Auto Loss Costs: Property Damage

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Property damage loss cost, after taking out Michigan, appears to have a positive relationship with the proportion of roads and the proportion of vehicle miles traveled in urban areas, but no other variables seem to have a substantial impact. Similarly, property damage frequency and severity are strongly affected by congestion, the proportion of urban roads, total industry GDP, as well as personal income.

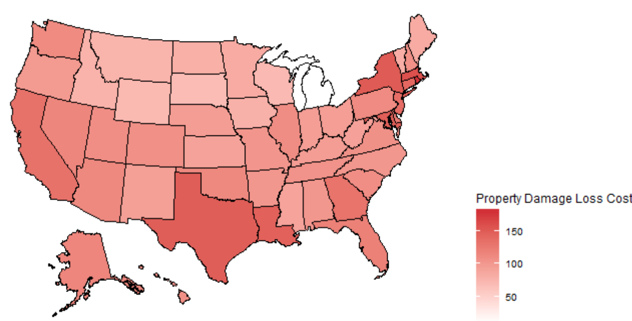
Introduction

Property damage (PD) liability coverage in most states pays to repair damage caused to another driver's vehicle or property in the case of an accident where the insured is at fault. For example, property damage may pay the expenses to tow and repair a vehicle, or to replace damaged property, such as a fence or mailbox.

Michigan

In the state of Michigan, property damage only applies to the damage of physical property and vehicles if the vehicle was parked at the time it was damaged. Because property damage in Michigan doesn't cover claims to other vehicles that were damaged while driving, the state has an extremely low PD loss cost (see Figure 1). To avoid unduly affecting the results, Michigan has been removed from the property damage analysis.

Figure 1
Average Property Damage Loss Cost, 2010 - 2018



Loss Cost

A random forest model was used to determine which variables had the largest impact on loss cost. In order to negate the effects of inflation over time, a linear model was first run on the natural log of loss cost by time, the residuals from this linear model were then used in the random forest model as the response variable.

The random forest model, shown in Figure 2, identified the biggest driver of loss cost to be the proportion of vehicle miles traveled in urban areas.

As demonstrated by the added variable plots in Figures 3 and 4, the proportion of vehicle miles traveled and the proportion of road miles in urban areas have strong positive effects on loss cost after accounting for other variables. Both of these variables suggest that states that are more urban and have more cars on urban roads tend to have higher loss costs.

