-02 269.406  < 2e-16 ***
mile_bin    3.215e-06  1.110e-06   2.895  0.00379 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 39.396  on 55  degrees of freedom
Residual deviance: 31.011  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 3
```



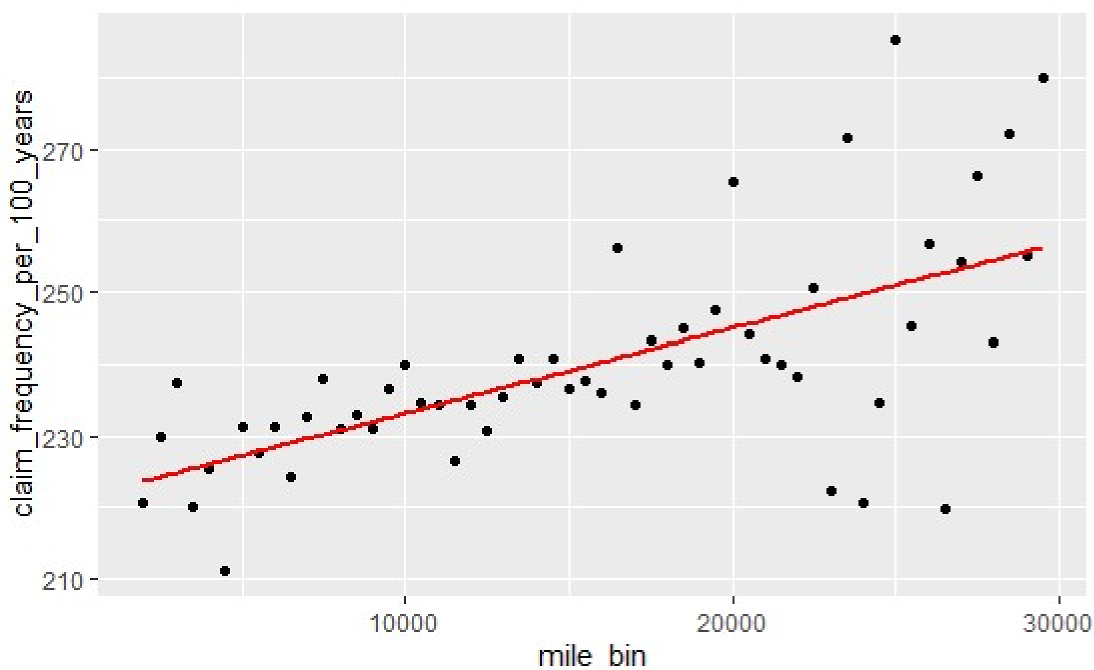
(Adult-Territory 3, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = adultT4Frequency)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.06847  -0.27861   0.02446   0.34353   2.66767

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.363e+00  1.973e-02 271.736  < 2e-16 ***
mile_bin    3.368e-06  1.103e-06   3.055  0.00225 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 34.616  on 55  degrees of freedom
Residual deviance: 25.281  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 3
```



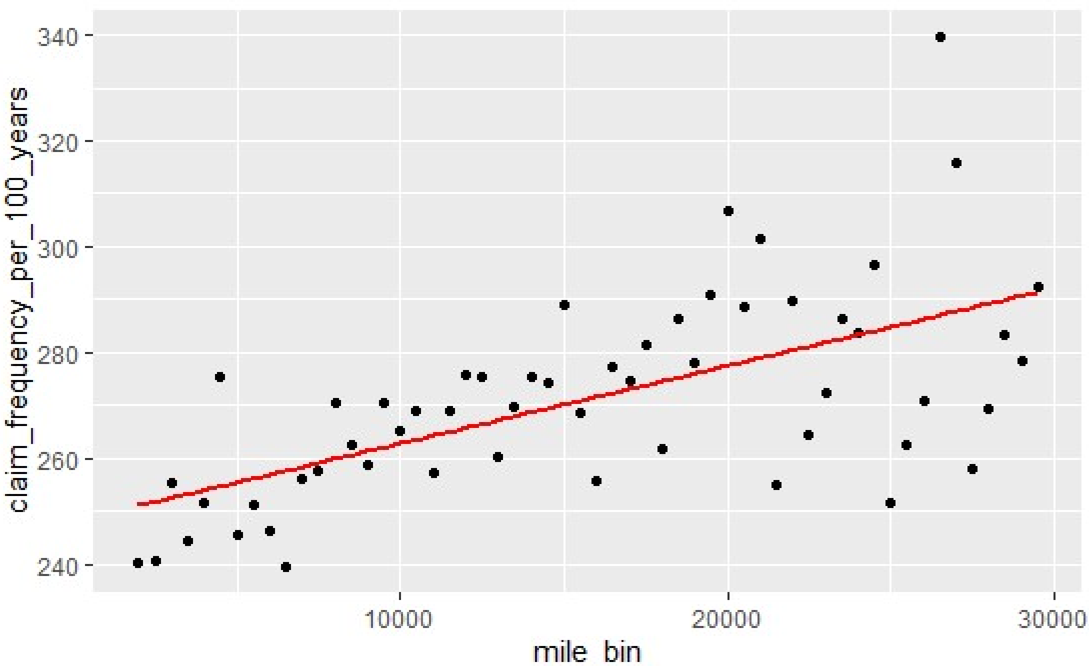
(Adult-Territory 4, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = adultT5Frequency)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.13095  -0.32021  -0.02461   0.24569   2.11721

