Is No-Fault Auto a No-Go?

By CALEB DAME*

In July 2003, Colorado's state automotive insurance policies changed to no longer mandate an additional purchase of Personal Injury Protection (PIP) by auto insurance policyholders. The change was made by the Colorado governor in an attempt to lower overall auto insurance prices. Using a Difference-In-Differences Regression clustered by State, we estimate very significant effects of the policy change on the price of liability insurance beyond in addition to the removal of the cost imposed by the PIP mandate. There are less significant results to suggest that a greater proportion of drivers were able to buy policies as a consequence. The Synthetic Control Analysis was less significant due to a small number of very differently-behaved Donor states, but strongly again supports the proof of lowered Liability Premiums and again casts doubt on any increase in policies taken out.

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While certain standards of automotive insurance are required at a federal level in the United States, there remain many decisions regarding pertinent policy that are made on the level of the state. One decision with a large direct impact on the total expense of automotive insurance is the mandate in so-called "No-Fault States" legislating that policyholders must purchase Personal Injury Protection (PIP) beyond the usual collision, comprehensive, and liability policy components. The moniker "No-Fault" is due to the limited PIP compensation benefits made available after any accident upon need to pay for health expenses, replace lost income, or cover funeral expenses whether or not the policyholder was deemed to be responsible. The justification for the imposed insurance is to prevent any litigation for smaller health, lost income, or funeral costs. In "At-Fault" States, conversely, those responsible for any damages rarely receive any such compensations while the other party is only compensated for property and injury damages from the former's liability insurance coverage after filing either winning or settling a lawsuit. The intent of this paper is to understand how a "No-Fault" policy affects the insurance sector's premiums, and, in-turn, the change in percentage of policyholders as a result.

The "No-Fault" policy had its inception in the 1960s, and was implemented across many states in the 1970s in an effort to cut down or eliminate the time and cost-intensive process which burdened both the insurer and the policyholder during a liability claim. This is to preserve the aligned incentives between the policyholder and the insurer in the case of large claims and high stakes and to avoid the misaligned incentives in addition to the legal and settlement costs to the insurer surrounding low stakes accidents where fault is in question. This alignment of incentives is achieved at the cost of paying for Personal Injury Protection, where the policyholder is insured in the event of any accident, raising the cost of the complete insurance plan. However, with fewer drawn out lawsuits, one would expect lower liability premiums under a no-fault policy, as fewer fees and fewer payments as settlement or lawsuit losses would be made than under an "At-Fault" policy, all else being equal

But all else is not equal. When a No-fault Policy is implemented, compensation is both more accessible and capped at a threshold determined by the state, usually around \$3000-\$5000. Additionally, insurance firms are still allowed to file for compensation against the responsible party, potentially funded by their liability coverage. This additional vulnerability may raise the cost of liability insurance for providers and result in higher prices for policyholders. For the policyholder to access the funds, medical or funerary authorization is required before policyholders can access any funds. These implications allow for two simultaneous possibilities. First, policyholder know that they may be able to access enough funds to receive more healthcare without a deductible before dipping into health insurance, and so may be incentivized to get treated more often. The second, and perhaps a more cynical possibility, is that medical providers know that they can encourage or persuade the policyholder to have access to services that would not otherwise have been suggested, benefitting the bottom line of the medical provider at no additional cost to the patient all while staying just under the maximum payment from PIP.

In July 2003, The Colorado Governor let expire the law making Colorado a "No-Fault" state and it has not required PIP since. The motivation on behalf of the Governor was to lower overall insurance prices to increase the affordability to get more Coloradoans to purchase auto insurance (Johnson). With the removal of PIP, the total premium would necessarily go down since a person is no longer guaranteed certain benefits and is more open to litigation, but we hope to assess the effect that this change in policy had on the number of policies purchased in Colorado due to the law change, and how the transition affected the price of Liability insurance. Therefore, we will test if liability premiums are in fact higher for "No-Fault" states and drop when the policy is reverse, and if the predicted price drop has an effect on number of policies taken out.