Figure 2
Loss Cost Variable Importance

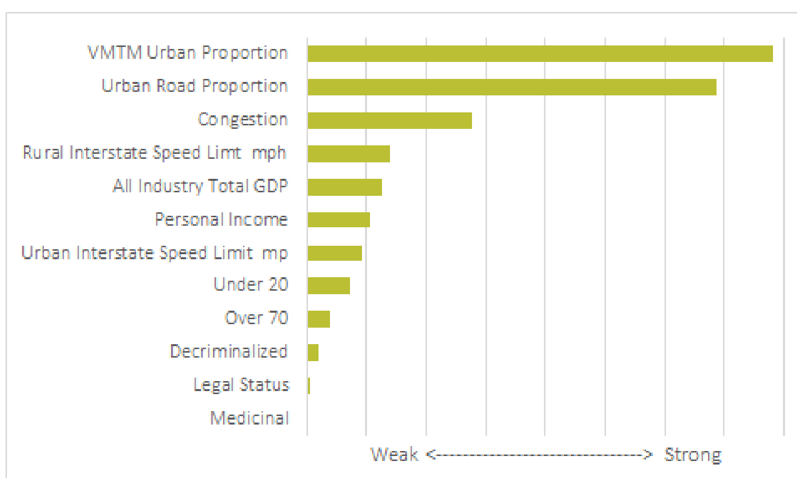


Figure 3
Proportion of Urban Roads Added Variable Plot

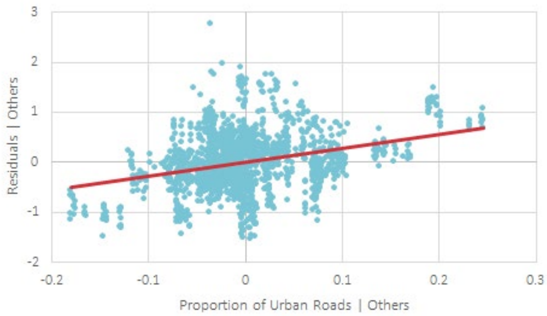
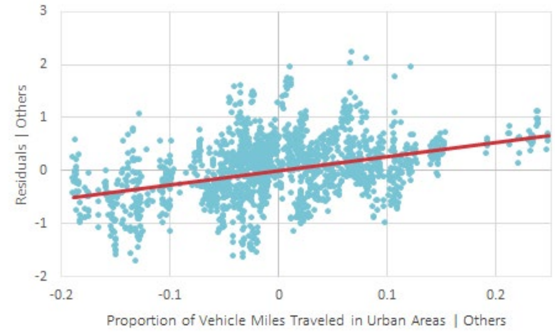


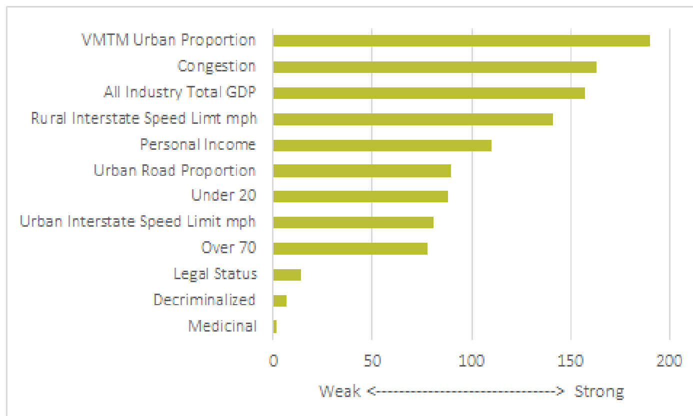
Figure 4
Urban Vehicle Miles Traveled Added-Variable Plot



Severity

As in the analysis of property damage loss cost, a linear model was run on the natural log of severity over time, and the residuals from this linear model were then used in a random forest model to determine which explanatory variables had the biggest impact on severity. The results of the random forest model are shown in Figure 5. The random forest model indicated that the following variables had the largest impact on severity: proportion of vehicle miles traveled in urban areas, congestion, total state GDP, and rural interstate speed limits.

Figure 5
Severity Variable Importance



<u>Proportion of Urban Vehicle Miles Traveled</u>

The proportion of urban vehicle miles has a weak, positive correlation with severity, indicating that the more urban a state is the more severe accidents are on average. This may be because in urban areas, there is more valuable property near the roads.

<u>Congestion</u>

Congestion, defined as the number of vehicle miles driven per mile of road, has a strong negative correlation with severity. This may be because as the road becomes more congested, cars move slower and less damage is caused. Accidents that happen at slower speeds tend to be less severe and have lower claims.