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.402e+00  1.921e-02 281.242  < 2e-16 ***
mile_bin    4.935e-06  1.068e-06   4.621 3.82e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 51.423  on 55  degrees of freedom
Residual deviance: 30.058  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 3
```



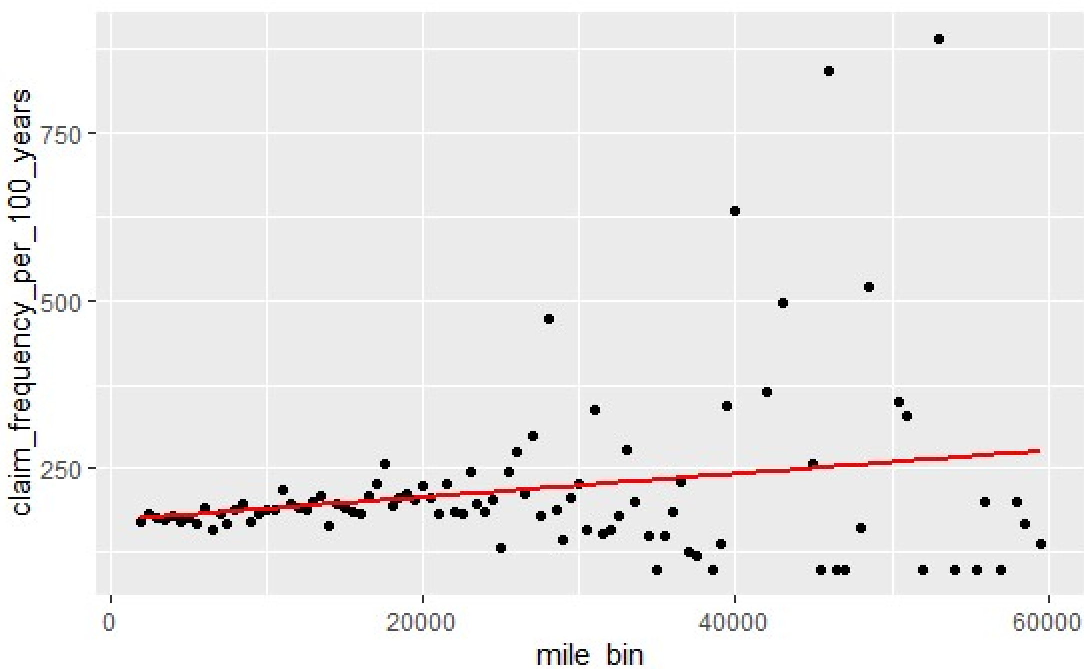
(Adult-Territory 5, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = adultT6Frequency)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.00340  -0.65493   0.07151   0.53702   3.00668

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.517e+00  1.810e-02 304.825  < 2e-16 ***
mile_bin    5.413e-06  1.005e-06   5.389  7.1e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 74.814  on 55  degrees of freedom
Residual deviance: 45.759  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 3
```