I. The Data

Data on statewide insurance pricing is made available via yearly a "Automotive Insurance Database Report" from the National Association of Insurance Commissioners (NAIC) where indicators of sales, claims, current policies, sector revenue, and sector costs are aggregated and reported by state. Each report is released at the end of the year to expand the indicators of the database to include data for an additional year, keeping 3 years between the present and the most recently updated reports during which the data is thoroughly vetted and maintained confidential. These reports publically available span the years 1985-1989, and 1994-2017, skipping reports for years perhaps 1990-1993 due to website architecture, though our team has notified the Commission of the potential administrative error.

While many reports available were converted to PDF formats friendly to web-scraping, those published for years before 1998 were scanned documents from the printed version of the document. It was decided that the reports before 1998 were to be entered by hand and verified since the text in the meta-data was irregular when scraped. In addition to data pulled from the NAIC, Census records supplied yearly population and median income estimates by state and year to be used as controls in the regression analysis.

In Table 1, we have the descriptive statistics for all 50 states, and Table 2 limits the description to the 12 No-Fault States (Hawaii, Kansas, Kentucky, Massachusetts, Michigan, Minnesota, New Jersey, New York, North Dakota, Pennsylvania, and Utah) and Colorado.

In the case of insurance, an exposure is the object being insured and the premium is what is paid for the insurance contract. In the case of this data, we have Exposures being the number of cars under a specific policy (Collision or Liability) and the Premium is the amount collected for insurance contracts in the state for a given year. The three variables Single Injury Min, Many Injury Min, Property Damage Min are the minimal coverage that must be purchased to cover the events that they are named for and largely determine the average cost of insurance as they largely determine the average coverage.

II. The Method

Due to Colorado being the only among many states to change policy regarding mandating PIP, the study will compare the results of Synthetic Control Analysis with a preliminary Difference-in-Differences model that may offer more perspective on the issue.

i. Difference-in-Differences Estimates

With 13 states, 23 time periods (1994-2016), and one state that undergoes treatment in 2003, we can easily build an initial Difference-in-Differences model once we determine necessary controls. The outcomes we wish to explain are the average state liability policy price and the number of insured exposures per capita. The latter is of interest to find whether or not more cars became insured per person, which would be of interest to policymakers in determining if Coloradoans as a whole became more mobile as a result of the policy change.

Controls for the premiums should include population to counteract population growth causing growth in objects insured and increased sales. Similarly, including a measure of state income for either would control for people in the state being able to purchase more or fewer cars or policies than before due to incomes rising or falling. A control tailor-made to influence the cost of the Liability Premium and Exposures would be minimum legal coverage requirements as mandating more

$$\begin{aligned} AveLiabPrem_{it} = \beta_0 + \beta_1 Min1_{it} + \beta_2 Min2_{it} + \beta_3 Min3_{it} + \beta_4 COafter2002_{it} \\ + \beta_5 Income_{it} + \beta_6 logInc + \beta_7 StateFixedEff_i \\ + \beta_8 YearFixedEff_t + \beta_9 After2002_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} LiabExpPerCap_{it} = \alpha_0 + \alpha_1 Min1_{it} + \alpha_2 Min2_{it} + \alpha_3 Min3_{it} + \alpha_4 COafter2002_{it} \\ + \alpha_5 Income_{it} + \alpha_6 logInc + \alpha_7 StateFixedEff_i \\ + \alpha_8 YearFixedEff_t + \alpha_9 After2002_{it} + \epsilon_{it} \end{aligned} \tag{2}$$

insurance typically means mandating more out-of-pocket expense to own insurance. Along with state, year, post-treatment fixed effects, and the dummy variable "COafter2002" we can build the following linear models to identify the effect of treatment on policy prices and numbers.

With set two regression estimates calculated for each of the above linear estimating equation of "No-Fault" States, we also include similar linear estimating equations ran on the full dataset of states with available data (47 States and the Distri of Columbia). The estimating equations used are identical, but with the addition of "No-Fault" fixed effects for the 13 States in the reduced analysis which includes Colorado for the whole timeperiod. The interaction term of "COafter2002", will thereby continue to show the effect of the policy change away from "No-Fault" on either outcome.