Figure 6
Urban Vehicle Miles Traveled Added-Variable Plot

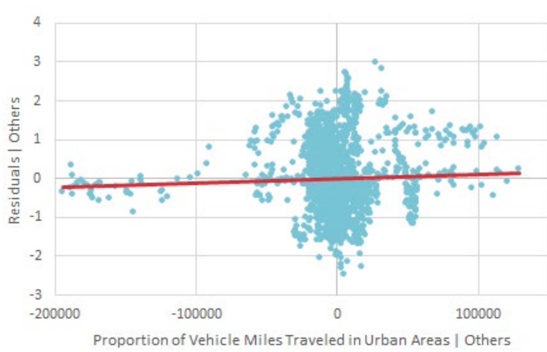
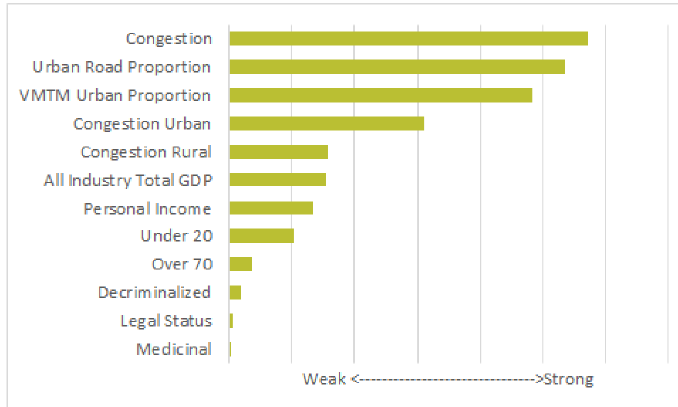


Figure 7
Congestion Added-Variable Plot

Frequency

Another random forest model indicated that the most important variables when modeling property damage frequency include: congestion, urban road proportion, total industry GDP, and personal income (Figure 8). Urban vehicle miles traveled in millions (VMTM Urban) and urban and rural congestion, although included in the random forest, are also incorporated in the congestion variable.

Figure 8
Frequency Variable Importance



Congestion

By dividing vehicle miles traveled (in millions) by total road length we were able to calculate a congestion variable, which the random forest model indicated was a strong factor in determining frequency, and was strongly correlated (0.694) with the frequency of property damage, as can be seen in Figure 9. The positive correlation indicates that as more cars are on the road, accidents are more likely. The added-variable plot (Figure 10), however, showed that after accounting for other variables, congestion had a negative impact on frequency. This could be because the congestion variable was derived from other variables in the model.

Figure 9
Frequency by Congestion

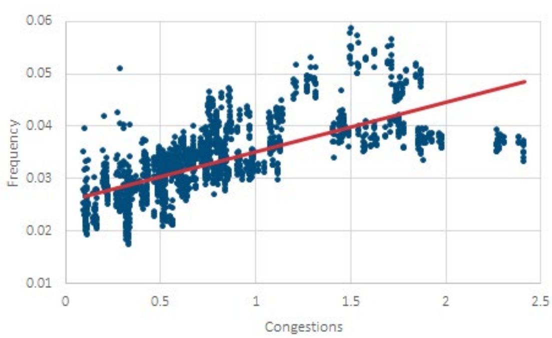


Figure 10
Congestion Added-Variable Plot

Urban Road Proportion

Similar to loss cost, two of the biggest drivers of frequency are measures of how urban a state is. Both the proportion of vehicle miles traveled in urban areas and the proportion of urban roads in a state have a positive effect on frequency as exhibited in Figures 11 and 12.

Figure 11
Proportion of Urban Roads Added-Variable Plot

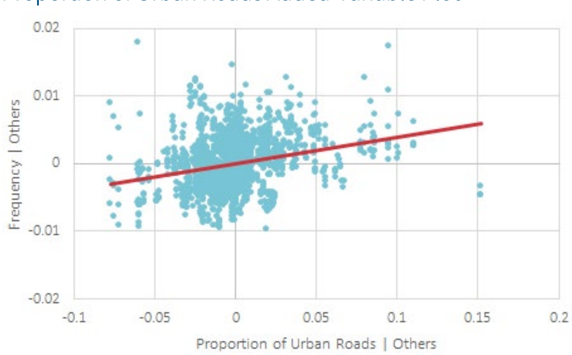
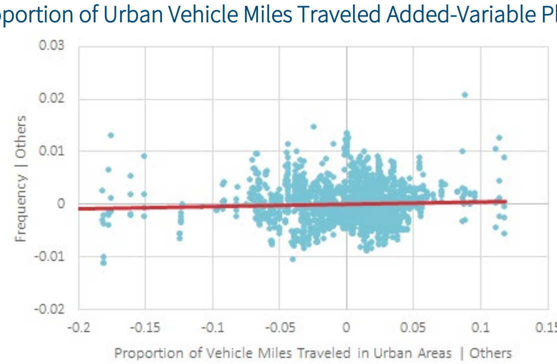


Figure 12
Proportion of Urban Vehicle Miles Traveled Added-Variable Plot



<u>All Industry Total GDP</u>
It is interesting to note that total industry GDP appears to have a positive correlation with frequency (Figure 13) while personal income is negatively related (Figure 14). As personal income goes up, the value of vehicles may similarly increase creating a more cautious population, and thus decreasing the frequency of accidents.

