The Evolution of Markups in the Automobile Insurance Industry in Ontario, Canada *

Andrew Paulley†

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Abstract

We document abrupt increases in the the markups of the automobile insurance industry of Ontario, Canada, specifically for private passenger vehicles, from 2001 to 2021. We adjust the standard differentiated-product pricing model for the case of no outside good, as auto insurance is a legal requirement in Ontario. Then within the context of our model, we test and reject the hypothesis that the markup increases after Ontario Regulation 34/10 in 2010 are simply a result of increased market concentration. Our estimates suggest Ontario consumers have paid an additional \$16.6 billion in markups for auto insurance from 2011 to 2021, and another \$5.7 billion in markups during 2020 and 2021 associated with COVID-19. For a consumer with an auto insurance policy from 2011 to 2021 this represents an additional \$2958 paid in premiums. We also provide reduce form estimates that complement our structural findings.

Keywords: market power; price regulation; auto insurance
JEL classification: L13; L98; G22

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†University of Toronto, Email: andrew.paulley@mail.utoronto.ca

1 Introduction

In 2022, while the Canadian stock market broadly suffered losses mainly attributed to COVID-19 as well as the war in Ukraine, a pocket of Canada's financial sector soared. Canada's publicly traded property and casualty insurance companies out-performed not only Canada's major banks but also the S&P/TSX Composite Index by 40% in 2022. The impressive stock performance of these property and casualty insurance companies is unexpected, as journalist Tim Kiladze wrote for The Globe and Mail: "They have found ways to make money off of auto insurance, which is notoriously hard to do in Canada".[1] It is considered difficult to make a profit in auto insurance in Canada due to strict regulatory frameworks and price controls that have been in place for decades. However, over the last ten years, evidence has come to light indicating profit margins on auto insurance are higher than previously perceived. In the province of Ontario, which accounts for 40% of the auto insurance market in Canada, the average premium is the highest in the country, and the average underwriting profit per vehicle has been steadily increasing. A report in 2015 by Lazar and Prisman and another by Lazar in 2018, both prepared for the Ontario Trial Lawyers Association, found evidence via public accounting data that the largest auto insurance firms were making after-tax profit margins upwards of 15%.[2] This after-tax profit margin significantly exceeds the Financial Services Regulatory Authority of Ontario (FSRAO)'s mandate to keep industry after-tax profit margins to just 6% (or pre-tax profit margin of 8%).

How much profit firms are making from auto insurance has long been a difficult question to answer. Insurance in Canada (including auto insurance) is sold by a brand, and a firm may own and underwrite multiple brands of insurance. An insurance brand is rarely, if ever, the sole part of a firm, and how company wide expenses are broken down by product line within a region will be determined differently by each firm or even each brand (Lazar and Prisman, 2015). The FSRAO has therefore held industry-wide assumptions when assessing the premiums charged by each brand. These assumptions include a 25% expense ratio, which is the percentage of premiums spent on the costs of business outside of paying claims (Lazar and Prisman, 2015). Therefore, to obtain an 8% pre-tax profit margin on premiums, the assumptions by the FSRAO results in a claims ratio (the percentage of premiums spent on claims), of 67%. During the COVID-19 pandemic the claims ratio was the smallest on record, reaching 51% and 52% in 2020 and 2021 respectively. Even without knowing the true nature of the relationship between premiums, claims, and expenses, it is clear that during 2020 and 2021, individuals paid far more in premiums relative to what the industry had historically paid out in claims and paid more than what would reflect a 6% after-tax profit margin.

This paper estimates the markups of the auto insurance industry in Ontario and determines how markups have evolved over time in response to changes in the level of market concentration, Ontario Regulation 34/10, and COVID-19. We focus on private passenger vehicles (PPV) which account for the vast majority of vehicles on the road. Ontario Regulation 34/10 was passed in the Ontario legislature in September of 2010 in hopes of reducing

[1] https://www.theglobeandmail.com/business/article-how-home-and-auto-insurers-trounced-the-big-six-banks-and-became/

[2] The 2015 report can be found here: https://andrewpaulley.ca/wp-content/uploads/2023/07/lazar_prisman_report_2015.pdfand the 2018 report can be found here: https://andrewpaulley.ca/wp-content/uploads/2023/07/lazar_report_2018.pdf

premiums by lowering the amount paid out for healthcare-related expenses from an accident. While industry wide claim costs fell 25% from 2010 to 2011, and has since stayed below 2010 levels in nominal terms, premiums have steadily increased. We lack information on firms' fixed costs for providing auto insurance, so we focus on markups instead of profit margins. We claim we can, in part, extend our results to profit margins as we believe fixed costs have remained flat over our time period as a percentage of premiums and in some cases could have fallen. For example, auto insurance brands are shifting online, which would reduce the need for land and local labour. Furthermore, there is no evidence to our knowledge that Ontario Regulation 34/10 and COVID-19 increased fixed costs.

We start by outlining a reduced-form model of average premiums per vehicle. We estimate that, on average, consumers overpaid by $260 per vehicle per year from 2011 to 2021 as firms limited the passthrough of the reduction in claim costs onto consumers after Ontario Regulation 34/10 was enacted. Summing across all private passenger vehicles from 2011 to 2021, the regulation change resulted in consumers overpaying by a total of $20.9 billion for auto insurance. We also find that over 2020 and 2021, consumers additionally were overcharged by $3.4 billion dollars as firms also limited the passthrough of the reduction in claim costs resulting from the COVID-19 pandemic. Combined, Ontario Regulation 34/10 and reduced claims during the COVID-19 pandemic resulted in $24.3 billion dollars in consumer overpayments over 11 years.

The main body of the paper employs both the simple and mixed logit models of demand for differentiated products as described in Barry, Levinsohn, and Pakes (1995) commonly referred to as BLP. The mixed logit model is the standard for demand estimation and has been employed to study a plethora of industries (for example, BLP 1995 for automobiles, Nevo 2000 for cereals, and Miller and Weinberg 2017 for beer). Our estimate of the random coefficient in the mixed logit model provides no significant explanatory power, and we describe possible reasons for this including the type of data we have access to. Unable to reject the simple logit case, we use the results from the simple logit model for the rest of our analysis. We find markups have grown by $21 or 6% from 2001 to 2021 which we attribute to mergers and acquisitions over the timeline increasing the level of concentration in the industry at the firm level. During this time period, our estimation suggests the Lerner Index has fallen over time from 33% to just 18%. However, our implied marginal costs from the model of demand do not fall with the average claim per vehicle paid out post-2010 after Ontario Regulation 34/10 was put in place.

We suggest that Ontario's auto insurance industry has collectively retained the claim cost savings from Ontario Regulation 34/10 by passing less savings onto consumers than it would historically, parting the industry from a previous equilibrium. Our model assumes one-shot Bertrand-Nash competition before the 2010 policy, and we use a linear parameter coined by Miller and Weinberg (2017) to estimate the average increase in markup across the auto insurance industry post-2010. We reject Bertrand-Nash post-regulatory change and find markups increased by $204 after 2010, totalling $16.6 billion paid in excess markups between 2011 and 2021. Our structural results are similar but lower to that of our reduced form estimation, and we anticipated the structural estimate being lower due to the structural estimation not including specialty insurers which provide riskier insurance and have much higher average premiums and average claims per vehicle. We estimate an additional increase in the markups during COVID-19 of $357 per year totalling an additional overpayment of $5.7 billion over 2020 and 2021. Adjusting our markup estimates, the Lerner index now increases after 2010, above pre-2010 levels, and peaks during the COVID-19 pandemic. We conclude that auto insurance markups have increased, in both levels and relative to premiums, since 2010. We find the top four firms have seen a larger increase in markups with respect to the rest of the industry, a reflection in the largest four firms increasing their total market share from 35% to 57% over our 21-year period.

This paper contributes to several areas of research. The literature surrounding insurance generally assumes consumers maintain their current policies until a shock, health, price, or otherwise, causes a switch in the consumers' choice for their level of insurance or their insurance provider. A large part of the literature focuses on how inattention, consumers being unaware of their own and other insurance prices changes, impacts the profitability of insurance (see Ho et al. 2017). Another area of the literature focuses on search and switching costs of insurance and its impacts on profitability (see Honka 2014 or Yeo and Miller 2018). There has been previous work on premium rates regulation as well, Lazar and Prisman (2015) determined new methods of estimating return on equity for single business lines of firms and used auto insurance in Ontario to demonstrate their methodology. We are, to our knowledge, the first to estimate marginal costs and markups of auto insurance via a demand model of differential products. An assumption of this model is that consumers choose an insurance provider each year and have full knowledge of premiums. This may be a strong assumption, however given our data is yearly, we find it reasonable to assume a consumer searches for a different insurance provider once a year.

We also contribute to the robust literature of demand estimation and post effects of mergers (see Ashenfelter et al. 2014 for a survey). The methodology is closest to that of Cilberto and Williams (2014) as well as Miller and Weinberg (2017) who modelled the airline and beer industries respectfully. In estimating our break from a previous pricing equilibrium, we use Miller and Weinberg's linearized estimator to determine an average excess increase in markups instead of the degree to which the firms colluding care about each other's profits.[3] To our knowledge, we are the first to consider a change in an industry's level of collusion instead of just a subset of firms. We are also the first to our knowledge to use a regulatory change within our model as a catalyst for increasing collusion instead of a merger or acquisition.

Finally, this paper relates to research on changes to markups and concentration levels over time. We consider a time horizon of 21 years and track the evolution of markups, similar to the work of Grieco et al. (2018) in their work to understand the evaluation of markups within the automobile industry. They find the Lerner index for the automobile industry has fallen over time, and through the increase in product quality, consumer surplus has risen. In our case, the main characteristic of an auto insurance policy, which is the payments received in the event of a claim, have fallen, and the gap between premiums and claims has widened in recent years. Benkard et al. (2021) find while almost all sectors in the economy are getting more concentrated, product level concentration has decreased over the last 20 years.

[3]See Miller and Weinberg's supplement to their 2017 paper for more information on the linearization of their estimation. `http://www.nathanhmiller.org/mwbeersupplement.pdf`

They characterize these trends as firms becoming larger and competing on more products. The Ontario auto insurance market has however seen both a concentration in firms and a concentration in brands. Autor et al. (2020) developed the idea of 'Superstar Firms', where companies within an industry enjoy raising market share over time and industry high markups. Ontario's largest auto insurer Intact has been the clear winner of the industry over the last 21 years, both in terms of its market share, and profits, as illustrated by its climbing dividend payments to shareholders over the last five years.[4]

The results of this paper are limited by data access, which limits both the scope and the model we estimate. We are restricted to only the data on the province of Ontario. Our reduced-form estimation using difference-in-difference is therefore within-market instead of between-market. We show that separating premiums and claims by coverage type still allows difference-in-difference to be used. The price data of our structural model is the average premium per vehicle at the brand-year level. This form of price data does not provide information on elements of the insurance policies purchased such as the amount of coverage or types of coverage, which limits the characteristics we can observe. Average premiums also limits the variance in prices for brands within a given year and remove consumer price sensitivity that would be observed if we could separate policies within brands by the amount of coverage. We suggest a reason why our random coefficients provided no new explanatory power is because of our access to only average premiums by brand. We show the simple logit with appropriate instruments produces plausible own price elasticities, and thereby analysis of the evolution of markups in the auto insurance industry can still be done. For the cost side of auto insurance, we have access to the expected claims paid by the industry per accident-year, also known as ultimate loss, but not disaggregated to the firm or brand level. This limits our ability to estimate a supply side of the model, however we will discuss possible industry-wide costs assumptions using the aggregate data to improve the explanatory power of our model. Furthermore, claims data for accident years 2018 to 2021 are not considered final, as the estimates are updated every year for the four following years proceeding each accident year. Therefore specifically our COVID-19 estimates are considered upper bounds on consumer overpayments. The statistical agency that collects claims data does not specify to what extent the data may adjust by in the coming years, however we assume from historical context that the ultimate loss estimates produced in the first year are accurate.

The rest of this paper proceeds as follows. Section 2 will provide a background of the auto insurance industry in Ontario. Section 3 outlines the data used, its sources, and descriptive statistics. Section 4 focuses on premiums and claims at the coverage level. The section includes a difference-in-difference estimation of the average treatment effect on the treated coverages for the years after Ontario Regulation 34/10, providing a preliminary estimate to the overpayments of premiums the industry has received that are attributed to the regulation change. Section 5 describes the model for demand, as well as our supply model. Section 6 outlines estimation of our demand and supply model as well as the instruments used. Section 7 will provide the results of the structural estimation elasticities, marginal costs, markups, and level of collusion. Finally, section 8 concludes the paper with policy implication, and avenues of future research.

[4] `https://www.intactfc.com/English/investors/shareholder/dividends/Common-Shares/default.aspx`

2 Industry Background

2.1 Overview of Auto Insurance in Ontario

Auto Insurance is understood to be providing value not only to the consumers who have insurance but to all other drivers and users of public roads. Costs of healthcare expenses, repairs, and other damages can cumulatively exceed tens of thousands of dollars per incident, and the inability for individuals to pay those large costs up-front hurts all parties involved in a claim. Every province in Canada has instituted mandatory auto insurance, which includes a minimum level of coverage required.[5] The first province to invoke mandatory auto insurance was Saskatchewan in 1946 while Ontario would not require auto insurance until 1990.

