The Canadian Puzzle: Why Have the American and Canadian P/C Insurance Cost Structures Evolved Differently?

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Abstract Kelly and Kleffner (2006) have documented that the structure in the Canadian P/C industry is materially different from that of the American P/C industry. As historical literature has rationalized the structure of the American P/C insurance industry, this represents a puzzle and a new explanation needs to be found. The attempt to solve the puzzle is relevant to actuarial practice as it directly impacts the business strategy of the insurer, to financial markets as it speaks to the efficient organization in the retail sector of the delivery of financial services, and to the theory of industrial organization as it speaks to the way the P/C insurance markets evolve. Using NAIC data from 1992-2010, the information on the distribution channel as documented in the A.M. Best's Aggregates and Averages for the matching period and quantile regression, the results on the structure of the American P/C insurance industry are reproduced, the rationalizations reviewed and the interpretations criticized. The P/C insurance industry is found to have been consolidating in the last two decades and this leads to the exploration of the role of economies of scale. The resolution of the puzzle finds its source in the role of economies of scale for various generic business strategies.

Keywords Financial service industry, economies of scale, differential evolution of markets

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1. INTRODUCTION

For many actuaries, as they evolve throughout their careers, they will find themselves participating in the strategic decisions of the firms they work for, many of which will be insurers. In the role of strategic decision makers, actuaries will be presented with many theories about which course of actions are preferable to others. It is therefore invaluable for strategic decision makers to develop key concepts to anchor discussions, methodological understanding to establish support for arguments, and a repertoire of key results that can be readily called upon.

The present paper aims to assist decision makers in the P/C insurance industry on all three fronts. We will do so by re-examining the results of the historical literature on cost efficiency in the P/C insurance literature. While we explicitly focus on the P/C insurance industry, it is our belief that many results are equally applicable to many retail financial services industries, such as retail banking. In the past, it has been found that direct insurers tend to have lower underwriting expenses due to earlier implementation of cost saving technology and, in the USA, tend to dominate Personal Lines requiring less personalized service. If the nature of the distribution channel is the key determinant of cost efficiency and of the line of business choice, with Canada being quite similar to the USA, the same industry structure should be observed. However, it has been found that the Canadian P/C insurance industry structure is quite different from that of the USA Methodologically, we will present and make use of quantile[1] regression, as this will allow us to examine the impact of covariates on the whole distribution of the dependent variable of interest. Unfortunately, while we would prefer to generate causal models[2], quantile regression does not in and of itself always lend itself to causal interpretation and care will be taken in the interpretation of the results. Conceptually, we will anchor ourselves in the Porter generic strategies framework to attempt to formulate a reconciliation of the industrial organization puzzle regarding the differential evolution of the P/C insurance markets across the borders. Having established the critical importance of economies of scale to the P/C insurance industry and having thought through the potential sources of economies of scale, we will discuss why the choice of the generic business strategy should come before the choice of the marketing strategy, including the choice of the distribution channel.

For the ratemaking actuary, the following aspects of the present research should be of particular interest. One, it is the hope of the author that the actuary will be better equipped to understand the relationship between the growth/size of the insurer and the expense ratio, and how the rates could adjust (or not) as a function of the market structure in which the insurer evolves. In particular, the ratemaking actuary will be better equipped to think through whether economies of scale should be passed on to customers and to what extent. Second, the author wishes to demonstrate the usefulness of quantile regression when the actuary is attempting to understand the impact of covariates on the distribution of dependent variables[3].