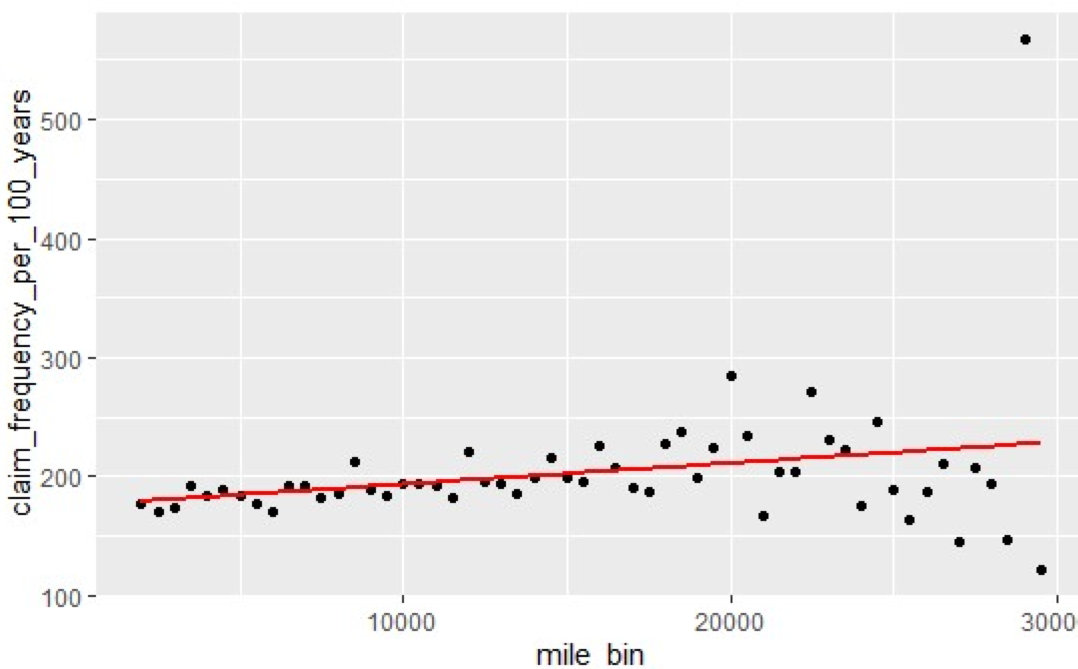
(Adult-Territory 6, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = seniorT1Frequency)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-12.1620   -3.8956   -0.4924    0.5715   29.9813

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.173e+00  1.422e-02  363.89   <2e-16 ***
mile_bin    7.793e-06  4.286e-07   18.18   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 5217.4  on 94  degrees of freedom
Residual deviance: 4889.8  on 93  degrees of freedom
  (21 observations deleted due to missingness)
AIC: Inf

Number of Fisher Scoring iterations: 5
```



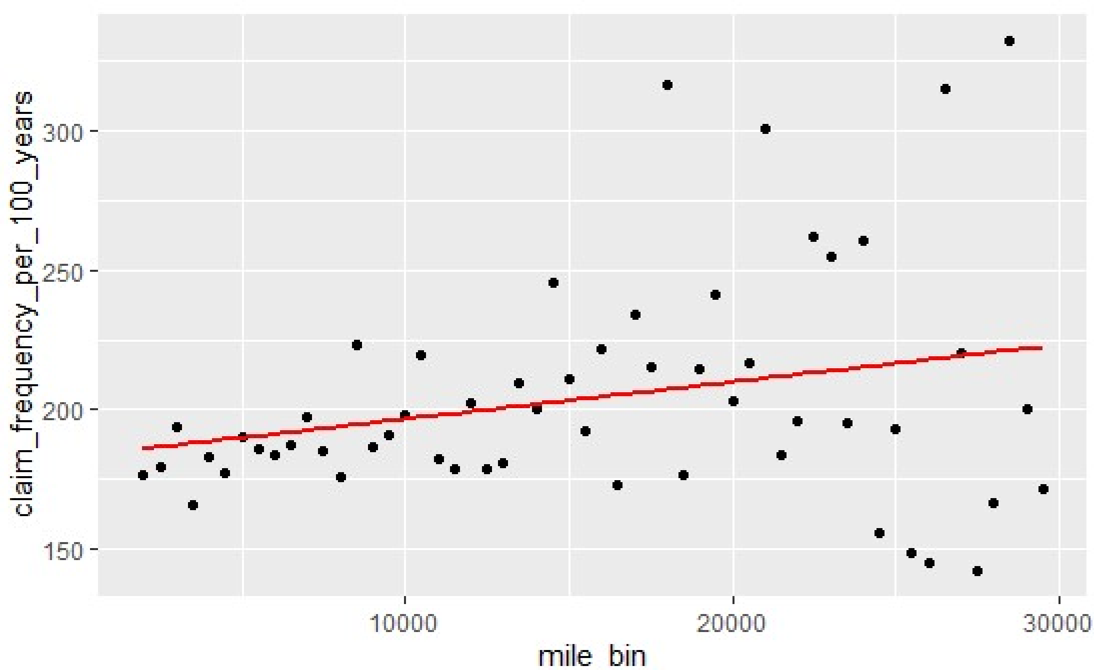
(Senior-Territory 1, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = seniorT2Frequency)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-7.7674  -0.9181  -0.2424   0.4852  18.8644

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.176e+00  2.113e-02 245.015  < 2e-16 ***
mile_bin    8.737e-06  1.160e-06   7.529 5.11e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 661.04  on 55  degrees of freedom
Residual deviance: 604.27  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 4
```