When a purchase is required by law, or the good is considered a necessity, the lower price elasticity of demand facilitates firms to achieve higher markups. To allow firms to be profitable while protecting consumers Ontario has a strict regulatory framework which began in 1988. The Financial Services Commission of Ontario (FSCO, and later the Financial Services Regulatory Authority of Ontario or FSRAO) was given power to oversee how each provider of auto insurance determined the premiums they would charge. The government of Ontario gave the FSRAO an original mandate of capping return on investment to 12%. Each firm or brand of auto insurance sets a base algorithm to determine the premium a consumer pays for insurance and any future changes of that algorithm are approved, denied, or adjusted by FSRAO. To determine if an auto insurance brand would surpass the benchmark after their proposed rate change the FSRAO has to make some assumptions about the industry when evaluating a premium rate change application. These assumptions include a benchmark average return on portfolios of 6%, an average tax rate of 26%, and expense ratio of 25%. The expense ratio is defined as all costs of running the auto insurance line of business outside of paying out claims divided by premiums. Costs would include labour and capital costs as well as any fixed costs. With these assumptions in place, Lazar's 2018 report shows the corresponding mandated after-tax profit margin on premiums has stayed around 6% from 1988 to present day.[6]

Given the report in 2015 by Lazar and Prisman and the report in 2018 by Lazar, we do not consider the FSRAO to be effectively holding firm profits in line with the FSRAO's mandate. Furthermore, during a telephone call on July 23rd, 2022, between the author and Anna Hahamovich, an employee of the FSRAO within the auto insurance branch, it was confirmed that only one rate change application has ever been denied, out of over 2500 such applications, since oversight began in 1988. We therefore do not explicitly account for the regulator in our structural model, and only compare estimated markups and possible profit margins with respect to the official 6% after-tax profit margin mandated to the FSRAO.

The types of coverage that are legally required, versus coverages that are considered optional or 'bonus', have stayed consistent in Ontario since 1990. These are outlined in Table

[5] In Canada, transportation, and thereby automobiles and auto insurance are under provincial jurisdiction.

[6] Lazar notes there have been two adjustments to the ROI cap, from 12% to 11.5% to 11% and then starting in 2015 it moved from an ROI cap to an after-tax profit margin on premium cap of 6%. Throughout the changes, the benchmark profit margin on premiums has stayed between 5.2% and 6%. We will use the 6% as the general benchmark when determining our estimated profit margin on premiums.

2.1.1. The first three coverages, Bodily Injury, Property Damage, and Direct Compensation, are traditionally referred to together under the term 'Third Party Liability'. Motorists and vehicles are considered underinsured if they have no insurance or if the insurance they do have does not cover the full cost of a claim. In many cases, underinsurance means the individual or vehicle is from another province of Canada or from the United States, where there are different minimum insurance requirements. The most expensive portion of a standard auto insurance policy is Bodily Injury and Accident benefits. These two coverages have accounted for over 50% of all premiums collected since 1996. It is important to note that these two coverages are under the umbrella of healthcare costs. As will be discussed further in section 2.3, Ontario Regulation 34/10 in 2010 specifically targeted healthcare related claims costs thereby reducing the costs for the largest elements of auto insurance policies.

Table 2.1.1: Descriptions of Auto Insurance Coverage Types

Coverage Type	Mandatory (M) or Bonus (B)	Type of incident or costs covered
Bodily Injury	M	Injury to a person involved in a collision.
Property Damage	M	Covers damage to another vehicle, or a residential or commercial building.
Direct Compensation	M	Costs of repairing a vehicle from an accident that is not entirely the fault of the insured.
Accident Benefits	M	Covers costs for supplementary medical expenses, rehabilitation, caregiver, and income replacement. Payments are not made on the basis of fault.
Underinsured Motorist	M	Covers costs if an accident was the fault of a motorist whose third-party liability limits were lower than the injured's coverage, a motorist left the scene of an accident (termed a 'hit and run'), or a motorist who did not have insurance.
Underinsured Automobile	M	Covers claims from an accident that involved a vehicle with insufficient insurance to cover the costs of the incident, or the vehicle was not insured.
All - Perils	B	Combines collision and comprehensive coverage.
Collision	B	Costs of repairing a vehicle from an accident that was deemed the fault of the insured.
Comprehensive	B	Costs of repairing a vehicle after non-collision events such as fire, severe weather, falling objects, or theft.
Specified Perils	B	Covers one or more elements found within comprehensive coverage.

Auto insurance is a renewing purchase. All auto insurance policies in Ontario are valid for one year. After each year the policy automatically renews, or the policy holder chooses to update the amount or types of coverage they hold, or buy a new policy from a different brand. The policies and level of coverage available at different brands or firms is very similar making auto insurance in Ontario a rather homogeneous good. If an individual can therefore buy the same amount or type of coverage from any brand, the characteristics of the brand or firm become an important determining factor for where consumers buy auto insurance. For example, reputation of the firm matters as a firm needs to be seen as willing and able to pay in the event of a claim. For this reason, many consumers therefore choose to buy auto insurance policies from their banks which have been around for over 100 years and have a long standing in the Canadian economy.

There are two distinct types of auto insurance brands that operate within Ontario. The first set are standard providers, which serve the general public, and the second set are specialty providers that serve individuals who have been denied insurance by standard providers. Even though insurance is a legal requirement, and consequently the province must ensure that anyone can buy insurance, standard insurers are still allowed to turn away those they see as too high-risk. High-risk individuals can be classified as those with multiple prior accidents, little to no driving record, convictions of driving while under the influence of drugs or alcohol, etc. The price of auto insurance from specialty providers reflects the higher-risk consumer base it serves, averaging two or three times higher than the average premiums from a standard insurer. Within any given year, specialty insurers collectively underwrite less than 2% of all insurance policies in Ontario but collect nearly 5% of the total industry premiums.

While our data used for reduced form estimation in Section 4 is not able to separate specialty insurers from the standard insurers, we will remove specialty insurers in our structural demand estimation as the two groups of firms serve distinctly different clients and can therefore be classified as separate markets. Since specialty insurers are not included in our structural estimation, they are not a part of our presentation of market structure and concentration in Section 2.2, or evidence of cooperation in Section 2.4. We will also restate within each relevant section whether or not specialty brands are included.

2.2 Market Structure and Concentration of Ontario Auto Insurance

Our firm level data set spans from 2001 to 2021. This time period saw a significant reduction in the number of insurance brands and firms selling auto insurance. In 2001 there were 54 brands and 37 firms but by 2021 there were only 37 brands and 21 firms. During this timeline, the market went from insuring 5.7 million vehicles in 2001 to 8.0 million vehicles in 2021. The number of brands and firms for each year is presented in Figure 2.2.1. The largest firm in Ontario in terms of auto insurance, Intact Insurance, has been the main contributor to the falling number of brands and firms. Over our 21-year time period, Intact has purchased five firms, which includes over ten insurance brands. In this consolidation Intact has doubled its market share from 10% in 2001 to 20% in 2021. Another example of a significant acquisition during our time period is Desjardins' purchase of State Farm Mutual Insurance for $10 billion in 2014. At the time of purchase, State Farm Mutual Insurance was the second largest brand of auto insurance in Ontario and the third largest firm by market share. The purchase of State Farm Mutual Insurance propelled Desjardins from the tenth largest firm to the second largest firm operating in Ontario.

The increase in concentration through mergers and acquisitions is reflected in the standard measures as seen in Figure 2.2.2. Both the C4 (total market share of four largest firms) and C10 (total market share of the ten largest firms) have grown by 20 points between 2001 and 2021. The Competition Bureau of Canada uses C4 instead of the HHI to assess the risks of a merger making an industry too concentrated. The point where the Bureau begins to consider intervention is when the C4 is at 65%; as of 2021, C4 for auto insurance in Ontario is 57%. While the Ontario auto insurance industry is still below the Bureau's benchmark, the degree to which the industry has increased concentration should be noted. Similarly, if we instead used the United States Department of Justice guidelines for concentration, an HHI of 1100 is still shy of a benchmark of 1500 to be considered 'moderately concentrated'. Similarly to the change in the C4, a growth of over 500 points of the HHI during 2001-2021 and the consistent increase of the HHI over that time suggests this moderately concentrated benchmark will be reached in the coming years.

Figure 2.2.1: Standard Brands and Firms in Ontario Auto Insurance Industry, 2001-2021

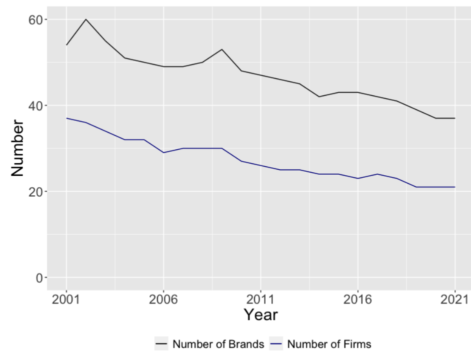
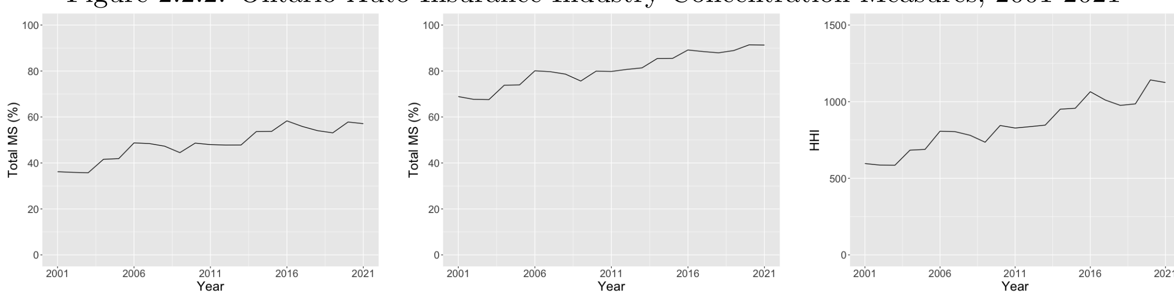


Figure 2.2.2: Ontario Auto Insurance Industry Concentration Measures, 2001-2021



a) C4 b) C10 c) HHI

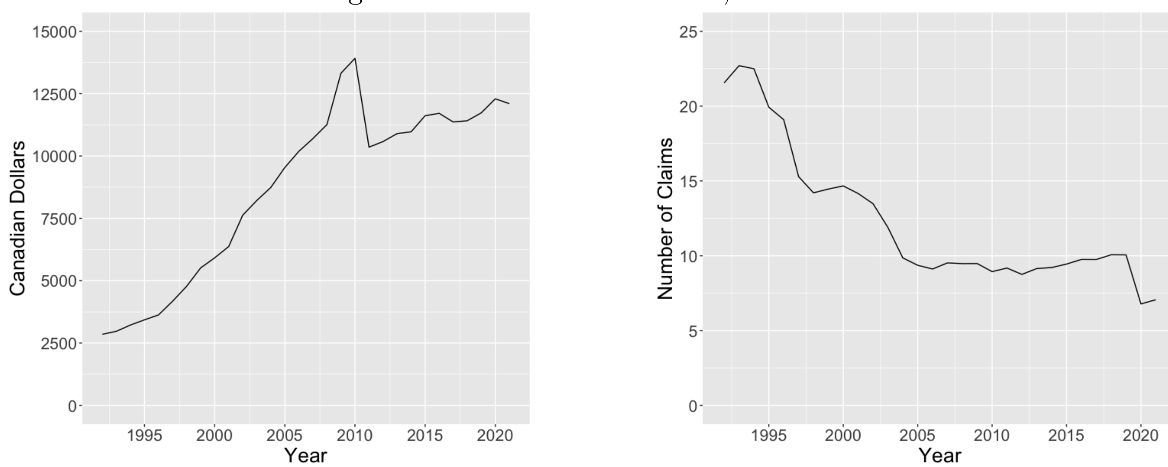
2.3 Ontario Regulation 34/10

The value of insurance directly relates to the resulting payouts received in the event a claim is made. The Ontario provincial government has imposed several regulatory changes around Ontario's auto insurance industry that modifies the minimal level of benefits insurers are required to provide for each coverage type. Figure 2.3.1 shows the ultimate average cost per claim and the ultimate number of claims per 100 vehicles by accident-year from 1992 to 2021, based on aggregate data described in Section 3. Accident-year refers to the year an accident occurs, so any payments made to the policy holder in any future year is accounted for in the total claims of the year of the incident. We note that the aggregate claim costs and number of claims cannot be separated between regular and specialty insurers and so Figure 2.3.1 includes specialty insurance providers. From 2004 to 2007 the minimum payout amounts increased 101% for attendant care benefits, 146% for caregiver benefits, and 20% for disability income benefits.[7] These benefits contributed to the quick rise in the average cost per claim as seen in Figure 2.3.1.a. In 2010 the Ontario legislature passed Ontario Regulation 34/10 in response to the rising claims costs. The core of the regulation change was a replacement of

[7] https://www.canadianunderwriter.ca/features/the-evolution-of-auto-reforms/

the benefit system. The new system, deemed the Minor Injury Guideline, would encapsulate a group of injuries and cap the claim paid out for each injury to \$3500. As 70% of all injuries sustained in an accident were listed within the Minor Injury Guideline, the guidelines would result in a substantial reduction of claim costs for auto insurance providers. Also included in Ontario Regulation 34/10 were reductions in the required level of payouts for care-giving costs and reductions in payments for rehabilitation or other medical expenses. The Minor Injury Guideline is still in place as of 2023, and the payment cap remains at \$3,500. Caregiver and rehabilitation benefits were reduced again, marginally, in a 2016 update to Ontario Regulation 34/10.