1.1 Outline

The remainder of the paper proceeds as follows. Section 2 is fully dedicated to the setting up of the puzzle. We will start by describing the data used in section 2.1.1. Then we will describe the main econometric strategy in section 2.1.2. In section 2.1.3, we'll describe a proxy variable that we'll use *in lieu* of the distribution channel, when it will be convenient to do so. In sections 2.1.4 and 2.1.5, we'll validate and rationalize the results of the historical literature on cost efficiency in the P/C insurance market: the cost advantage of direct writers and the relative preference of broker writers for Commercial Lines. Section 2.1.6 will cover other relevant historical findings. In section 2.2, we'll review findings related to the structure of the Canadian P/C insurance industry. In section 2.3, we will discuss the econometric flaw in the interpretation of results in the historical literature. Section 3 will be fully dedicated to discussing economies of scale in the P/C insurance industry. We'll start by

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[1] Quantiles are points taken at regular intervals from the cumulative distribution function of a random variable.

[2] Causal models are particularly preferable when the actuary is undertaking a budgeting exercise, as the actuary can then use the implied 'action-reaction' interpretation of causal models and use it for planning and forecasting purposes.

[3] As will be discussed below, quantile regression isn't ideal when the expected dollar value is of interest, but quantile regression could be quite useful for actuaries when they are, for example, attempting to understand how different insured's characteristics are affecting the distribution of the retention or conversion ratio.

providing the first hint that economies of scale are available in section 3.1. In section 3.2, we'll discuss potential sources of economies of scale. In section 3.3, we'll discuss some determinants of insurer size/growth. In section 3.4, we'll quickly discuss potential consequences of growth. In section 4, we'll provide a beginning of a reconciliation of the puzzle by appealing to Michael Porter's generic business strategies.

2. SETTING UP THE PUZZLE

In the section, we will set up the puzzle that we will attempt to resolve in the next sections. Significant portions of the text will be dedicated to discussing the available data and material hypotheses related to its treatment. We will also present the main econometric strategy of quantile regression. We will also review historical results and critic their interpretation.

2.1 The Cost Structure of the American P/C Insurance Industry

2.1.1 Data

The data that will be described here serves as the basis of most of the analysis found in the present and subsequent sections. The data comes from two main sources: (1) the National Association of Insurance Commissioners databases of regulatory Property/Casualty financial statements from years 1992 to 2010, and (2) the Best's Aggregates & Averages: Property-Liability from year 1993 to 2011[4]. We will describe the material data gathering hypothesis starting with how the NAIC data was put together for the purposes of the current analysis.

First, insurers were considered on a group basis: that is, if a group code was present in the NAIC data, the data that was kept was the data coded at the group level; otherwise, if a group code was unavailable, the individual insurer was treated as a group. When multiple companies reported as "combined" for a given group code, we used the total for the group code[5].

Second, the following is a table that describes which expense exhibit lines were used to form different categories of expenses. Which code was used is year dependent, following the documentation of the NAIC databases.

Claims Adjustment Services, Direct	01A, 01.1
Commission, Direct	02A, 02.1
Contingent Commission, Direct	02D, 02.4
Advertising	04
Equipment	14, 15
Total Expenses Incurred	22, 25

[4] As the Aggregate & Averages book covers financial information for up to the preceding calendar year, the calendar year of the NAIC data match those of the Best's Aggregates & Averages.
[5] That was uncommon.

Third, in the following table, the rules of groupings of lines of business are documented.

Automobile	Automobile liability, Automobile physical damage[6]
Commercial Lines Non-Auto	Commercial multiple peril, Ocean marine, Inland marine, Medical malpractice, Fidelity, Surety, Burglary and theft, Boiler and machinery, Other liability, Products liability, Farmowners multiple peril, Fire
Personal Lines Non-Auto	Homeowners multiple peril, Allied Lines, Earthquake