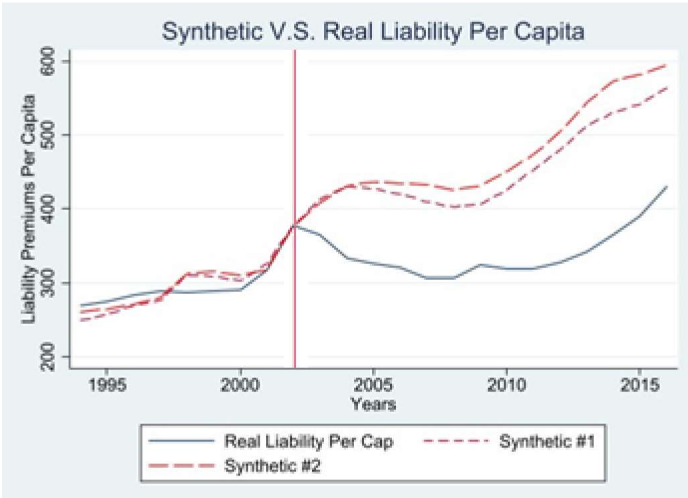
Something promising about the Difference-in-Differences is that it appears that the policy change in Colorado has a negative and significant effect on the Average Liability Premiums for all trials save the first, the trial with the least statistical strength. This suggests that the policy change may have done its job in lowering the cost of liability coveral in Colorado post-2002. Interestingly, as well, the the treatement seems to have had consistently positive estimates on the effect on Exposures per capita, but none were close to significance. It is clear that the relationship between the covariates and Average Premium was very strong and much more significant than the relationship between the covariates and Exposures per capita. This is not surprising, as the main indication of quantity sold is price, and its removal both biases and lowers the strength of our regression, and unfortunately there is not an instrument to proxy for price to have a stronger, less biased estimator. As Difference-In-Differences is far from conclusive we turn to a Synthetic Control Method of Significance Testing.

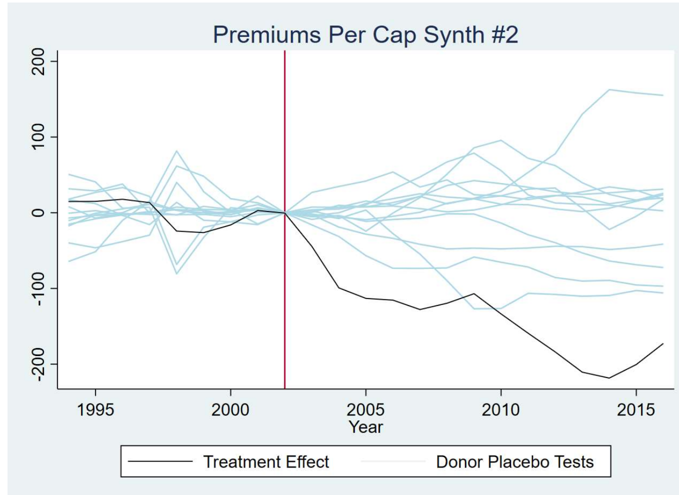
i. Synthetic Control Methods

Via Synthetic Control, we hope to establish a counterfactual Colorado as a weighted combination of the other 12 "No-Fault" states. In order to train the model to build a Synthetic Colorado to predict premium prices and number of exposures, criteria to match upon need to be defined. To best make a combination of larger and smaller states to look like Colorado we will match on Premiums per capita as well as Exposures per capita since both are gross figures and the per capita normalization best reduces the variance between individual state trajectories. Also, in an attempt to get the best pre-treatment fit we need to avoid matching on too many characteristics since with every additional matching specification it becomes less and less likely that we will find better pre-treatment fit out of a limited number of donors. Therefore, in addition to matching on the own variable's values, additional matching criteria are specified below with the goal of best modeling the entire state insurance industry trends:

Liability Premium:

> **Matching Critera #1**: per capita Collision Premiums (Matching on similar price levels)
> **Matching Critera #2**: per capita Liability Exposures, per capita Collision Premiums (Match on other premiums and the number of exposures)



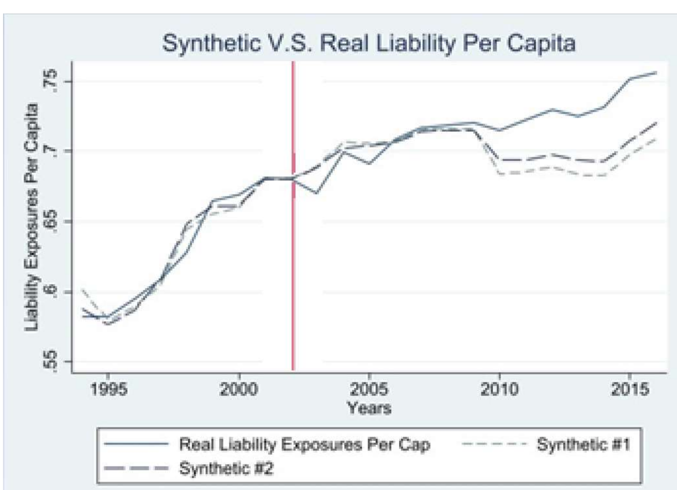


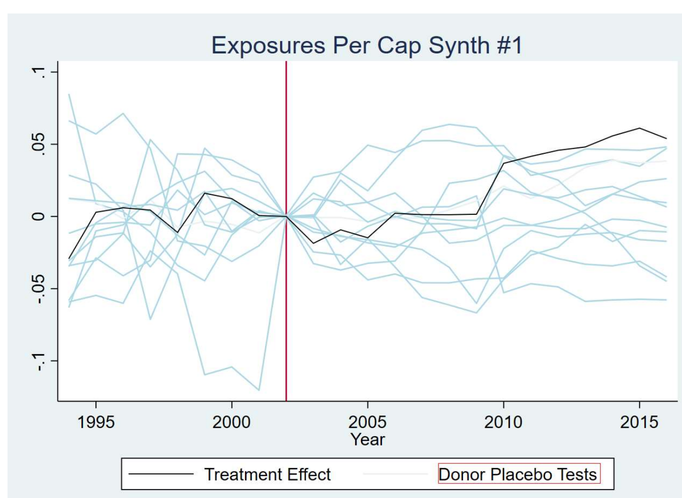
Liability Exposures:

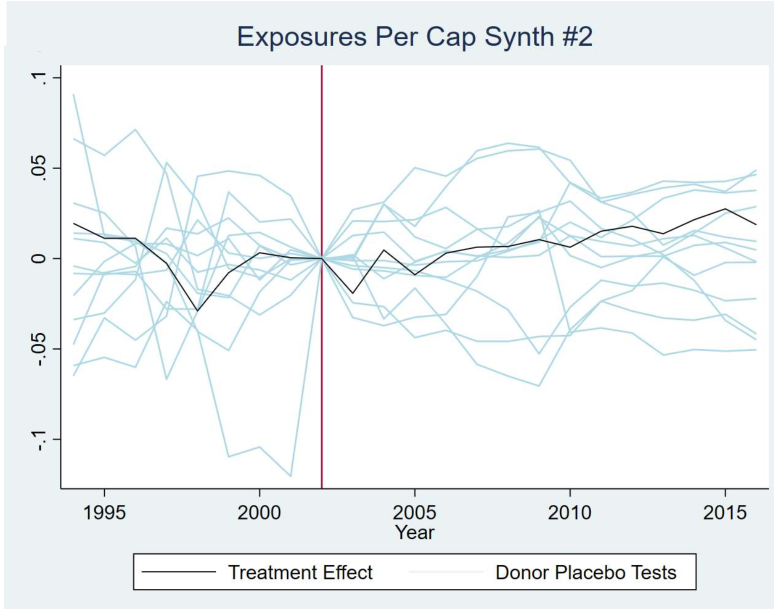
Matching Critera #1: per capita Collision Exposures (Matching on similar number of different exposures)