Figure 2.3.1: Claims in Ontario, 1992-2021

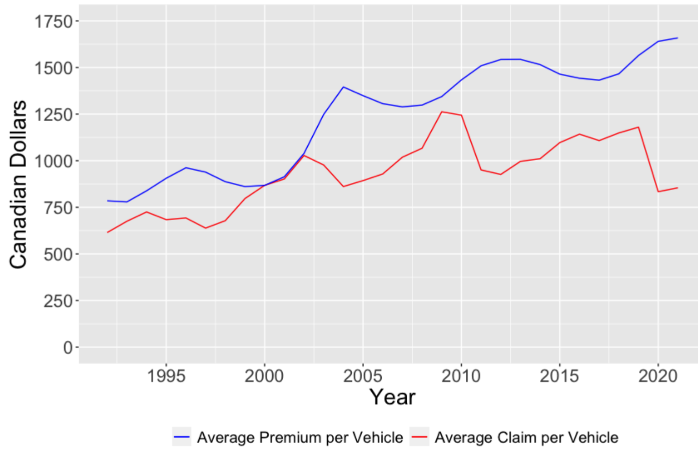


a) Average Cost per Claim

b) Number of Claims per 100 Vehicles

Ontario Regulation 34/10 change was marketed by the government to the public by claiming that the regulation would reduce premiums by 15% in subsequent years by bringing down the costs of the auto insurance providers. As seen in Figure 2.3.1.a, the average cost of a claim fell by 26% between 2010 and 2011. Again, Figure 2.3.1.a includes both standard and specialty insurers. The number of claims per 100 vehicles remained unchanged in the years following the policy change as seen in Figure 2.3.1.b. Figure 2.3.2 uses aggregate data from the same source as Figure 2.3.1 and shows the average premiums and average claim per vehicle by accident year from 1992 to 2021. Between 2010 and 2011 the average claim per vehicle fell 24%. In the years since the regulatory change, both the average claim as well as the average claim per vehicle never again reached the 2010 peak. Premiums, however, have continued to rise, suggesting that the promised cost savings were not passed on to consumers. Rather, the difference between premiums and claims expanded following the implementation of Ontario Regulation 34/10 and has not returned to levels seen prior to 2010.

Figure 2.3.2: Average Premium and Claim per Vehicle, 1992-2021

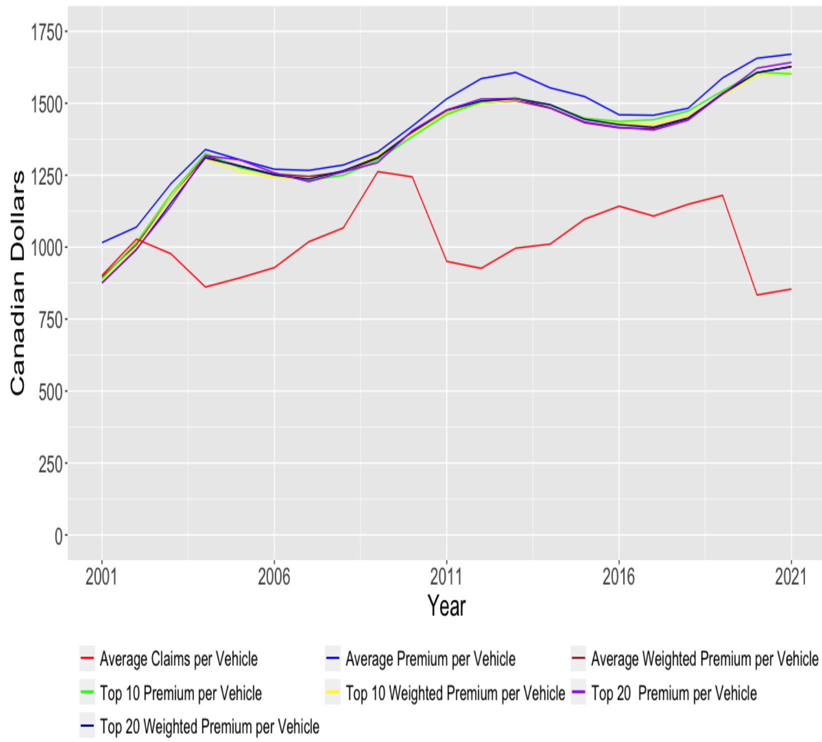


2.4 Industry Cooperation after Ontario Regulation 34/10

While the Ontario auto insurance industry (and the Canadian auto insurance industry as a whole) has historically been well organised, we argue that there has been a distinct change in the level of cooperation in the industry since Ontario Regulation 34/10. The 2010 regulation saw a long-term lowering of claim costs which, given a constant level of market competition, should mean that the auto insurance industry in Ontario would collectively lower premiums and return to the same markups they were making prior to 2010. However, Figure 2.4.1 shows that premiums did not fall for a variety of groups. The data by brand used in the figure is described in Section 3 and does not include specialty insurance brands. The average premium of the largest 10 brands by market share, as well as the average premiums of the largest 20 brands by market share, identically follow their unweighted average counterpart. Therefore, within the largest 20 brands, there has been no collective force to push premiums lower as a result of the lowering claims costs after 2010. Furthermore, the average unweighted premium for the entire industry is consistently above all our other averages, suggesting that, even amongst the smallest brands, premiums have not fallen with reduced costs.

At the individual brand level, it is clear that some brands did lower premiums after 2010 however the declines were minimal. We see from 2010 to 2013 that brands representing a total of 7% of the 2010 market had lower average premiums. Of these brands that lowered premiums, their consumers saw an average decline of $24 weighted by brand's market share. By 2015, 42% of brands by market share lowered their average premium, and consumers of these brands in 2015 paid $61 on average less than what they paid in 2010. The average premium in Ontario was around $1500 around this time, suggesting that premiums on average only fell by 4% for less than half of consumers. One explanation as to why brands did not lower premiums is that firms which saw to reduce premiums following the reduction in claims costs where bought off by the largest players in the market. Indeed, from 2010 to 2015, 11 auto insurance brands were purchased, five of which were bought by Intact. However the brands purchased were very small, having less than 0.05% market share at the time of there purchase. Furthermore, in the years leading up to the purchase of each of the insurance brands, the average premiums of these brands were not declining. We therefore conclude that sustained premiums were not the effort of just a few large firms.

Figure 2.4.1: Average and Weighted Average Premium per Vehicle, 1992-2021



With very little evidence to indicate that the auto insurance industry lowered premiums in response to the fall in claim costs after the implementation of Ontario Regulation 34/10, economic theory would suggests the industry has seen either a decrease in competition or possibly an increase in cooperation. From 2001 to 2010, there were 25% fewer individual firms in the industry, and the C4 and the C10 both increased by 10 points. With a more concentrated industry, markups are expected to be higher, which we will estimate in Section 7. Any excess increase in markups not associated with the rise in concentration can then be seen as evidence of an increase in cooperation. Therefore, we treat the years of 2011 to 2021 as a shift in the level of competition in the industry. We will estimate how this time period's markups differ from the decade prior that cannot be explained by an increase in concentration. Finally, we will estimate the amount of money consumers paid in additional markups.

3 Data and Descriptive Statistic

Data for yearly aggregate premiums, claim expenses, number of claims, and the number of insured private passenger vehicles in Ontario, separated by coverage type, is collected by the General Insurance Statistical Agency (GISA) from each auto insurer. The data is by accident-year, where all claim expenses are sorted by the year of the claim or incident, not the year payment was made. Furthermore, GISA publishes claim expenses and number of claims as estimates projected to the ultimate level, referred to as ultimate loss, that is the expected number of claims and claim payments made for each accident-year. GISA updates ultimate level estimations each year for four years after the accident-year, and reports an accident year in the dollar amount measured at the fifth year. As an example, accident year 1992 is reported in 1996 dollars, accident 1993 is reported in 1997 dollars, and so on. This means however that for accident years 2017 to 2021, all data is in 2021 dollars as that is the most current data available at the time of writing.[8] From the yearly aggregates we can construct yearly averages, including average premium per vehicle (total premiums divided by the number of vehicles), average claim per vehicle (total claim expenses divided by total number of vehicles), average cost per claim (total claim expenses divided by total number of claims), as well as the number of claims per 100 vehicles. This dataset is from 1992 to 2021, however some coverages were not being tracked until 1993, or in some instances until 1996.

Table 3.1 outlines the data by coverage type. There is a large spread among all statistics. Perhaps expectantly, the highest premium per vehicle belongs to All Perils, as it combines Collision and Comprehensive (see Table 2.1.1). All Perils also has the largest number of claims per 100 vehicles. The smallest number of claims per 100 vehicles falls to that of Underinsured Automobile and Underinsured Motorist. As it is legally required to have auto insurance in Ontario, we would expect these claims to happen less frequently. Claims for Underinsured Automobiles and Motorists are also more costly, as the individual with insurance covers more if not all the costs.

Table 3.1: Descriptive Statistics by Coverage Type

		Premium Per Vehicle		Claim Per Vehicle		Number of Claims Per 100 Vehicles		Cost Per Claim	
Coverage	Number of Years	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Accident Benefits	30	375.5	109.0	318.6	96.2	1.18	0.27	28,667	10,537
All Perils	30	379.1	47.8	286.2	46.5	6.69	2.19	4,702	1,597
Bodily Injury	26	328.0	118.6	231.6	53.1	0.17	0.03	133,504	21,199
Collision	30	240.4	35.4	173.6	32.1	3.51	0.86	5,274	1,715
Comprehensive	30	110.8	18.3	82.3	18.3	4.87	3.35	2,169	926
Direct Compensation	26	220.9	49.3	153.0	34.4	3.21	0.49	4,886	1,343
Property Damage	26	13.7	1.9	7.6	1.5	0.15	0.03	5,367	2,166
Specified Perils	30	57.1	14.9	39.6	22.2	0.96	0.51	4,822	2,421
Underinsured Automobile	29	15.0	3.4	11.1	3.2	0.04	0.04	35,956	16,974
Underinsured Motorist	30	15.9	2.1	6.1	2.1	0.00	0.00	167,933	55,900
All	287	175.7	154.7	131.4	121.1	2.13	2.62	38,981	60,674

The primary data source of this paper is the FSRAO, via public information requests made by the author from June 2022 to November 2022. The first release from the FSRAO

[8] While accident years 2018 to 2021 have not been finalised, we assume initial ultimate loss estimates are accurate, however when pressed GISA was not willing to confirm by how much future reports may adjust these numbers. Estimating the change in ultimate loss estimates would require each annual report by GISA to track the changes year over year. We however only have the finalised data, the most recent report, and the 2019 report. Comparing 2018 data from its first year release in 2019 to its revised forth year release in 2022, ultimate loss estimates increased by 2.7%. As another example, ultimate loss estimates for accident year 2017 were only increased by 1.8% after two years.

contains yearly market share data by brand from 2001 to 2021. We have two different measures of market share, the percentage of vehicles insured that are insured with that brand, and the share of total premiums that were collected by that brand. When describing brands by market share however we will only refer to market share by percentage of vehicles. Given the data is by brand, we can remove the vehicles and premiums of specialty insurers and derive adjusted market shares for standard auto insurance. From the GISA aggregates we can thereby source average premiums per brand per year from 2001 to 2021. We choose to remove small brands that have less than 0.005% of the market share or percent of premiums for a given year, which corresponds to dropping 100 observations from our dataset. [9]

The second release is the name changes within the auto insurance industry since 1999. This includes the current or most recent status of each auto insurance brand or firm, and specifically when brands were closed or integrated into another brand of the same firm. The release is not complete with respect to our dataset as many of our firms owned multiple brands or changed names before 1999. To create a complete ownership table, we also pulled from the Government of Canada's Office of the Superintendent of Financial Institutions as they list firm and brand legal updates since 1965. We also searched press releases by each firm and brand to track merger and acquisitions that were not determined through a record of a name change.

We combine premium data on each brand with ownership data and complement it with characteristics of auto insurance brands to complete the dataset needed for our demand model. Characteristics of auto insurance brands and firms include country of ownership, if the firm or brand is associated with a Canadian bank, and if the brand's base of operation is within Ontario. We have two variables for country of ownership, US Owned which is a brand owned by an American firm, and Non-NA Owned, which is a brand owned by a firm outside of North America. The remainder from Non-NA and US Owned firms are brands owned by Canadian firms. A brand's base of operation is independent of its country of ownership, for example State Farm is an American company, but its Canadian operation is based out of Toronto, so the brand is based out of Ontario. Data on characteristics was collected directly by the author. For the sake of our regression analysis, characteristics are considered yearly and can vary throughout the lifetime of the brand or firm. The characteristics of a brand in a year are the value of the characteristics on December 31st of that year.

Table 3.2 outlines our brand-year price and characteristics data. In terms of our characteristics, there are some clear trends. Country of ownership has not changed with respect to the U.S during our timeline, and one major change occurred for Non-NA Owned brands, and that was Intact becoming a Canadian company in 2009. The percentage of brands that are run by a Canadian bank has more than doubled during our timeline. Weighted average pre-

[9] These small brands are removed as turning the small market shares into average premiums for a brand, the average can be skewed by rounding. As an example, St. Paul Fire & Marine Insurance Company received a 0.004% share of premiums and had a 0.002% market share of vehicles in 2002. This implies an average premium twice as high as the market average, but if premium and vehicle market shares were 0.0035% and 0.0024% respectively, then the average premium would only be 1.5 times the market average, a very different result. As the market shares get larger, this rounding error becomes smaller and smaller but still present. We choose 0.005% as the minimum to balance reducing the error while not removing too many observations from our dataset.

mium per vehicle varies by brand within each year, and interestingly the standard deviations are consistently between \$250-\$300, suggesting the band around the industry wide average premium as remained consistent.