Fourth, ratios that relate to income are all computed using Earned Premium as the denominator. Two main ratios will serve to measure cost efficiency: (1) the underwriting expense ratio and (2) the underwriting income ratio. Using a measure of underwriting expense as a ratio to Earned Premium allows us to avoid needing to transform the measured expenses before being able to model them[7], as the resulting distribution of ratios is roughly symmetric and relatively light-tailed[8]. There are potentially some flaws with measuring cost efficiency using a ratio to premium. In a possible market structure[9], it could be the case that all gains in efficiency are entirely kept by firms in the way of profit such that the insureds never see any rate decrease associated with increased efficiency. In that case, the expense ratio would exactly reflect efficiency gains. In another possible market structure[10], insurance prices may shift without any related changes to the cost function such that the measured change in the expense ratio would not be reflective of (in-)decreased efficiency. The effective assumption made here is that neither pure scenario is reflective of reality: we acknowledge that the expense ratio is an imperfect measure of efficiency while maintaining its use, thus assuming that it is still a useful and practical measure of efficiency[11]. Another problem associated with using the underwriting expense ratio is that it ignores the fact that different insureds receive different levels of service. For example, it is sometimes assumed that insureds dealing with brokers receive

[6] Note that Commercial Automobile is included in Automobile because it cannot be separated for all considered years.

[7] In (Shi and Frees 2010, 307), the authors note that un-scaled and un-transformed expense have a long-tail distribution. The proposed approach used here is a re-scaling by Earned Premium. The authors note that re-scaling may not always be appropriate as, for predictive purposes, an estimate of the future values of the denominator first needs to be formed. However, in the case of Earned Premium, a significant portion of a one year ahead forecast is based on a realized value of Written Premium, such that the criticism loses some force.

[8] See tables below.

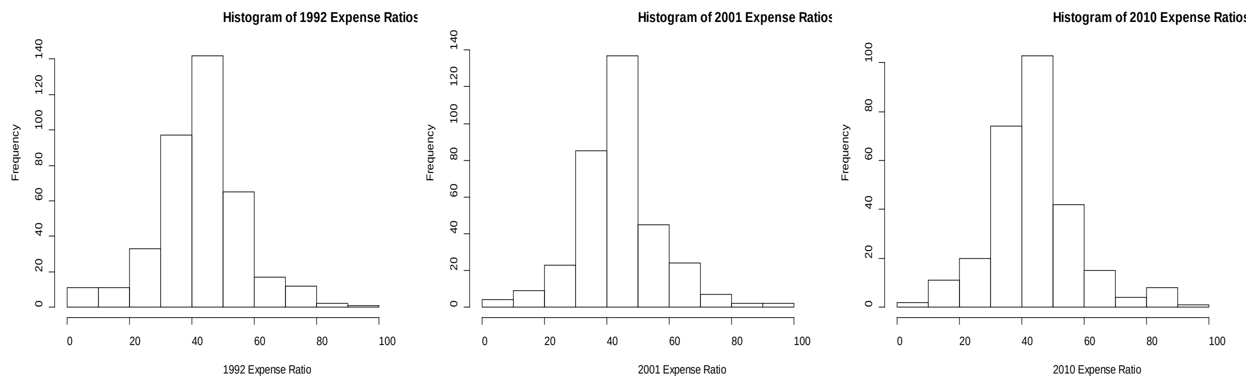
[9] See, for example, (Allen, Clark and Houde 2008) where the authors have assumed that any efficiency gains made by banks that are able to 'lead' customers to a more intensive use of less expensive electronic banking technology are not passed on to customers in decreased prices. In that model, banks are balancing the profit they are losing from customers driven away by decreased service with the profits gained on retained customers that switch to a lower cost technology. In that market structure, decreased competition and market dominance facilitate the adoption of internet banking.

[10] See, for example, (Brown and Goolsbee 2002), where prices may change without any change in the cost structure. In that model, the introduction of a technology that reduces search costs is assumed to force insurers to reduce their profits as markets become more competitive and insurers have to give up the rent they built up using price discrimination. The authors, unfortunately, fail to consider how an insurer that may generate significant growth using the internet channel may see its efficiency grow due to economies of scale.