Matching Critera #2: per capita Collision Exposures, per capita Liability Premiums (Match on other numbers of other exposures and price level)

Matching various combinations of Exposures and Premiums per capita should provide a synthetic Colorado with an insurance sector composition most similar to its real counterpart in all ways possible once compensated for changes in population (deemed necessary as certain areas were growing much more rapidly than others which could contribute to either the premium or the number of exposures. Once the algorithm is run each all four ways we have the following synthetic and real values compared. The Synthetic Colorados trained for Premiums per capita have a clear and large divergence from their real counterpart starting immediately in 2003, which is ideal and provides a stronger claim towards a causal relationship than





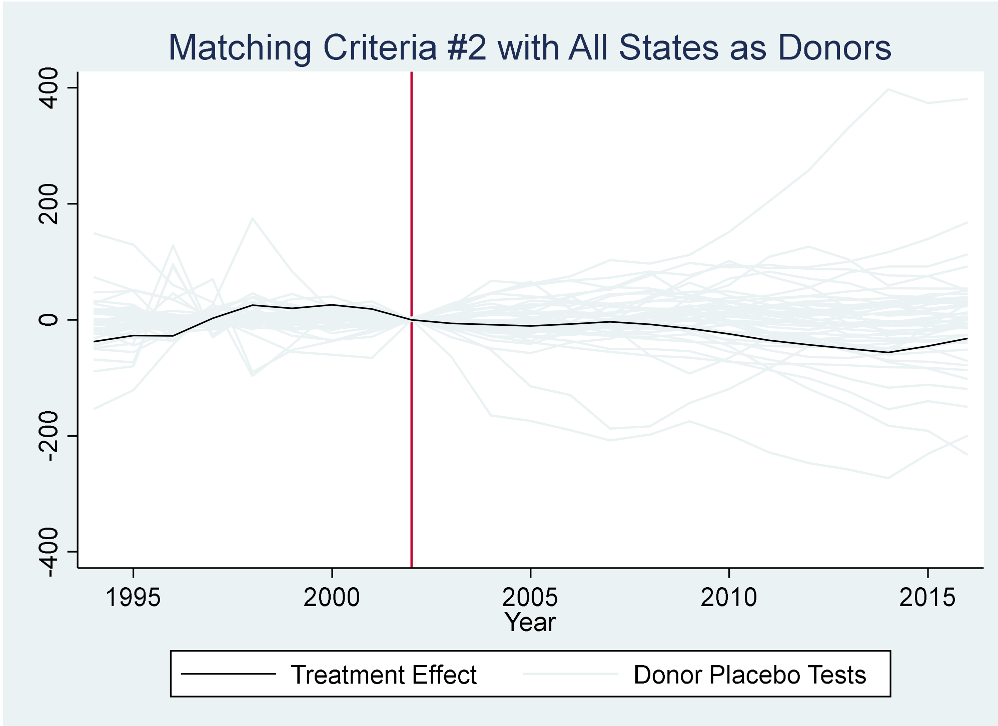


divergence at the endpoint alone. Throughout the trajectory of the effect on liabilities, both Synthetic Colorados is the most negative effect of all 13 test, save in 2009, meriting a p-value 1/13 with added emphasis stemming from the immediate divergence from the factual Colorado's path and its continuation.

Of the Colorados trained for Exposures per capita, neither have a convincing split from the actual path until long after the treatment starts and is less convincing since the spread, once started, is still not very distinguishable from the placebo noise. While the first Matching Criteria's model ends with a p-values of 1/13, the second Matching Criteria is never even close to being significantly different from the surrounding noise. Also, reminiscent of the Difference-In-Differences statistical insignificant across the board, the Exposures Synthetic Models tend to have much noisier fits than the Premiums' fits. The pre-period placebo tests seem to be even noisier than the post period fits, so there is not much inference possible in for Exposures.