Table 3.2: Descriptive Statistics at Brand Level

	Number of		Premium Per Vehicle				Share of Brands			
Year	Brands	Firms	Mean	SD	Max	Min	Banks	US Owned	Non-NA Owned	Based in Ontario
2001	54	37	897	305	2,284	626	0.15	0.15	0.28	0.81
2002	60	36	1,009	271	1,940	354	0.13	0.17	0.32	0.83
2003	55	34	1,172	220	1,872	819	0.15	0.16	0.31	0.82
2004	51	32	1,317	249	2,103	831	0.18	0.12	0.31	0.78
2005	50	32	1,282	232	1,992	674	0.18	0.12	0.32	0.78
2006	49	29	1,254	198	1,841	822	0.16	0.12	0.31	0.78
2007	49	30	1,246	213	1,808	840	0.16	0.14	0.35	0.78
2008	50	30	1,261	221	1,947	841	0.18	0.14	0.34	0.78
2009	53	30	1,309	255	2,304	894	0.23	0.13	0.21	0.77
2010	48	27	1,396	267	2,426	984	0.25	0.12	0.12	0.81
2011	47	26	1,469	353	2,803	1,011	0.26	0.13	0.13	0.81
2012	46	25	1,502	389	3,257	1,138	0.26	0.11	0.13	0.80
2013	45	25	1,509	426	3,528	1,187	0.24	0.13	0.13	0.80
2014	42	24	1,483	366	2,652	1,190	0.24	0.12	0.14	0.79
2015	43	24	1,432	426	3,417	1,130	0.23	0.12	0.16	0.79
2016	43	23	1,414	269	2,164	1,150	0.33	0.12	0.19	0.77
2017	42	24	1,412	265	2,148	1,098	0.33	0.12	0.19	0.74
2018	41	23	1,446	256	2,199	1,107	0.37	0.10	0.20	0.73
2019	39	21	1,535	295	2,527	1,161	0.36	0.10	0.21	0.72
2020	37	21	1,606	301	2,491	1,075	0.38	0.11	0.14	0.70
2021	37	21	1,627	289	2,419	1,153	0.38	0.11	0.14	0.70
All	981	574	1,342	344	3,528	354	0.24	0.13	0.23	0.78

Non-NA refers to brands that are not owned by a North American Company. Mean Premium Per Vehicle is weighted by brand market share of vehicles. Brands with less than 0.005% market share of either premiums or vehicles were dropped. Specialty Insurance Brands were also dropped. Final size of Dataset: 981

4 Reduced Form Estimation of Premiums

Throughout Section 4 we will analyse all private passenger vehicles insured in Ontario which includes vehicles insured by standard brands and vehicles insured by specialty brands. Therefore, all statistics and results in this chapter (ex: average premium per vehicle and average claim per vehicle for example) include specialty insurers.

As claim costs make up the majority of all costs in providing auto insurance, we would expect claim costs to be strongly correlated with premiums. Table 4.1 gives correlations of average premium per vehicle to average claim per vehicle by coverage type. Column (i) is the correlation between premiums and claims in the same year, whereas column (ii) is the correlation between premiums, and claims lagged by one year. In every case but Specified Perils, correlation is higher in column (ii) than in column (i). Since the industry is based on single-year policies, prices can only adjust once a year for each consumer. Therefore, at least in part, premiums charged in the current year are set based on the costs, or claims, expected to be paid out for claims in the previous year. Our estimation will therefore use lagged average claims per vehicle instead of just average claims per vehicle, however we repeat the estimates using claims without the lag in Appendix A.

Table 4.1: Average Premium Per Vehicle correlation with Average Claim Per Vehicle by Coverage Type

Coverage	i	ii
Accident Benefits	0.50	0.69
All Perils	0.32	0.50
Bodily Injury	0.55	0.69
Collision	0.28	0.59
Comprehensive	0.32	0.57
Direct Compensation	0.42	0.63
Property Damage	0.71	0.72
Specified Perils	0.58	0.53
Underinsured Automobile	0.37	0.55
Underinsured Motorist	0.60	0.69

Column i is the correlation of the average premium per vehicle and the average claim per vehilce of the same year. Column ii is the correlation of the average premium per vehicle and the average claim per vehilce lagged by one year. Years used: 1992 to 2021.

Earlier from Figure 2.3.2 it was clear that on the total premiums and claims level, there had been a change in the relationship between premiums and claims after 2010 and again during COVDI-19. Generally, all 10 of the coverage types have separation between premiums and claims growing in 2020 and 2021. Four coverages show a peak in average claims per vehicle in 2010 that do not appear in the other coverages (see Appendix B). The average premium per vehicle in these coverages do not fall in the same way, and some coverages even see an increase in average premium per vehicle while average claim per vehicle is falling. The coverages with the 2010 peak in average claims per vehicle are the only coverages that pay out medical and healthcare related costs, which were the only types of costs impacted by Ontario Regulation 34/10 in 2010.

We use difference-in-differences regressions to quantify the overpayment of premiums paid per vehicle for the affected coverages of Ontario Regulation 34/10 accounting for lagged claims. As we have data only for Ontario, coverages not impacted by the policy change act as our control group. The following regression equation specifies the average premium per vehicle of coverage l in accident year t according to:

$$p_{lt} = \beta_1 c_{l,t-1} + \beta_2 \mathbb{1}\{\text{ONReg34/10}\}_t + \beta_3 \mathbb{1}\{\text{ONReg34/10}_t \times \text{Effected}_l\}_{lt} \\ + \beta_4 \mathbb{1}\{\text{COVID-19}\}_l + \beta_5 \mathbb{1}\{\text{Bonus}\}_l + \epsilon_{lt} \quad (1)$$

which includes the lagged average claim per vehicle of that coverage type $c_{l,t-1}$, indicator variables for Ontario Regulation 34/10 (0 for 2010 and earlier, 1 for 2011 and later), and the coverage types impacted by Ontario Regulation 34/10 after the policy takes effect. A dummy variable for COVID-19 is also included as it is a large shock to claims. As a robustness check, Appendix A includes reduce form estimates without years 2020 and 2021. We add a variable for bonus coverages as from Table 4.1 they have structurally lower correlations between premiums and claims than mandatory coverages. Our β_3 is our average treatment on the treated, making it our variable of interest. We will also add both coverage and time fixed effects as alternative specifications. We note that coverage fixed effects prevent the estimation of β_5 while time fixed effects prevent the estimation of β_2 and β_4. We forgo a linear time trend as premiums peaked in different years for different coverages (see Appendix B).

Table 4.2 presents the estimates of equation (1). Column (i) is standard OLS with no coverage fixed effects. As expected, lagged average claim per vehicle has a large explanatory power for average premium per vehicle. Our results do not show any significance of the regulation change. Our average treatment on the treated β_3 is positive and large as expected but insignificant. COVID-19 is positive and significant, and since it is a time variable affects all coverage types, read explicitly, the value of β_4 at 28 means that for each coverage type, the average premium per vehicle was \$28 higher during 2020 and 2021. Summing across all coverage types and all vehicles during 2020 and 2021, our estimate suggests total overpayments of \$3.4 billion during the COVID-19 pandemic. Unexpectedly there was no statistically significant effect on bonus coverage types.

As seen in column (ii), coverage fixed effects alone provide a great deal of explanatory power. This is because as per Table 3.1, coverages differ by a large margin in terms of average premium per vehicle, and average claim per vehicle is always at a similar scale to its average premium counterpart. Therefore without coverage level fixed effects, lagged claim per vehicle has a strong explanatory power simply because similarities is average premium per vehicle within a coverage type and the differences between average premium per vehicle between coverage types. Notably, with the addition of coverage fixed effects or both coverage and time fixed effects the average treatment effect increases by more than 50%. While only significant at the 90% level, as the four coverage types affected by the Ontario Regulation 34/10 are all mandatory, this would mean that each year from 2011 to 2021, on average consumers were overcharged by \$260 per vehicle per year. Summing across all vehicles from 2011 to 2021, we get a total overpayment of \$20.9 billion dollars. Our β_4 for COVID-19 shows no small positive change after adding in coverage fixed effects and is still statistically significant at the 95% level. Adding overpayments from COVID-19, our total is now \$24.3 billion dollars. In 2021, the Auto Insurance Industry of Ontario collected \$13.2 billion dollars in premiums.

Table 4.2: Results of Average Premium Per Vehicle Estimation

	i	ii	iii
c, lag = 1	1.210***	0.728***	0.733***
	(0.074)	(0.099)	(0.104)
ON Reg 34/10	-0.687	-6.318	
	(9.393)	(4.954)	
ON Reg 34/10 X Effected	40.67	65.18*	65.24
	(30.79)	(35.32)	(37.68)
COVID-19	28.06**	29.43**	
	(10.93)	(11.85)	
Bonus	22.05		
	(13.00)		
Num.Obs.	277	277	277
R2	0.915	0.946	0.957
R2 Within		0.543	0.499
FE: Coverage		X	X
FE: Year			X

* p < 0.1, ** p < 0.05, *** p < 0.01

Estimation is with OLS. The dependent variable is average premium per vehicle. Observations are at the coverage type - year level. Standard errors in parentheses below each result. Robust White Standard Errors clustered on coverage type in all columns.

To further build out our understanding of the impacts of Ontario Regulation 34/10, we will consider two more regression equations. First, we consider regressing on the log of the average premium per vehicle:

$$log(p_{lt}) = \beta_1 log(c_{l,t-1}) + \beta_2 \mathbb{1}\{\text{ONReg34/10}\}_t + \beta_3 \mathbb{1}\{\text{ONReg34/10}_t \times \text{Effected}_l\}_{lt} + \beta_4 \mathbb{1}\{\text{COVID-19}\}_l + \epsilon_{lt} \quad (2)$$

The interpretation now changes for our β's, as it is now the percent increase in the average premium per year per coverage. We use logs to attempt to reduce the standard errors on our β_3. Our estimate of \$65 dollars per coverage type is noisy as the four coverage types affected by the regulation change have very different average premium per vehicles, and in fact average premium per vehicle per year for Underinsured Motorists and Vehicles are substantially below \$65. If Ontario Regulation 34/10 led to a similar cost passthrough rate across impacted coverage types rather than a similar level pass through, then our results will have lower relative standard errors. This makes (2) a more realistic estimate. We also consider regressing on the difference between average premium per vehicle and lagged average claim per vehicle:

$$p_{lt} - c_{l,t-1} = \beta_2 \mathbb{1}\{\text{ONReg34/10}\}_t + \beta_3 \mathbb{1}\{\text{ONReg34/10}_t \times \text{Effected}_l\}_{lt} + \beta_4 \mathbb{1}\{\text{COVID-19}\}_l + \epsilon_{lt} \quad (3)$$

Taking the difference allows us to determine if the gap between average premiums and claims have just been widening over time or if the regulation change on affected coverage can help explain the larger gap.

Table 4.3: Further Estimation of Average Premium per Vehicle

	i	ii	iii	iv
log(c), lag = 1	0.320**	0.270**		
	(0.111)	(0.109)		
ON Reg 34/10	0.011		-9.386	
	(0.051)		(6.005)	
ON Reg 34/10 X Effected	0.283***	0.295***	61.503*	61.587
	(0.083)	(0.090)	(32.641)	(34.710)
COVID-19	0.129**		28.657**	
	(0.041)		(10.522)	
Num.Obs.	277	277	277	277
R2	0.987	0.991	0.526	0.619
R2 Within	0.509	0.423	0.205	0.160
FE: Coverage	X	X	X	X
FE: Year		X		X

* p < 0.1, ** p < 0.05, *** p < 0.01

Estimation is with OLS. The dependent variable for (i) and (ii) is log average premium per vehicle whereas the dependent variable for (iii) and (iv) is average premium per vehicle minus the lagged average claim per vehicle. Observations are at the coverage type - year level. Standard errors in parentheses below each result. Robust White Standard Errors clustered on coverage type in all columns.

The estimation results of equations (2) and (3) are presented in Table 4.3. In columns (i) and (ii) of the table, the dependent variable is the log of the average premium per vehicle. Our β_3 now has a much lower relative variance than our estimates in equation (1) and is now statistically significant at the 99% level. A β_3 value of 0.283 represents an average of \$267 per vehicle per year from 2011 to 2021 in overpayment of premiums, for a total of \$21.5 billion dollars. The β_4 of 0.129 produces the same total figure as before, \$3.4 billion dollars in overpayments paid during COVID-19, however the relative variance is lower than the variance of β_4 of equation (1). Columns (iii) and (iv) of Table 4.3 show similar estimates for β_3 and β_4 to that of equation (1). Given each β_3 extrapolates to our original number of \$260 per vehicle per year, and we consider (2) to be a realistic model to estimate the effect of the policy change, we will use this figure as the result of our reduce form estimation to be compared to. The \$260 per vehicle per year totals to \$20.9 billion from 2011 to 2021. Furthermore, COVID-19 led to an additional overpayment of \$3.4 billion in 2020 and 2021. For both Ontario Regulation 34/10 and COVID-19, the overpayment of premiums has large welfare effects for the entire province. To understand the auto insurance industry further, we move to a structural model where we can determine markups and price elasticities, which then provide a better context for analysing changes in welfare.

5 Structural Model

5.1 Demand

We begin with a standard set up a discrete choice model of differentiated products with heterogeneous consumers as described in BLP (1995). There are $1, ..., I$ consumers choosing

$1, ..., J_t$ products in $1, ..., T$ markets. A product j in market t has price p_{jt} and has characteristics x_{jt} which is a vector of size K. Utility for consumer i for choosing product j in market t is defined as:

$$u_{ijt} = \sum_{1}^{K} (\beta_k + v_{ikt}) x_{jkt} - (\alpha + v_{i0t}) p_{jt} + \xi_{jt} + \varepsilon_{ijt} \tag{4}$$

where β_k is the mean marginal taste for characteristic k, α is scalar marginal utility of money and ξ_{jt} are characteristics of product j in market t known by the firm but unobserved by the econometrician. Utility allows for consumer heterogeneity through a taste vector for consumer i, $v_{ikt} \sim H(v, \sigma_v)$. Finally, $\varepsilon_{ijt} \sim G(\varepsilon, \sigma_\varepsilon)$ is the taste shock of product j in market t for consumer i. Redefining utility to separate out consumer heterogeneity, we now write utility as:

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt} \tag{5}$$

where

$$\delta_{jt} = \beta x_j - \alpha p_{jt} + \xi_{jt} \tag{6}$$

and

$$\mu_{ijt} = \sum_{1}^{K} v_{ikt} x_{jkt} - v_{i0t} p_{jt}. \tag{7}$$

We define δ_{jt} as the mean utility level for product j in market t, and μ_{ijt} is i's consumer heterogeneity for product j in market t.