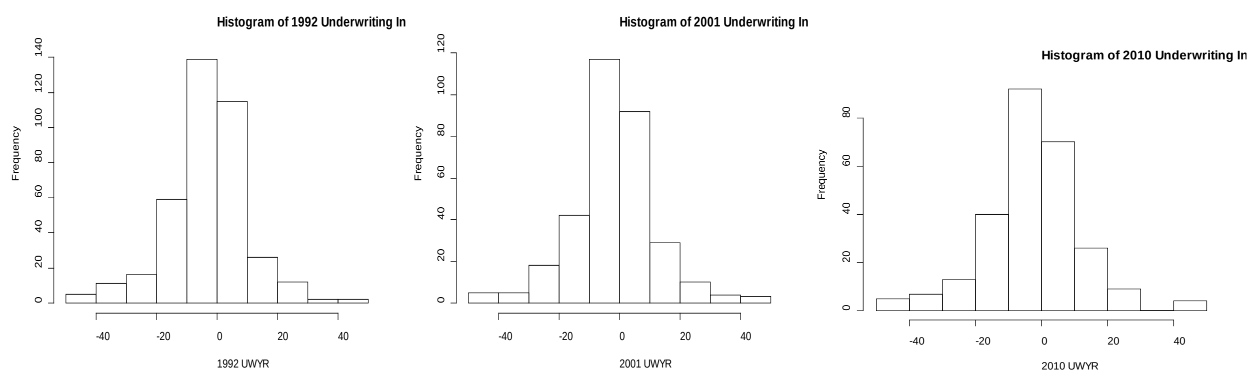
[11] An ideal measure of cost efficiency would consider the different costs incurred by two insurers when they are servicing observationnally equivalent insureds. Unfortunately, the NAIC database does not contain number of insureds information and much less their characteristics.

supplementary assistance from the broker in the claims handling process[12]. To the extent that extra costs incurred are related to value-added activities, the increase in costs is not the result of an efficiency loss: thus, the underwriting expense ratio is also flawed in this way. A proposed remedy is to use the underwriting profit ratio instead, as this ratio would include an inflated denominator if all value-added activities were effectively paid for by the insured. Another way that the underwriting income ratio could serve to alleviate some of the flaws related to the underwriting expense ratio is that it can reflect different sources of economies of scale such as: (1) increased efficiency in loss adjustment, (2) lower loss ratio due to the impact of market power in the repair/replacement good market[13], (3) increased effectiveness in costing or modeling of insureds[14], *etc.*

Expense Ratio



Underwriting Income Ratio



Fifth, for quantile regression purposes, the biggest insurers that together compose 95% of the market share in any given year were kept for all years they are available. All together, these provide

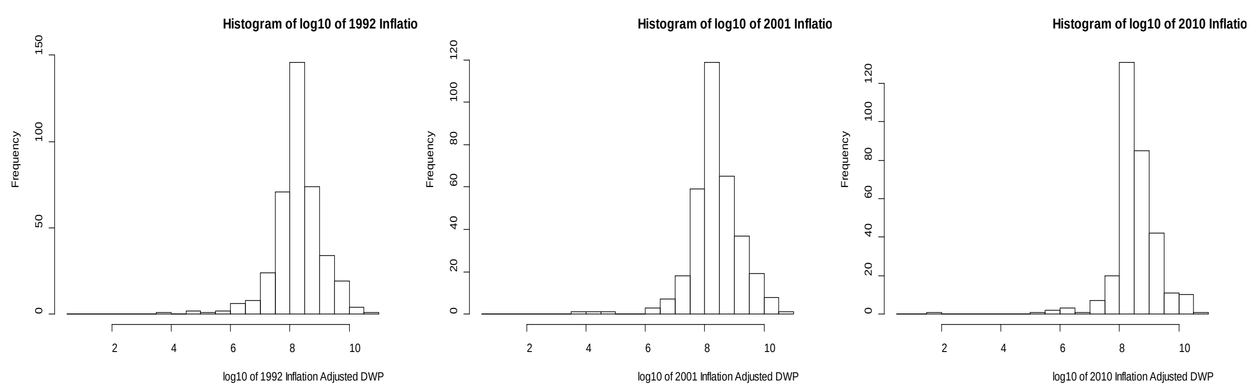
[12] See, for example, (Regan and Tennyson, Agent Discretion and the Choice of Insurance Marketing System 1996, 642).
[13] See, for example, (Nell, Richter and Schiller 2009).
[14] See, for example, (Intact Financial Corporation 2010, 6).

over sixty-five hundred insurer-year observations and over eight trillion inflation adjusted dollars of direct written premium.