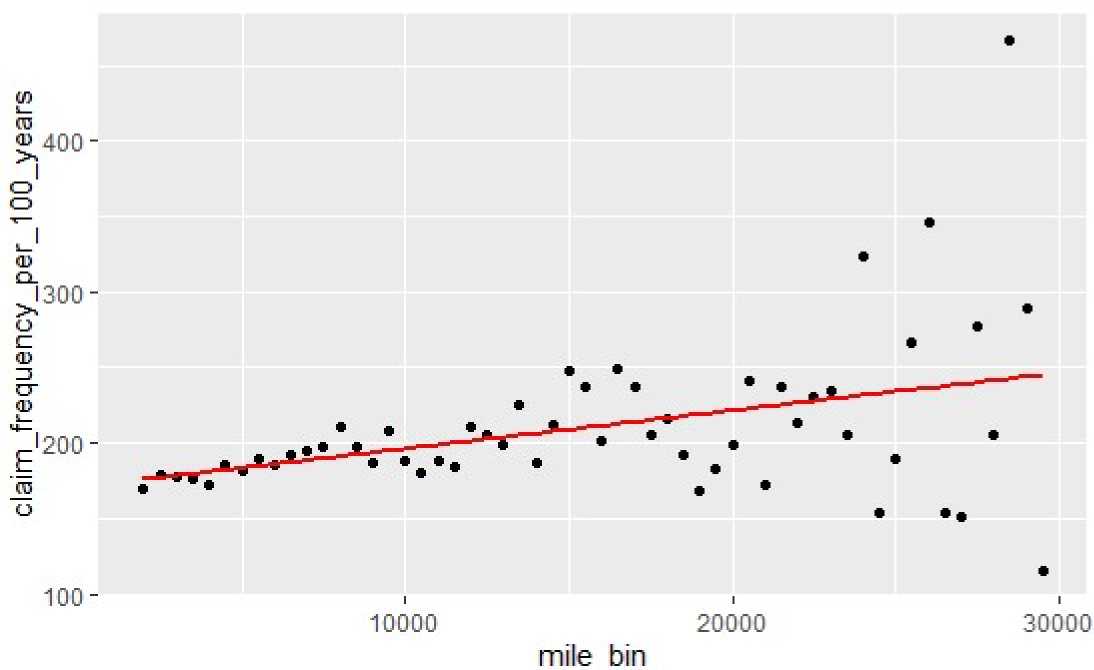
(Senior-Territory 2, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = seniorT3Frequency)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-5.6263  -1.3929  -0.4017   0.6133   7.0517

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.215e+00  2.094e-02 249.096  < 2e-16 ***
mile_bin    6.545e-06  1.158e-06   5.652 1.58e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 423.28  on 55  degrees of freedom
Residual deviance: 391.30  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 4
```



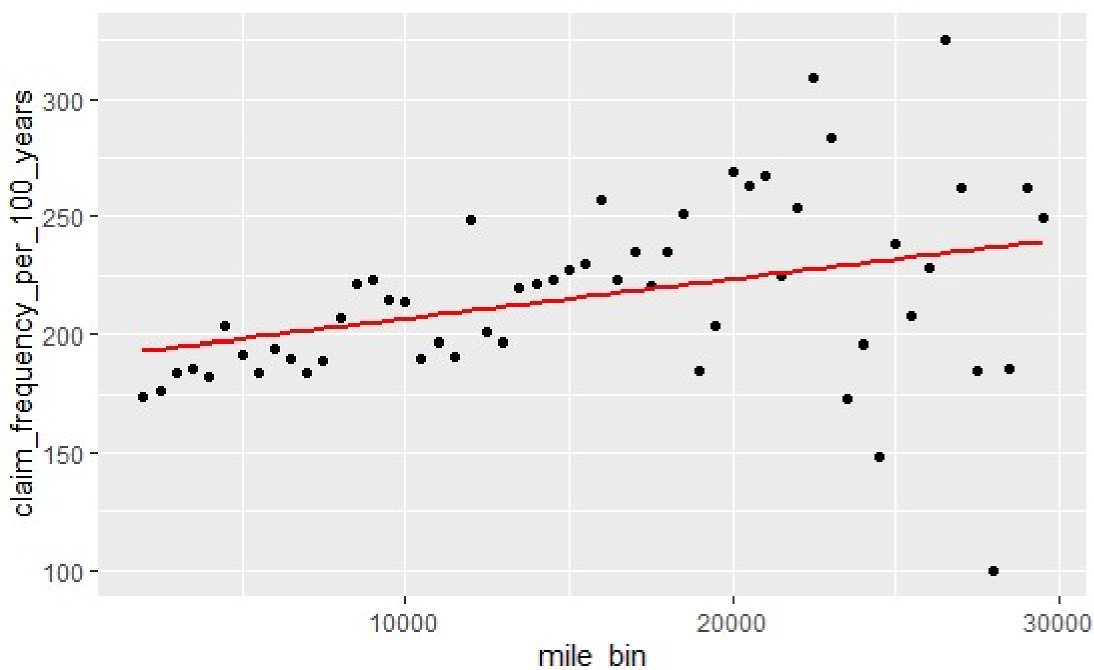
(Senior-Territory 3, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = seniorT4Frequency)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-9.3514  -1.0644  -0.0409   0.8639  12.6064

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.156e+00  2.101e-02  245.38   <2e-16 ***
mile_bin    1.202e-05  1.142e-06   10.52   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 644.87  on 55  degrees of freedom
Residual deviance: 533.81  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 4
```