In every market there is also an outside good $j = 0$ which allows consumers to avoid buying the inside goods. The market is defined to make sure it is larger than the number of goods sold within that market. BLP for example defines the size of the new car market as one new car per household in the United States in a year. The share of the outside good is then defined as the remaining market share after accounting for the inside goods. Without an outside good, if prices of all goods in the market rose, each consumer would still need to choose a product to buy and no effect from the price change would be realised. Utility from the outside good is defined as:

$$u_{i0t} = \delta_{0t} + \varepsilon_{i0t} \tag{8}$$

and consumer i in market t picks product j to maximize there utility such that:

$$u_{ijt} \geq u_{ij't} \quad \forall j' \in J_t \cup \{0\} \tag{9}$$

The legal requirement to obtain auto insurance in order to drive on public roads provides two distinct differences to the discrete choice model described above. The first is that the size of the market is very well defined, that is the size of the auto insurance market is simply all owners of vehicles who drive on public roads. One can imagine a translucent edge to this market, where there are those that drive without insurance, or vehicles that are driven only on private roads but the consumer would buy insurance in order to drive on public roads if the cost of insurance were to go down. It is true that there are uninsured vehicles on public roads. However, since it is illegal to drive without insurance, fines for being caught without auto insurance start at \$5000, or nearly three years of premiums for the average Ontarian driver. We therefore assume that there is a discontinuity in individual's preferences for driving on public roads between driving with and driving without auto insurance, and that there is no systematic movement of people moving between the two throughout time. Our market definition therefore does not include those you drive on public roads illegally without insurance. We are also assuming the group of vehicles or consumers that drive on private roads and would buy auto insurance to drive on public roads if the price were to fall to be small and inconsequential.

We further restrict our market to those that purchase from standard auto insurance providers. As we have noted earlier, those who have been deemed too high risk by standard auto insurance providers are restricted to speciality insurance providers. Speciality insurance providers therefore do not directly compete with standard insurance providers, and form two distinct markets within auto insurance, and we choose to focus on the latter. A more sophisticated model would incorporate the cost of a consumer moving from the standard market to the speciality market, thereby increases their expected premium, but this addition to the model is outside the scope of this paper.

With the market being set as the number of vehicles insured in a given year by standard auto insurance providers, this gives our second implication for demand, there is no outside good. We are therefore assuming that all individuals will buy insurance even if all prices in the market rise. We consider this to be similar to utilities like water and hydro. If prices rise people may consume less of it, in the case of auto insurance purchasing less coverage, but they will no go without the product entirely. Consumers will still buy auto insurance because the implications of not are too high. Either an individual drives without insurance, risking fines and other legal action, or they can no longer use their vehicle which causes another set of financial and other implications. We assume that both choices bare heavier burdens than paying the additional auto insurance costs and thus their is no true outside option.

To adjust the standard model to fit auto insurance, we select an insurer to be the pseudo 'outside option'. We remove from the set of inside goods from each market and set it to the notation of $j = 0$. We now account for how prices change relative to the outside good. This means however that if all prices rise the same amount including the price of our pseudo outside option, their is no price effect in the market.

Utility location and scale is not identified in discrete choice models, so as with standard practice, we set those ourselves. Location will be discussed here while scale will be set the following chapter covering our estimation and use of instruments. BLP and the literature that has been built around it normalises the utility location or level by setting the mean utility level of the outside good to 0, i.e $\delta_{0t} = 0 \forall t \in T$. We however define our outside good as a designated inside good, which has a price and characteristics. We therefore choose to normalise the location of our utility by subtracting each utility of each good by the utility of the pseudo outside good. We now redefine utility as:

$$u'_{ijt} = \delta'_{jt} + \mu'_{ijt} + \varepsilon'_{ijt} \tag{10}$$

where δ'_{jt} is our redefined mean utility level expressed as:

$$\delta'_{jt} = \beta(x_j - x_0) - \alpha(p_{jt} - p_{0t}) + (\xi_{jt} - \xi_{0t}) \tag{11}$$

and μ'_{ijt} is our redefined consumer heterogeneity written as:

$$\mu'_{ijt} = \sum_{1}^{K} v_{ikt}(x_{jkt} - x_{0kt}) - v_{i0t}(p_{jt} - p_{0t}) \tag{12}$$

We also redefine the utility of our pseudo outside good:

$$u'_{i0t} = \delta'_{0t} + \mu'_{i0t} + \varepsilon'_{i0t} \tag{13}$$

which we write as:

$$u'_{i0t} = \varepsilon'_{i0t} \tag{14}$$

as δ'_{0t} and μ'_{i0t} are 0 by our definition. We have therefore essentially arrived at the same point as the standard BLP model, where are mean utility of the outside good is 0.

Consumer i in market t now picks product j to maximize there re-defined utility such that:

$$u'_{ijt} \geq u'_{ij't} \quad \forall j' \in J_t \cup \{j' = 0\} \tag{15}$$

and then the choice probabilities for each product j in market t is the market share s_{jt} defined as:

$$s_{jt} = \int_v \int_\varepsilon \mathbb{1}[u'_{ijt} \geq u'_{ij't}] \quad \forall j' \in J_t \cup \{j' = 0\}] \, dG(\varepsilon) \, dH(v). \tag{16}$$

Our model, like the standard BLP model, assumes only one product is chosen. This assumption holds well for our case, as you cannot insure the same vehicle twice. The model also assumes uniform pricing within each market t. In BLP, consumers may pay different prices for the same vehicles, but all face the original sticker price. Auto insurance has a high degree of discriminatory pricing, where your address, age, gender, and family status can influence your yearly premium. We move to a different assumption, where each insurer knows the same characteristics of each consumer i and two consumers with the same characteristics face the same yearly premiums. As more information updates insurers' priors of the risks associated with each consumer, we claim that all insurers would attempt to retrieve as much information on each consumer as possible, and would therefore have the same information set.

5.2 Supply

On the other side of the market, F insurers play a static Bertrand-Nash game within each market t. Insurers can have multiple insurance brands, and maximize profit over all brands. Therefore firm $f \in F$ which own insurance brands J_f in market t face the following problem:

$$\max_{p_j : j \in J_f} \sum (p_j - mc_j) s_j(p) \tag{17}$$

where mc_j is the marginal cost of insuring another vehicle under brand j.

6 Estimation and Instruments

6.1 Demand

To set the scale of our utility, paralelling with standard practice, we let the ε'_{ijt} be independently and identically distributed by Type-1 Extreme Values. For clarity and completeness, we begin with the case with no consumer heterogeneity, where $v_i = 0\,\forall i \in I$. This is commonly referred to as the simple logit. Utility is therefore:

$$u'_{ijt} = \delta'_{jt} + \varepsilon'_{ijt} \tag{18}$$

and the market share of j in the full choice set of market t, that is $j \in J_t$ and $j = 0$ is:

$$s_{jt} = P(u'_{ijt} >= u'_{ij't}, \forall j') = \frac{e^{\delta'_{jt}}}{\sum_{j' \in J_t, 0} e^{\delta'_{j'}}} \tag{19}$$

Thus own-price elasticities are:

$$\frac{p_{jt}}{s_{jt}} \frac{\partial s_{jt}}{\partial p_{jt}} = -\alpha p_{jt}(1 - s_{jt}) \tag{20}$$

and cross-price elasticities are:

$$\frac{p_{jt}}{s_{lt}} \frac{\partial s_{lt}}{\partial p_{jt}} = \alpha p_{jt} s_{jt} \tag{21}$$

Equations (20) and (21) show the inflexibility of this demand model where there is no consumer heterogeneity. When product j in market t changes price there are only two values for elasticities, one value for its own elasticity, and one value for its cross-price elasticity for all other products.

From the derived elasticies implied by the simple logit model, we can solve the multibrand firm's problem of equation (17). The first order condition for each product j owned by firm f in market t is therefore:

$$p_{jt} - mc_{jt} = \frac{1}{\alpha(1 - s_{ft})} \tag{22}$$

where s_{ft} is the sum of the market shares of each product j in market t owned by firm f. Therefore if we can estimate α, then given prices and market shares we can identify markups and thereby c_{jt}.

To estimate α we take the natural logs of equation (19) to linearize the function which can then be estimated by OLS:

$$\ln(s_{jt}) = \ln(\frac{e^{\delta'_{tj}}}{\sum_{j' \in J_t, 0} e^{\delta'_{j'}}}) \tag{23}$$

which becomes:

$$\ln(s_{jt}) - \ln(s_{0t}) = \beta(x_{jt} - x_{0t}) - \alpha(p_{jt} - p_{0t}) + (\xi_{jt} - \xi_{0t}) \tag{24}$$

as $\delta'_{0t} = 0$. Equation (24) is linear in all parameters, which allows us to estimate α by OLS. We note that if we had a traditional outside good, which would make $x_{0t} = 0$, $p_{0t} = 0$, and $\xi_{0t} = 0$, then we would arrive at the standard simple logit regression equation.

We now consider the case where v_i is allowed to be non-zero, refereed to as the mixed logit model. The reason we describe in detail the implications of the simple logit model is because the market shares in the full random coefficients model conditional on realisations of v_i:

$$s_{ijt}(\delta', \sigma, v_i) = \frac{e^{\delta'_{jt} + \sum_{k=1}^{K} \sigma_k v_{ik} x'_{jtk} - \sigma_0 v_{i0} p'_{jt}}}{\sum_{j' \in J_t, 0} e^{\delta'_{j'} + \sum_{k=1}^{K} \sigma_k v_{ik} x'_{j'k} - \sigma_0 v_{i0} p'_{j'}}} \tag{25}$$

where

$$x'_{jt} = x_{jt} - x_{0t} \tag{26}$$

$$p'_{jt} = p_{jt} - p_{0t} \tag{27}$$

has been shown to not have a closed form solution (BLP, 1995). Instead, we draw ns times from the distribution of $H(v, \sigma_v)$ to simulate s_{jt}:

$$s_{jt}^{sim}(\delta', \sigma) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{e^{\delta'_{jt} + \sum_{k=1}^{K} \sigma_k v_{ik} x'_{jtk} - \sigma_0 v_{i0} p'_{jt}}}{\sum_{j' \in J_t, 0} e^{\delta'_{j'} + \sum_{k=1}^{K} \sigma_k v_{ik} x'_{j'k} - \sigma_0 v_{i0} p'_{j'}}} \tag{28}$$

and then find the δ' that solves $s = s^{sim}(\delta, \sigma)$. To find the such a δ' we we take our set of M instruments z that satisfy the population moment conditions $E[\xi'|z] = 0$, which with $E[\xi'] = 0$ imply:

$$E[z_m \xi] = 0 \, \forall m = 1, ..., M \tag{29}$$

and the corresponding smaple moments are:

$$g_m(\theta) = \frac{1}{JT} \sum_{t=1}^{T} \sum_{j=1}^{J} \xi'_{jt}(\theta) z_{m,jt}. \tag{30}$$

Stacking our g_m's, the GMM estimates are given by:

$$\arg\min_{\sigma} Q(\sigma) = g(\sigma)' W g(\sigma) \tag{31}$$

Then starting from an original value of σ we calculate $Q(\sigma)$ and then adjust σ until $Q(\sigma)$ is minimized.

For our estimation of the mixed logit model, we use the BLPestimatoR package for R developed by Daniel et al (2017). BLPestimatoR sets W to be the standard weighting matrix for 2SLS. To estimate the mixed logit model we are also required to specify the distribution of consumer heterogeneity, $H(v, \sigma_v)$. For our case we choose to only place a random coefficient on p_{jt} and not on our characteristics. We limit the number of random coefficients for simplicity and as our focus is on estimating price elasticities, so we are mainly concerned about the consumer heterogeneity around price. We let consumers' preferences around price take a log-normal form. This means that v_{i0t} is always positive so no consumer gains utility from a higher price, they only differ on their degree of dislike of higher prices. This is similar to how consumer heterogeneity around price is treated in BLP (1995), however they define price as a non-linear variable of the income of consumer i divided by the price and then have a log-normal consumer heterogeneity distribution around that. Finally we set the number of draws to be 500, and specify the sampling method as Modified Latin Hypercube Sampling.

6.2 Instruments

Identification requires at least one instrument for price. Price or premiums are likely to be correlated with structural error terms because firms set prices with knowledge of product- and market-specific consumers. Firms also see the realisations of each ξ_{jt} and factor them into price suggesting price should be positively correlated with ξ_{jt} even though they go unobserved by the econometrictian. Furthermore our data is average premiums per brand per year, and as Nevo (2001) points out, the use of average prices produces a measurement error bias, another reason premiums might be correlated with the error term. For the simple logit case, we then have a standard 2SLS regression where the first stage estimates price. The mixed logit case is similar where we use instruments to produce sample moments to minimize the GMM objective function. We outline the two instruments we use price used now and provide the results of the first stage of the simple logit case in Section 7.

BLP provide possible price instruments for their discrete choice model of which we use two. We use the number of brands a firm owns within market t and the number of competing brands in that same market t as our instruments. We expect the number of brands a firm owns to be positively correlated with their premiums as owing multiple brands reduces the loss from raising premiums, as some of the consumers that leave the brand in question may substitute into another brand owned by the same firm. On the other hand, the number of brands in a market not owned by a firm should be negatively correlated with their premiums as more competition pushes premiums down. We would not expect the number of brands or the number of other brands in a market to enter the consumer's utility, thereby our instruments only effect market shares through premiums. For independence between our instruments and the unobserved characteristics of each brand, we present the following argument from BLP (1995). We assume that all firms first choose weather to enter market t. After all entries, firms learn ξ_{jt} for each brand they enter. Then firms choose the corresponding p_{jt}, in part based on the number of brands the firm entered into the market, the number of other brands, and the realisation of ξ_{jt}. Since firms learn the value of our instruments before learning ξ_{jt} our independence assumption is satisfied.

6.3 Supply

We estimate the supply side of the model taken as given the results of the demand estimation. We also parameterize the marginal cost (mc) of product j in market t as follows:

$$mc_{jt} = w_{jt}\gamma + \sigma_j + \eta_{jt} \tag{32}$$

where w_{jt} is a vector of cost shifters, σ_j is brand specific unobserved costs we can control for with fixed effects, and η_{jt} we leave as a structural error term.