As for the composition, of the both sets of Synthetic Colorados, they all pulled from Utah, Wisconsin, Pennsylvannia, and Minnesota with varying yet similar weights. All are somewhat rural, any not too densely populated: things to consider when looking at the importance and use of automobiles. None have too low of price levels and none have ones too high. In any case, this does not seem as objectionable as it would have been if Synthetic Colorado were composed entirely of a weighted average of New York and New Jersey.

While the other 37 for which we have data did not have a no-fault insurance during the duration of the studied period, we can similarly use them to construct



placebo tests, albeit less robust ones. To do so, one would have to assume that the trends which the new donors will have are possible with a no-fault policy and that building a Synthetic Colorado from “At-Fault” states would still preserve the counterfactual trend seen if Colorado had stayed “No-Fault”.

Above we have the placebo tests for Premiums per capita performed with the whole set of states used as the donor pool, whether or not the state has a “No-Fault” mandate. While it appears to be on the lower end, the results are far from significant. However, it is a hard ask to assume that “At-Fault” and “No-Fault” states have similar reactions to events in terms of price and exposures or that one does not react more aggressively when increasing or decreasing than the other. Such differences would complicate the construction of a linear combination Synthetic copy.

III. Conclusion

In both the Difference-in-Differences and the Synthetic Control analyses we received information that corroborated each other, namely that there is strong evidence ($p = 1/13$ in Synthetic Control and $p < 0.01$ in Difference-in-Differences) that Liability Premiums declined after 2003 as a result of the policy change implemented in Colorado switching from “No-Fault” to “At-Fault”. Additionally, point estimates for the effect on the number of exposures suggest a positive effect for both synthetic Control (p=1/13 or p=4/13) and very statistically tenuous effects for Difference-in-Differences.

One possible explanation for the lack of significance around the increase in policies taken out would be that a car is a expensive durable good where the price was just lowered by a small fraction. When prices drop slightly (when the $80-$100 PIP payment goes away and Liability coverage drops by $50-$80), the marginal cost of owning and justifying another car does not shift significantly, so few will act immediately in response to a price change. As time goes on however, and one can gets a new car faster or buy and own a first or next car for less than before. This would show a gradual revving up in automobile market and be reflected in registrations and auto coverage. Price is far more responsive to market forces under competition and changes immediately, as illustrated by the Synthetic Control's clean divergence immediately after 2002.

Further study must be conducted to establish exactly where all the money goes under a "No-Fault" policy, as there are definite policy spill-overs outside of the PIP premium paid every six months. Where "No-Fault" is conceived with the intention of simply providing a baseline care, with premiums carefully set by Casualty and Health actuaries, they show to potentially be more expensive than realized and costs spilling over into other independent policies. Continued research along this vein may prove helpful to policymakers in Utah, a "No-Fault" state the neighbors Colorado and may have very similar reactions to a policy change as did Colorado, lowering prices and potentially increasing the Utahan's mobility without spending another dime on public transportation.

Works Cited

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Table 1: Descriptive Statistics for all US States (and D.C.)

Variables	Count	Mean	St Dev	Min	25%	50%	75%	Max
Year	1173	2005	6.636	1994	1999	2005	2011	2016
Collision Exposures	1165	2514709.71	2738176.16	116058	688221	1744053	3161410	18934675
Liability Exposures	1169	3510567.79	3794782.81	122025	967910	2501139	4229751	26860298
Collision Premiums	1167	721433484.5	919305686.2	31352018	173217024.5	421166957	882095770	8023475371
Liability Premiums	1169	1676884852	2051222647	40245521	411786715	1078729415	2025257025	13989189313
Single Injury Min*	1173	22.941	7.343	10	20	25	25	50
Many Injury Min*	1170	45.944	14.775	20	40	50	50	100
Property damage Min*	1173	14.241	6.773	5	10	10	20	25
Median Income	1173	45810.98	10196.82	23564	38591	45044	52201	76260
Population	1170	5748907.81	6441054.56	480283	1548297.75	3971526.5	6621654.75	39250017