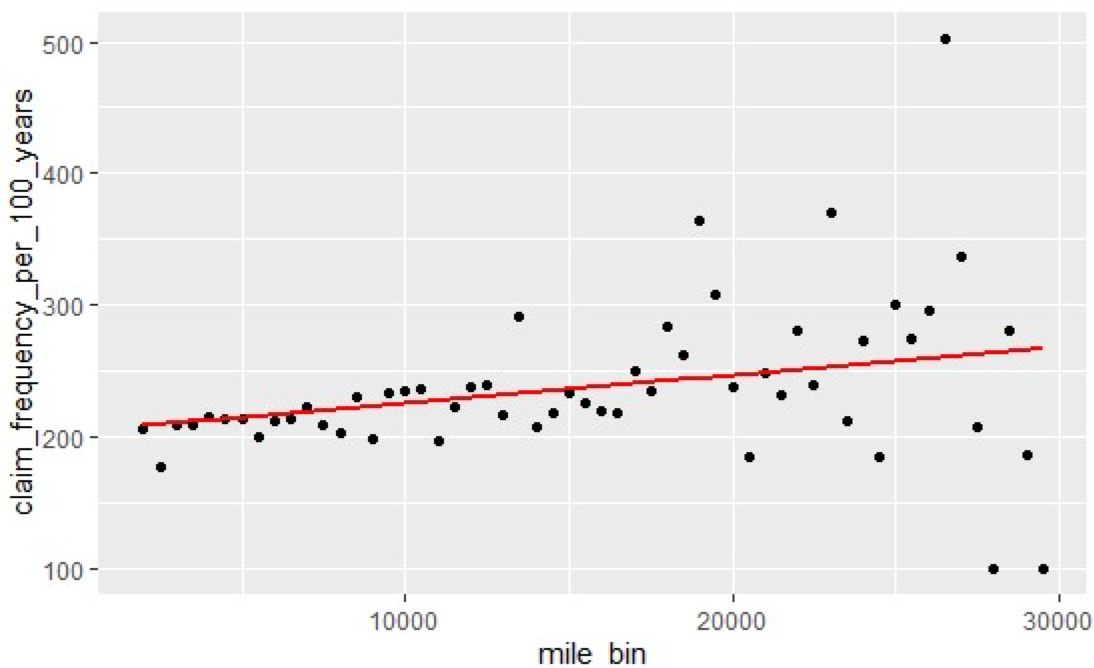
(Senior-Territory 4, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = seniorT5Frequency)

Deviance Residuals:
     Min         1Q     Median         3Q        Max
-10.0953   -1.0980    0.1872    1.1739    5.5808

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.251e+00  2.044e-02  256.95  < 2e-16 ***
mile_bin    7.803e-06  1.126e-06    6.93  4.2e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 385.42  on 55  degrees of freedom
Residual deviance: 337.33  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 4
```



(Senior-Territory 5, Poisson Regression: No <1 Month Policies)

```
Call:
glm(formula = claim_frequency_per_100_years ~ mile_bin, family = poisson(link = log),
    data = seniorT6Frequency)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-11.7917   -1.1483   -0.1968    0.7222   13.2288

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.327e+00  1.957e-02 272.154   <2e-16 ***
mile_bin    8.974e-06  1.074e-06   8.354   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 808.07  on 55  degrees of freedom
Residual deviance: 738.17  on 54  degrees of freedom
AIC: Inf

Number of Fisher Scoring iterations: 4
```



(Senior-Territory 6, Poisson Regression: No <1 Month Policies)