With markups estimated from our demand model, we now have everything we need to estimate a new collusion parameter $\tilde{\kappa}$. We suppose a game as described in the supplementary material of Miller and Weinberg (2017) in which all firms are in a coalition and increase prices above Nash-Bertrand levels by the same amount $\tilde{\kappa}$. Letting MU_{jt} be the estimated markup from the results of our demand side, we present the following equation that can be estimated by OLS:

$$p_{jt} - MU_{jt} = \tilde{\kappa}\tau_t + w_{jt}\gamma + \sigma_j + \eta_{jt} \tag{33}$$

Equation (44) therefore describes the price minus the estimated markup under Bertrand-Nash is equal to a our parameterised marginal cost plus an excess markup agreed upon by the industry wide coalition. To test if the industry has left a Bertrand-Nash equilibrium, we set τ_t to be zero before 2011 and one from 2011 onward. If the estimated $\tilde{\kappa}$ is non-zero we then move to reject Bertrand-Nash pricing post 2011. If $\tilde{\kappa}$ is indeed non-zero, then our estimates of marginal cost change as now we have two markups, the Bertrand-Nash markup and our additional markup $\tilde{\kappa}$. We then describe an adjusted marginal costs c'_{jt}, in our markets t from 2011 onward:

$$mc'_{jt} = p_{jt} - \tilde{\kappa} - MU_{jt} \tag{34}$$

7 Results

7.1 Demand

We start by choosing Gore Mutual as our pseudo outside option, which will be used for the entirety of this section. Gore Mutual is in each period, and as always been the only brand of the firm by the same name. Gore Mutual has been independently Canadian owned and based in Ontario for over 100 years, so all its characteristics are the same in every market. With our outside option in place, we can write our regression equation for the simple logit based on equation (24):

$$\begin{aligned} ln(s_{jt}) - \ln(s_{0t}) = \alpha\,\Delta p_{jt} + \beta_1 \Delta bank_{jt} + \beta_2 \Delta ontario_{jt} + \beta_3 \Delta US_{jt} \\ + \beta_4 \Delta nonNA_{jt} + \epsilon_{jt} \end{aligned} \tag{35}$$

where the regressor is the difference in the log of the market shares between brand j in market t and Gore Mutual in market t and it is regressed on the differenced prices and the differenced characteristics. It is common to include an intercept as a characteristic, however in this case because we use the differences in characteristics, the constant term is differenced away. Equation (35) has the first stage:

$$\begin{aligned} \Delta p_{jt} = \delta_1 + \delta_2 num\_brands_{jt} + \delta_3 other\_brands_{jt} + \delta_4 \Delta bank \\ + \delta_5 \Delta ontario + \delta_6 \Delta US_{jt} + \delta_7 \Delta nonNA_{jt} + \epsilon'_{jt} \end{aligned} \tag{36}$$

which includes our two price instruments num_brands_{jt}, the number of brands owned by the owner of j in market t, and $other\_brands_{jt}$, the remaining brands in the market, along with our differenced characteristics. We also include an intercept here, which as the interpretation of the average difference between all other brands' premiums and Gore Mutual. We do not implore brand level fixed effects in this regression equation, as for many brands their characteristics do not change over time, and adding fixed effects would remove our ability to estimate some of our characteristics.

We provide evidence of our instruments' validity by presenting the results of the first stage of the simple logit in Table 7.1. Notably our intercept in the first stage is large and statistically significant, suggesting that on average brands have a significantly higher average premium than Gore Mutual. Our price instruments are the predicted signs, and the number of other brands in the market is statistically significant. Overall, our first stage has an R^2 of 0.115 and an F-Statistic of 20.6, well above the F-Statistic of 10 considered the minimum standard for reliable inference (Stock, Wright, and Yogo, 2002).

Table 7.1: Results of First Stage

	Δp
(Intercept)	434.39***
	(150.11)
num_brands	32.20
	(21.14)
other_brands	−7.40***
	(2.49)
Δbank	84.31
	(69.51)
Δontario	−26.21
	(69.13)
ΔUS	175.88**
	(89.39)
ΔnonNA	−103.17*
	(52.98)
R2	0.115
F-Statistic	20.6
Num.Obs.	960

* p < 0.1, ** p < 0.05, *** p < 0.01

Results of first stage of simple logit model, estimation done by OLS. Gore Mutual as the outside option. Observations are at the brand - year level. Standard errors in parentheses. Robust White Standard Errors clustered on brand.

With evidence that we have valid instruments, we present the results of our demand estimation in Table 7.2 for the simple and mixed logit models, using the same price instruments for both models. We include columns OLS and GMM to show the need to instrument on price. As expected, the estimate for alpha is increasingly negative once we instrument for price in the simple logit case. As the unobserved characteristics should be positively correlated with price, our OLS estimate of alpha is biased upwards toward zero. When we compare the simple logit with IVs (2SLS) to the mixed logit with IVs (GMM + IV) it is clear that while the value of the coefficients are nearly identical, the addition of the random coefficient on price, $LogNormal * \Delta p$ has removed the significance of our main coefficients. The mixed logit estimation has resulted in large standard errors relative to the estimates of both alpha and the random coefficient on price making them both statistically insignificant. The random coefficient on price has been used to an extreme to fit the data to the sample moments, resulting in a high degree of heterogeneity for the individual taste for price. We believe the issue of the GMM estimators lie in the data. With the use of average premium per vehicle at the brand-year level, our prices are quite similar, and thereby we do not have extremely high (or low) premiums for consumers who are not very (or very) sensitive to price. Therefore, due to our data limitations, our GMM estimates have high standard errors. As well, given the estimates of the mixed logit, since the random coefficient on price is zero, we fail to reject the simple logit as a valid model for our dataset. We therefore move to use the simple logit estimates for our analysis and for the basis of our supply estimation.

Our only other significant parameter is $\Delta bank$, and since Gore Mutual is not associated with a bank (and its bank characteristic is therefore zero) this means a brand being associated with a bank increases the market share of that brand. Our intuition for this as previously discussed is that consumers when picking an auto insurance provider look for trust, a brand or firm they expect will be able to pay claims in the case of an accident. As Canadian banks are generally considered safe and have been around for more than 100 years, it is easy to see how consumers would place their confidence with the banks. Our geography and ownership characteristics require a different explanation. Our β_2, β_3, and β_4 are positive but insignificant, and we suggest they are positive due to firm size. As Gore Mutual is from Ontario, $\Delta ontario$ is zero when the brand is based in Ontario and negative one otherwise. This means that a positive β_3 implies brands not based in Ontario have higher market shares after adjusting for average premium per vehicles and our other characteristics. Therefore, positive β_2, β_3, and β_4 imply larger market shares for brand not based in Ontario, and brands owned by non-Canadian firms. As multinational firms are generally larger than non-multinational firms, we would expect that multinational firms that attempt to enter a new market would have the capital to acquire a larger market share. Similarly, firms that are based in other Canadian provinces would have substantial capital to then expand into other provinces, and hence have the ability to acquire more market share.

We begin by calculating the implied own- and cross-price elasticities from our 2SLS demand estimation. Summary statistics on elasticities are presented in Table 7.3. Our means are not weighted and own-price elasticities are at the firm level. The first sign that our estimate of alpha is realistic is we have no implausible own-price elasticities, also known as no own-price elasticities above negative one. We note own-price elasticities have generally gotten more negative over our timeline, which reflexs a rising markup over time. As given the equation for markups implied by the simple logit model, markups rise with market concentration which increased during out timeline.

Table 7.2: Results of Demand Estimation

	OLS	2SLS	GMM	GMM+IV
Δp	−0.00287***	−0.00377***	−0.00418	−0.00381
	(0.00052)	(0.00130)	(0.00260)	(0.09197)
Δbank	0.984**	1.201**	1.090**	1.202**
	(0.402)	(0.526)	(0.487)	(0.509)
Δontario	0.637	0.533	0.639	0.534
	(0.481)	(0.494)	(0.489)	(0.521)
ΔUS	0.497	0.769	0.694	0.770
	(0.450)	(0.573)	(0.658)	(0.573)
ΔnonNA	0.127	0.192	0.181	0.191
	(0.278)	(0.300)	(0.325)	(0.302)
Log Normal * diff_price			0.00036	0.00002
			(0.00044)	(0.05503)
Price	Exogenous	Endogenous	Exogenous	Endogenous
Num.Obs.	960	960	960	960

* p < 0.1, ** p < 0.05, *** p < 0.01

Columns OLS and 2SLS are results of the simple logit model where the dependent variables is the log market share of product j in market t minus the log market share of the outsdie option in market t. GMM and GMM+IV are the results of the mixed logit model where the dependent variable is the marketshare of product j in market t. Columns OLS and GMM treat price as exogenous, while 2SLS and GMM+IV treat price as endogenous. Gore Mutual as the outside option. Observations are at the brand - year level. Standard errors in parentheses. Robust White Standard Errors clustered on brand.

It is the largest firms in the auto insurance industry that is pushing up the average weighted markup. Just considering the four largest firms, the average markup weighted by market share has risen from \$293 in 2001 to \$315 in 2021. If we were to remove the largest four firms, the average weighted markup would have only changed from \$277 in 2001 to \$282 in 2021. Therefore, while the four largest firms in Ontario auto insurance saw a rise of 7.5%, the rest of the industry saw a 1.8% increase in their markups. The gains in markups concentrated in the largest firms is another example of what Autor et al (2020) discribe as 'Superstar Firms', where only a select few firms in an industry see consistently rising markups as well as market shares. Intact, with its consistent purchase of other auto insurance brands, would be considered auto insurance in Ontario's clear 'Superstar'.

Moving back to industry wide average premiums, average premiums have clearly risen by more than 6% from 2001 to 2021, this means while markups have increased, the Learner index, the markup as a percentage of price, as actually fallen. From the weighted average

Table 7.3: Implied Own- and Cross-Price Elasticities from Demand Estimation

	mean	sd	min	max
All				
Own Price Elasticity - Firm Level	−4.939	1.224	−12.498	−1.334
Cross Price Elasticity	0.110	0.131	0.000	0.697
2001-2005				
Own Price Elasticity - Firm Level	−4.275	1.057	−8.606	−1.334
Cross Price Elasticity	0.079	0.097	0.000	0.554
2006-2010				
Own Price Elasticity - Firm Level	−4.676	0.884	−8.730	−2.792
Cross Price Elasticity	0.098	0.119	0.000	0.681
2011-2015				
Own Price Elasticity - Firm Level	−5.507	1.388	−12.498	−3.633
Cross Price Elasticity	0.125	0.141	0.000	0.671
2016-2021				
Own Price Elasticity - Firm Level	−5.433	1.086	−9.368	−3.780
Cross Price Elasticity	0.143	0.154	0.000	0.697

markup and weighted average premium, the Learner index has fallen from 32% in 2001 to just 18% in 2021. A 6% increase in markups and a 14-point fall in the Learner index should be considered good news for Ontarian consumers. It suggests that while the number of brands and firms have fallen over time, the profit margins of these firms have still steadily declined. The declining Learner index suggests costs have increased for the firms, as a larger percentage of price is now attributed to marginal costs. As over 60% the costs of auto insurance brands are claims experience, we would expect if costs were raising for average claim per vehicle to be raising as well. Figure 7.4 provides the weighted average premium per vehicle and average claim per vehicle as well as the weighted estimated marginal costs implied by the calculated markups. The average claim per vehicle is for all insured vehicles in Ontario, as we cannot separate out speciality insurers from the cost side. Clearly, while our estimated marginal costs have continued to raise, claims have leveled out or even fallen. We will therefore estimate our supply side of the model to achieve estimates of marginal costs that more aligned with our claims data and then adjust markups appropriately.

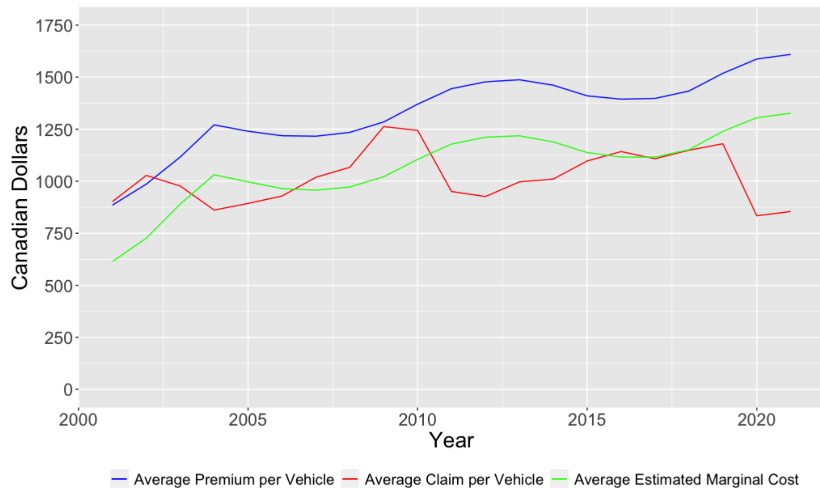
7.2 Supply

We estimate our supply side described in equation (32). Due to data limitation, our parameters are only time specific and not brand or firm specific. Our cost parameters include the average claim per vehicle in a particular year and a dummy variable for COVID-19, and our kappa is a dummy variable for Ontario Regulation 34/10. Our regression equation is therefore:

$$p_{jt} - MU_{jt} = \tilde{\kappa}\mathbb{1}\{\text{ONReg34/10}\}_t + \gamma_1 c_t + \gamma_2 \mathbb{1}\{\text{COVID-19}\}_t + \epsilon_{jt} \tag{37}$$

where MU_{jt} is the estimated markup from our simple logit demand results. We implore brand-level fixed effects but not time dummies as time dummies would not allow us to estimate $\tilde{\kappa}$

Figure 7.4: Marginal Cost Implied from Demand Estimates



or γ_2. Given our data limitations specifically average claim per vehicle being at the year level instead of the brand-year level, we expect that our estimate of γ_1 will not have a lot of explanatory power in this current form. We therefore consider two other regression equations each with an added assumption about a year's average claim per vehicle. Our first possible assumption is that all standard insurance brands have similar consumers with similar levels of coverage. In this case, average claim per vehicle is the same across brands, and we factor them into average premium per vehicle. The regression equation for this assumption is therefore:

$$p_{jt} - MU_{jt} - c_t = \tilde{\kappa}\mathbb{1}\{\text{ONReg34/10}\}_t + \gamma_2\mathbb{1}\{\text{COVDI-19}\}_t + \epsilon_{jt} \tag{38}$$

Our second possible assumption is that instead of firms facing similar consumers, they set premiums which achieve that year's industry claims ratio. As we have seen earlier in Figure 2.4.2, in any given year brands can have average premiums as low as \$1000 per vehicle and as high as \$2000. If all our brands faced the exact same average claim per vehicle, some of our brands would be consistently losing money while others would be achieving extreme profits. The similar claims ratio assumption therefore suggests brands face different sets of consumers, with varying average claims per vehicle. We write the regression equation for this assumption as:

$$p_{jt} - MU_{jt} - (cr_t * p_{jt}) = \tilde{\kappa}\mathbb{1}\{\text{ONReg34/10}\}_t + \gamma_2\mathbb{1}\{\text{COVID-19}\}_t + \epsilon_{jt} \tag{39}$$

where cr_t is the claims ratio in period t which is the Ontario wide average claim per vehicle divided by the Ontario wide average premium per vehicle.