*in thousands

The difference in counts is due to two states incompletely reporting various data for years 1994,1995, and 1996. Neither of the states (Texas or South Carolina) were "No-Fault" so the count for the 13 "No-Fault" states is homogenous. The Difference-In-Difference and Synthetic Control Analysis performed on the whole US dataset will not contain these states for consistency, so the "full" dataset will refer to the other 47 states and the District of Colombia

Table 2: Descriptive Statistics for all 12 "No-Fault" States (and Colorado)

Variables	Count	Mean	St Dev	Min	25%	50%	75%	Max
Year	299	2005	6.6001	1994	1999	2005	2011	2016
Collision Exposures	299	3133954.87	2379633	224510	1321233	2623964	4270009	10946919
Liability Exposures	299	4281784.86	3079436.06	351062	1971080	3642475	6014808	13434810
Collision Premiums	299	932904351	760170764.3	31352018	302691880	653265627	1513455103	3419050083
Liability Premiums	299	2499374457	2372094329	70139657	698142441	1659128089	3757713680	12225988916
Single Injury Min*	299	21.488	5.376	10	20	25	25	30
Many Injury Min*	299	43.361	11.264	20	40	50	50	65
Property Damage Min*	299	10.903	5.151	5	10	10	10	25
Median Income	299	48324.78	10089.53	26595	41053	47877	55731	72266
Population	299	7332063.42	5770812.21	631680	2777305	5262824	10022278	20612439

*in thousands

Regression Table Estimates With State-Clustered Standard Errors (Year, State and Period Fixed Effects Not Shown):

Av. Liability Premiums	13 No Fault States		48 Available States		Liability Exposures Per Capita	13 No Fault States		48 Available States	
Variables	1	2	3	4	Variables	1	2	3	4
Colorado*After2002	**-59.90** **	**-81.73**	**-59.08**	**-61.99**	**Colorado*After2002**	**0.0144** **	**0.00227** **	**0.0064** **	**0.0018** **
	(37.43)	(16.99)	(12.79)	(8.47)		(0.00100)	(0.00996)	(0.0089)	(0.0073)
Single Injury Min	**4.07** *	**6.60**	**-4.45**	**-3.04**	**Single Injury Min**	**0.00320**	**0.00456**	**0.00284** **	**0.00349** **
	(3.36)	(1.97)	(1.91)	(1.16)		(0.0014)	(0.000678)	(0.00098)	(0.00214)
Many Injury Min	**1.18** **	-	**1.89**	**1.71**	**Many Injury Min**	**-0.00181**	**-0.00240**	**-0.0016)** **	**-0.001697** **
	(2.46)		(0.707)	(0.67)		(0.00056)	(0.000499)	(0.0009)	(0.00348)
Property Damage Min	**6.53**	**7.45**	**1.24** **	-	**Property Damage Min**	**-0.0003942** **	-	**0.00054** **	-
	(2.72)	(2.86)	(1.66)			(0.0019)		(0.00163)	
Population	**0.0000302** **	**0.0000361** *	**0.0000079** **	-	**Population**	**-1.59e-09** **	-	**-1.28e-08** **	**-1.35e-08** *
	(0.0000180)	(0.0000195)	(0.000008)			(7.62e-09)		(7.89e-09)	(6.76e-09)
Median Income	**-0.0188079** **	**-0.0070871** **	**-0.0049** *	**-0.00279**	**Median Income**	**-0.00000736** **	-	**-0.0000019** **	-
	(0.01266)	(0.004146)	(0.0029)	(0.00123)		(0.00000553)		(0.0000020)	
Log Median Income	**634.38** **	-	**128.20** **	-	**Log Median Income**	**0.51** **	**0.16** **	**0.113** **	-
	(611.97)		(141.34)			(.32)	(.10)	(.113)	
No Fault	-	-	**110.16**	**15.32** **	**No Fault**	-	-	**-0.068**	**0.095** **
			(21.69)	(19.71)				(0.019)	(0.10)

*** over 5% ** over 10%**