Figure 13
All Industry GDP Added-Variable Plot

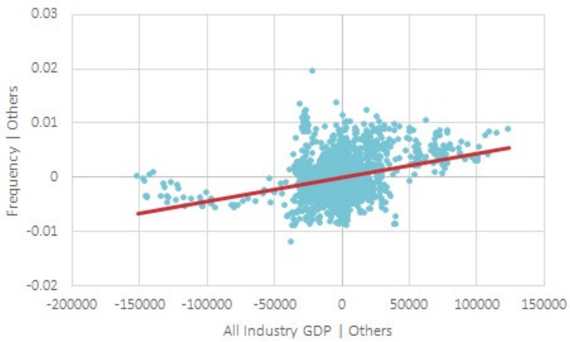


Figure 14
Personal Income Added-Variable Plot

Conclusion

Property damage loss cost, after taking out Michigan, appears to have a positive relationship with the proportion of roads and the proportion of vehicle miles traveled in urban areas, but none of our other variables seem to have a substantial impact. Similarly, property damage frequency and severity are strongly affected by congestion, the proportion of urban roads, total industry GDP, as well as personal income.

Additional Tables

Parameter	Loss Cost Linear Model			
	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-2.134	0.2701	-7.902	4.82E-15
VMTM Urban Proportion	2.699	0.1574	17.151	< 2e-16
Congestion	-0.443	0.06344	-6.983	4.09E-12
All Industry Total GDP	0.000005816	4.051E-07	14.355	< 2e-16
Rural Interstate Speed Limit	0.0006079	0.003667	0.166	0.868
Personal Income	-6.782E-09	4.883E-10	-13.891	< 2e-16
Urban Road Proportion	2.749	0.2066	13.306	< 2e-16

Parameter	Severity Linear Model			
	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-1.017	0.4632	-2.196	0.0282
VMTM Urban Proportion	2.918	0.2043	14.28	<2e-16
Congestion	-0.7616	0.08274	-9.205	<2e-16
All Industry Total GDP	0.000001136	6.781E-07	1.676	0.094
Rural Interstate Speed Limit	-0.002665	0.006098	-0.437	0.6621
Personal Income	-1.14E-09	8.194E-10	-1.391	0.1643

Parameter	Frequency Linear Model			
	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.0205	0.00127	16.111	< 2e-16
Congestion	-0.014	0.00182	-6.286	4.1E-10
Urban Road Proportion	0.0387	0.00344	11.264	< 2e-16
VMTM Urban Proportion	0.00472	0.00214	2.211	0.027182
Congestion Urban	0.00592	0.00103	5.753	1.03E-08
Congestion Rural	0.00414	0.00141	2.934	0.003387
All Industry Total GDP	4.46E-08	3.14E-09	14.177	< 2e-16
Personal Income	-5.35E-11	3.77E-12	-14.171	< 2e-16
Under 20	-0.0323	0.00912	-3.545	0.000402
Over 70	-0.0128	0.00634	-2.011	0.044508
Decriminalized Reduced	-0.000791	0.000357	-2.217	0.026737
Decriminalized Yes	0.0000865	0.000767	0.113	0.910227
Decriminalized Yes	-0.00203	0.00119	-1.71	0.08738
Legal Status Mixed	-0.00111	0.00062	-1.798	0.072403
Medicinal Yes	-0.00079	0.000638	-1.238	0.215713