The results of the estimation of the three supply side regression equations described above are presented in Table 7.5. The columns of Table 7.5 correspond to the three regressions in the order they were described. We confirm our expectations that as a regressor, average claim per vehicle for the entire market has no explanatory power. Our kappa estimate in column (i) is positive, large, and statistically significant. We can therefore reject Bertrand-Nash competition for 2011 onward. An increase of \$234 above Bertrand-Nash level markups from 2011 to 2021 gives a total payment of additional markups of \$19 billion dollars. Our COIVD-19 estimate suggests another \$2.1 billion dollars in markets from 2020 to 2021. Our kappa estimate is close to our reduced form estimate of \$260 in increased premiums per vehicle per year whereas our COVID-19 estimate is low. As the average claim per vehicle declined by over \$300 between 2019 and 2020, we expect that since average claim per vehicle doesn't give any explanatory power in column (i), that this produces an inaccurate estimate of COVID-19. Moving to our two different average claim per vehicle assumptions, we see that our COVID-19 estimates doubles producing what we consider a more realistic estimate while our $\tilde{\kappa}$ decreases slightly. We would expect our kappa to be lower than what we estimated in our reduced form estimation in Section 4, as in Section 4 we had to include speciality insurers. Since speciality insurers take on more risk per consumer, we would expect a decrease in expected claim costs from Ontario Regulation 34/10 to impact speciality insurers more than standard insurers. Furthermore, the estimation in Section 4 does not account for the increase in firm concentration, which increased markups on average by \$11 per vehicle per year between 2011 and 2021.

Table 7.5: Supply Side Estimation

	i	ii	iii
c	0.098		
	(0.069)		
ONReg34/10	234.49***	207.59***	203.94***
	(24.79)	(24.96)	(9.13)
COVID-19	132.26**	328.06***	356.49***
	(52.11)	(41.39)	(20.67)
Num.Obs.	981	981	981
R2	0.631	0.593	0.558
R2 Within	0.257	0.282	0.478

* p < 0.1, ** p < 0.05, *** p < 0.01

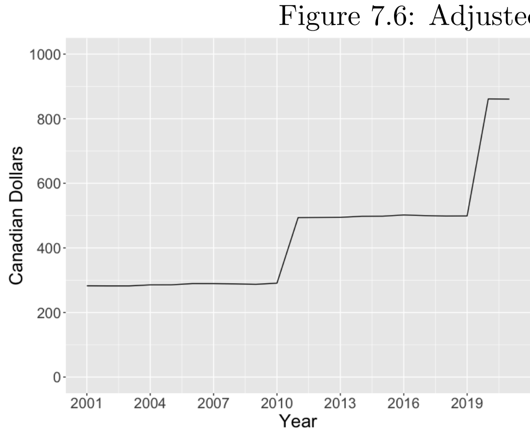
Column (i) is our original equation where the dependent variable is the average premium minus estimated markup from our demand estimation. Column (ii) includes our first assumption, where all brands face the same average claim per vehicle. Column (iii) includes our second assumption, where all brands achieve the same claims ratio. Observations are at the brand-year level. Standard errors in parentheses, 95% confidence interval below each result. Robust White Standard Errors clustered on brand in all columns.

Column (iii) of Table 7.5, which has the assumption that brands all achieve the same claims ratio, has the highest Within Groups R^2 and lowest standard errors of all our regression equations. Of our two industry claims assumptions, we consider the same claims ratio more plausible than the same average claim per vehicle. We therefore move to use the estimates of column (iii) to adjust our markups and marginal costs implied from our demand estimates. Interpreted strictly, our aggregate estimates then become \$16.6 billion in markups paid above Bertrand-Nash levels from 2011 to 2021, and \$5.7 billion in additional markups during COVID-19, totalling \$22.3 billion. For a consumer who had auto insurance from 2011 to 2021, these estimates suggest the consumer paid \$2958 in additional markups, or more than an additional one and half years of the average premium.

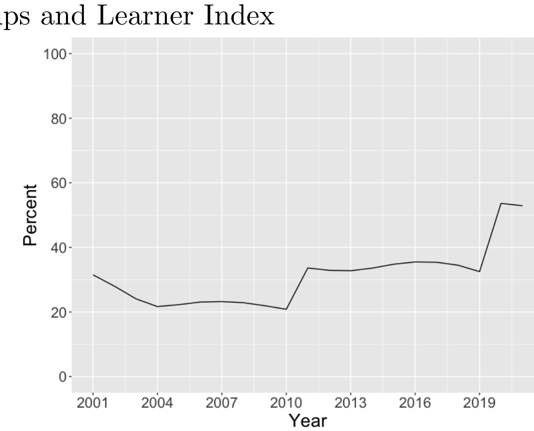
We first adjust our estimates of markups using our estimates of kappa and COVID-19 and present markups and the corresponding Learner Index in Figure 7.6. From 2001 to 2010, our markups are the same as before, as we assume Bertrand-Nash holds and therefore kappa is zero. From 2011 to 2021, our estimate of kappa is added. Now the Learner index returns to 2001 levels instead to continuing to fall as we saw originally. Our COVID-19 estimates give another increase in markups and the Learner Index for 2020 and 2021. We consider our markups and Learner Index to be realistic. Firstly, as our model does not account for fixed costs, the Learner Index is therefore an upper bound on the profit margin. Secondly, from 2001 to 2010, the 2015 report by Lazar and Prisman estimated that the Ontario Auto Insurance Industry essentially broke even, suggesting that given our markup estimates, fixed costs for the industry are around 25% of premiums. This would be equivalent to the FSRAO assumption that firms expense ratio is 25% if we considered claims to be the only marginal cost. When considering the additional cost of insuring a single extra vehicle, the marginal costs of labour and other expenses should be small, as insurance companies cover millions of vehicles each year. From 2011 onward, Lazar's 2018 report estimates profit margins well above 10%, which given no change in the percentage of premiums allocated to fixed costs, corresponds to our increase in the Learner index. While Lazar has not issued a report that includes 2020 or 2021, given the claims ratio in Ontario was 51% and 52% respectively, there were large profits made during these years, and our estimates reflect that.

Our adjusted markups minimize the markups gained by the largest firms in our market given by our demand estimates compared to the market wide markup gains from Ontario Regulation 34/10 and the COVID-19 pandemic. The introduction of Ontario Regulation 34/10 corresponds to a 70% increase in the estimated markup, and another 72% increase in the estimated markup in 2020 and 2021 during COVID-19. We would required cost or claims data at the brand level to analyse the distribution of the increase in the average markup to see if Ontario Regulation 34/10 or COVDI-19 favoured the largest firms.

Figure 7.6: Adjusted Markups and Learner Index



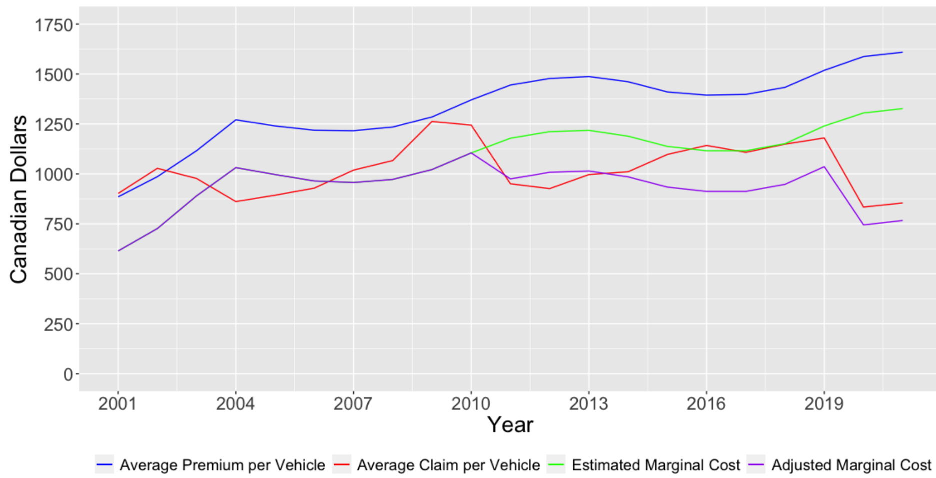
a) Adjusted Markups



b) Adjusted Learner

Finally, we present the updated marginal costs in Figure 7.7. Now marginal costs are no longer increasing over time, and better reflect the movement of average claim per vehicle. As our estimate of $\tilde{\kappa}$ is for years 2011 and onward, our estimates of marginal costs do not fall to the same degree that average claim per vehicle does from 2010 to 2011, and do not raise from 2013 to 2019. We do however have similar movements between estimated marginal costs and average claim per vehicle during COIVD-19. Therefore, average premiums per vehicle have continued to raise while marginal costs have stayed flat, causing an increase in the Learner index that we contribute to a combination of rising concentration, Ontario Regulation 34/10 and later COVID-19. The latter two have led consumers in Ontario to have paid an additional $22.3 billion in markups for auto insurance.

Figure 7.7: Adjusted Marginal Costs



8 Summary and Conclusion

This paper summarizes our empirical investigation into the changes in the markups of Ontario's auto insurance industry. Our results are a signal to the Competition Bureau of Canada for further investigation. The Ontario auto insurance industry has become more concentrated, and while it has yet to reach the Bureau's point of interest of a C4 above 65%, we have provided evidence that the auto insurance industry of Ontario has managed to increase coordination and retain an additional $22.3 billion in markups from 2011 to 2021. We are unable to make strict claims on if the increase in markups correspond directly to increases in profit, however this is little to suggest fixed costs as a percentage of premiums have increased over time as seen in the FSRAO not changing their assumptions on the expense ratio. This suggests at the very least that the increases in the Learner index should correspond to increases in the profit margin. Our estimates are economically significant, as overpayments of billions of dollars each year by consumers has large welfare consequences. Our empirical analysis does not inform how the industry has achieved these coordinating effects, and indeed a challenge for future work is to understand if the increase in concentration from 2001 to 2010 allowed for the increase in markups after Ontario Regulation 34/10.

Our results provide clear insights into the limitations of the Ontario regulator. The first is the inability to react to a negative shock in claim costs and thereby a positive shock in the profits of the industry. The COVID-19 pandemic resulted in the most profitable years for the industry on record, and even if the regulator did not permit a single rate increase during 2020 and 2021, that would still have been the case. A policy implication of our results would then be to create a mechanism for the regulator to force firms to give rebates in years of unexpectedly low claim costs. The second insight is that we have provided further evidence to the 2015 report by Lazar and Prisman and the 2018 report by Lazar that indeed firms are well exceeding the 6% after-tax profit margin that was mandated to the Ontario regulator. Lazar suggests this is due to the scope of information by brand that the regulator uses to assess each brands profitability. Even with no changes to the scope of information the regulator uses, our findings would suggest that the regulator should set a rate freeze on the auto insurance industry until the target claims ratio is restored.

There are many avenues of future research to pursue. As this paper is focused on the auto insurance market of Ontario, it is a natural extension to begin considering other provinces of Canada. Five other Canadian provinces have private auto insurance markets and require auto insurers to apply for premium rate changes to their respective regulators. We can therefore consider if concentration in the auto insurance market is a Canada wide issue, or if other provinces have managed to limit the coordinating effects of the auto insurance industry. The requirements of rate applications also allows for research into price leadership in the auto insurance industry. If the largest firms are indeed leading the industry in raising premiums, this may be a cause of any coordinating effects.

9 References

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A Appendix: Robustness Check of Reduce Form Estimates

To provide more reduce form evidence of excess premium payments, we consider a parameter change and a data restriction. We begin by use the current year average claim per vehicle instead of the lagged average claim per vehicle. We repeat the estimation of section 4 with this change, beginning with Table A.1 which shows estimation with and without coverage level fixed effects. In all columns compared to Table 4.2 the estimates for additional premiums paid for the coverages impacted by the regulation, COVID-19, and Bonus coverage types are higher and statistically significant. We note however that standard errors are higher and the R^2 is lower in all cases compared to Table 4.2. We expected a lower level of explanatory power of the model as average premium per vehicle is less correlated with average claim per vehicle than lagged average claim per vehicle. Overall Table A.1 suggests that controlling for lagged claims over current claims provides more accurate, or lower standard errors, and inflate the estimates of our variables of interest. Therefore it reinforces the realism of our estimates in Table 4.2.

Table A.1: Reduced Form Estimation with no lag on Claims

	i	ii	iii
c, lag = 0	1.172***	0.592***	0.591***
	(0.084)	(0.097)	(0.084)
ON Reg 34/10	-8.795	-9.233	
	(11.882)	(5.999)	
ON Reg 34/10 X Effected	65.09	84.01*	84.00
	(39.05)	(43.56)	(46.24)
COVID-19	47.73*	39.69*	
	(21.37)	(17.55)	
Bonus	26.42		
	(15.32)		
Num.Obs.	287	287	287
R2	0.885	0.929	0.941
R2 Within		0.442	0.372
FE: Coverage		X	X
FE: Year			X

* p < 0.1, ** p < 0.05, *** p < 0.01

Estimation is with OLS. The dependent variable is average premium per vehicle. Observations are at the coverage type - year level. Standard errors in parentheses below each result. Robust White Standard Errors clustered on coverage type in all columns.

Continuing to our other specification but with current average claims per vehicle, we consider the results presented in Table A.2. For the logarithmic specification of the model, we again see higher estimates of the effect of Ontario Regulation 34/10 on the impacted coverages. The estimates are statistically significant at the 1% level, and if interpreted strictly would suggest consumers made yearly overpayments of \$325 from 2011 to 2021 for a total of \$26.2 billion dollars, over 20% more than our reduce form estimates in Section 4. The estimates for overpayments from COVID-19 are also higher in this specification, suggesting consumers overpaid by an additional \$3.9 billion. The premium and claim difference specification shows similarly higher results compared to the version in Section 4 where lagged average claim per vehicle is used. We conclude therefore that our reduce form evidence is robust to the use of lagged average claim per vehicle over current average claim per vehicle. Furthermore this robustness check provides confidence in our original results as all estimates presented are higher than original results.

Table A.2: Further Reduced Form Estimation with no lag on Claims

	i	ii	iii	iv
log(c), lag = 0	0.279**	0.238*		
	(0.103)	(0.111)		
ON Reg 34/10	0.000		-17.797*	
	(0.053)		(7.886)	
ON Reg 34/10 X Effected	0.345***	0.346**	88.272*	88.209*
	(0.103)	(0.112)	(41.482)	(44.117)
COVID-19	0.147**		45.343*	
	(0.051)		(20.052)	
Num.Obs.	287	287	287	287
R2	0.985	0.990	0.484	0.572
R2 Within	0.470	0.379	0.266	0.212
FE: Coverage	X	X	X	X
FE: Year		X		X

* p < 0.1, ** p < 0.05, *** p < 0.01

Estimation is with OLS. The dependent variable for (i) and (ii) is log average premium per vehicle whereas the dependent variable for (iii) and (iv) is average premium per vehicle minus the average claim per vehicle. Observations are at the coverage type - year level. Standard errors in parentheses below each result. Robust White Standard Errors clustered on coverage type in all columns.

We now turn to removing the COVID-19 years, 2020 and 2021, from our data set to remove the shock to average claim per vehicle driven by the reduced cars on the road during these two years. Estimates of equation (1) with the years 2020 and 2021 removed are found in Table A.3. Similarly to the original results, the effect of the Ontario Regulation 34/10 on the impacted coverages is statistically significant at the 5% level when accounting for coverage level fixed effects. The estimates are larger and the R^2 is nearly identical to the original version with COVID-19 years included. This suggests their may be more weight given to COVID-19 in the original model which suppressed the estimate for Ontario Regulation 34/10 on the impacted coverages. Therefore the estimates of (1) with the COVID-19 years removed suggests our original reduce form estimates are not an upper bound.

Finally we repeat our estimates of (2) and (3) with the COVID-19 years removed and present the results in Table A.4. Estimates on Ontario Regulation 34/10 on impacted coverages are again higher than our original estimates and statistically significant at the 1% level for columns (i) and (ii) and 5% level for columns (iii) and (iv). The R^2 of the estimations in Table A.4 also closely follow the original estimates, again suggesting that our original estimated premium overpayments from Ontario Regulation 34/10 is not an upper bound. We conclude that our reduce form results are robust to of removal of the years 2020 and 2021.

Table A.3: Reduced Form Estimation with COVID-19 Years Removed

	i	ii	iii
c, lag = 1	1.197***	0.743***	0.722***
	(0.072)	(0.112)	(0.117)
ON Reg 34/10	-0.545	-8.611	
	(9.639)	(5.514)	
ON Reg 34/10 X Effected	42.24	70.54*	71.22*
	(29.93)	(34.96)	(38.05)
Bonus	24.83*		
	(12.71)		
Num.Obs.	257	257	257
R2	0.920	0.948	0.959
R2 Within		0.552	0.535
FE: Coverage		X	X
FE: Year			X

* p < 0.1, ** p < 0.05, *** p < 0.01

Years 2020 and 2021 not included in dataset. Estimation is with OLS. The dependent variable is average premium per vehicle. Observations are at the coverage type - year level.Standard errors in parentheses below each result. Robust White Standard Errors clustered on coverage type in all columns.

Table A.4: Further Reduced Form Estimation with COVID-19 Years Removed

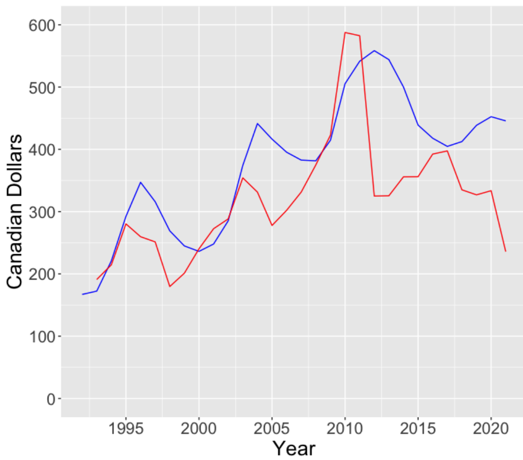
	i	ii	iii	iv
log(c), lag = 1	0.314**	0.248**		
	(0.114)	(0.106)		
ON Reg 34/10	-0.003		-10.124	
	(0.050)		(6.566)	
ON Reg 34/10 X Effected	0.319***	0.339***	63.618*	63.691*
	(0.078)	(0.087)	(31.988)	(34.132)
Num.Obs.	257	257	257	257
R2	0.987	0.991	0.503	0.596
R2 Within	0.488	0.462	0.174	0.173
FE: Coverage	X	X	X	X
FE: Year		X		X

* p < 0.1, ** p < 0.05, *** p < 0.01

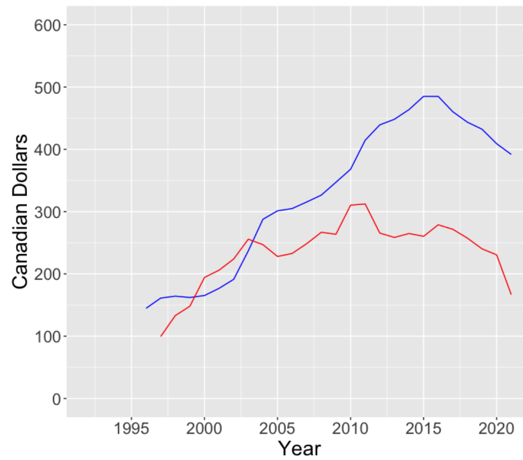
Years 2020 and 2021 not included in dataset. Estimation is with OLS. The dependent variable for (i) and (ii) is log average premium per vehicle whereas the dependent variable for (iii) and (iv) is average premium per vehicle minus the lagged average claim per vehicle. Observations are at the coverage type - year level. Standard errors in parentheses below each result. Robust White Standard Errors clustered on coverage type in all columns.

B Appendix: Yearly Premiums and Claims by Coverage Type

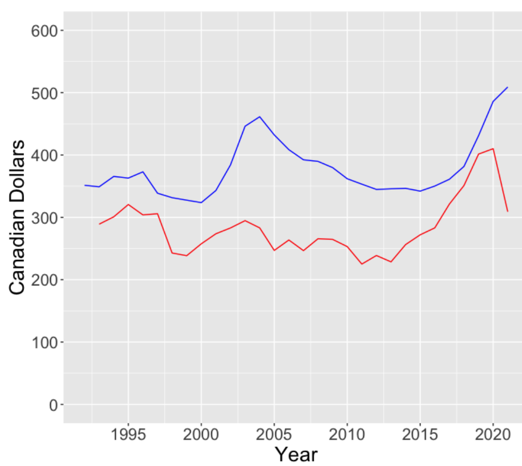
Figure B.1: Average Premium per Vehicle (Blue) and Lagged Average Claim per Vehicle (Red) by Coverage Type



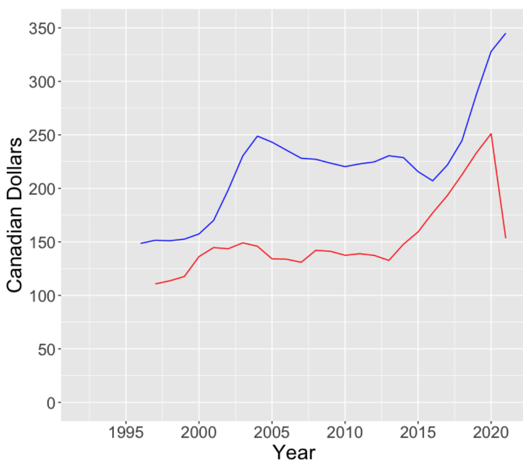
a) Accident Benefits



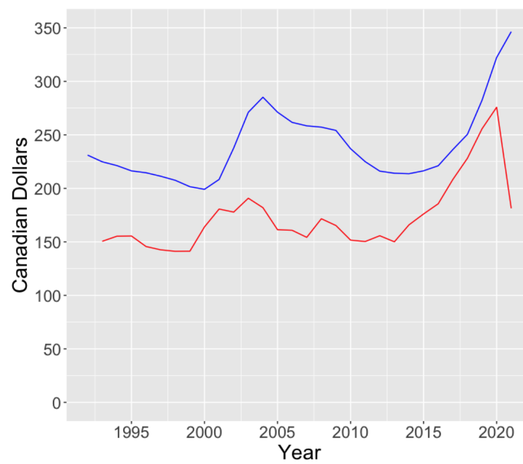
b) Bodily Injury



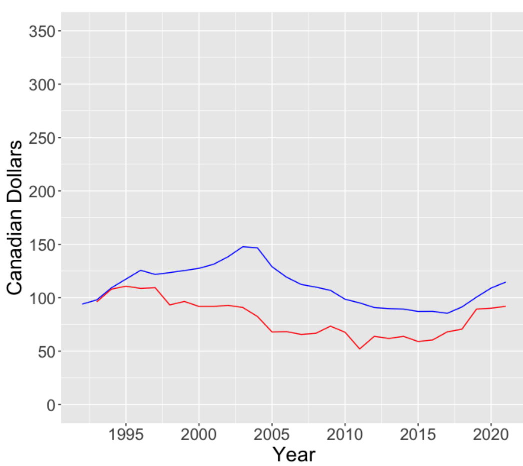
c) All Perils



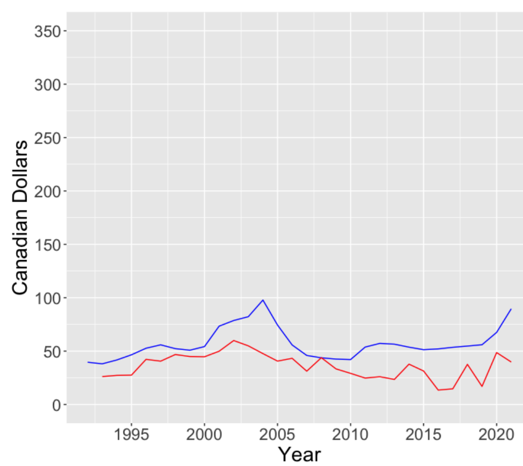
d) Direct Compensation



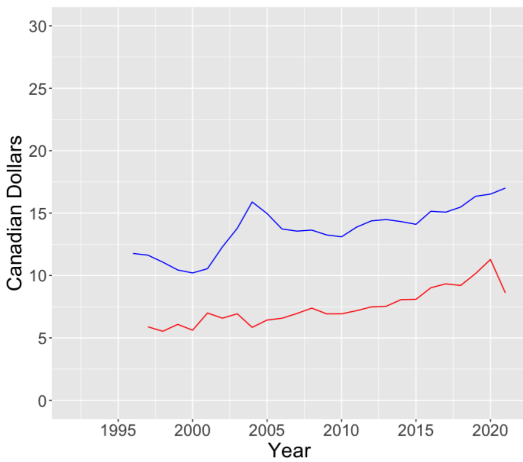
e) Collision



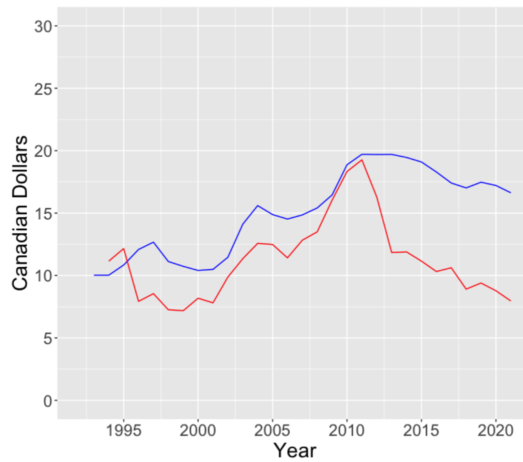
f) Comprehensive



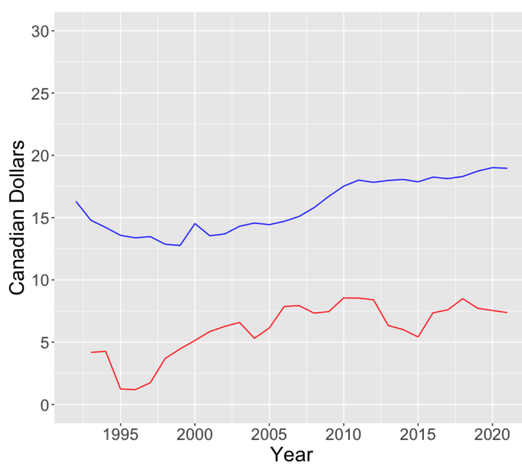
g) Specified Perils



h) Property Damage



i) Underinsured Automobile



j) Underinsured Motorist