Sixth, as there are times were some information is absent or composed ratios have a denominator of 0, the used quantile regression of R, rq, was set to omit missing information.

Seventh, inflation adjusted Direct Written Premium were put at 2010 level using the Consumer Price Index[15]. Inflation adjusted Direct Written Premium will serve as a measure of the size of a P/C insurer. Inflation adjustment is critical because it would be otherwise impossible to make inter-temporal comparisons. Inflation adjusted payroll or salaries could also have served as a measure of size. One advantage of payroll as a measure of size is its decreased sensitivity to the underwriting cycle and to rate levels[16]. Another advantage of using a non-claim related measure of size is that it avoids the introduction of a bias related to measurement of potential economies originating from the claims process[17] as, assuming economies of scale in the claiming are passed on to customers, premium growth will be a biased down measure of size. However, as can be visualized from the histograms presented below, inflation adjusted DWP is amply sufficient to allow us to discriminate between a very small insurer and a very large insurer, and everything in between.

$\log_{10} DWP_{inflation \quad adjusted}$



Eight, using (A.M. Best Company. 1993-2011), based on the "Total All Lines" sheet, where the distribution channel is documented for an insurer group, over 732 insurer years were assigned to the documented distribution channel. The following table documents how channels were consolidated in "Agency" or "Direct" when multiple codes were available.

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15 As measured in (Bureau of Labor Statistics 2011).

16 Another measure of insurer size that does not necessarily suffer from those weaknesses is trend adjusted indemnity paid; however, as noted in (Skogh 1982, 219), the volatility of insurance losses causes a bias because of "the presence of a stochastic component in claims paid in various years."

17 This in part motivates why (Skogh 1982) uses payroll, or compensation paid, to measure insurer size.

Market Type	Simplified Market Type	COMMENT
A	AGENCY	
AB	AGENCY	(A FOR AGENCY; B FOR BROKER)
AD	MIXED	(A FOR AGENCY; D FOR DIRECT)
AK	MIXED	(A FOR AGENCY; K FOR OTHER DIRECT)
AR	REINSURER	(CODE FROM 1993 TO 2002)
B	AGENCY	B FOR BROKER
D	DIRECT	
DA	MIXED	(A FOR AGENCY; D FOR DIRECT)
DB	MIXED	(D FOR DIRECT; B FOR BROKER)
DL	MIXED	(D FOR DIRECT; L FOR GENERAL AGENT)
DR	REINSURER	(CODE FROM 1993 TO 2002)
E	DIRECT	
EA	MIXED	(E FOR EXCLUSIVE/CAPTIVE AGENTS; A FOR AGENCY)
ED	DIRECT	(E FOR EXCLUSIVE/CAPTIVE AGENTS; D FOR DIRECT)
GB	MIXED	

Ninth, the following table describes the variables used in quantile regressions. Note that each variable can be for the same year as the year considered and, in that case, the variable name is appended by $\_minus\_0$, it can be for the year prior to the year considered in which case the variable name is appended with $\_minus\_1$.

DWPt_onl	Direct Written Premium adjusted for inflation
log10_DWPt_onl	$\log_{10} DWP_{inflation\ \ adjusted}$
CCCR	Commission and Contingent Commission Ratio (to Earned Premium)
AdvR	Advertising Ratio (to Earned Premium)
EquipR	Equipment Ratio (to Earned Premium)
ExpR	(Underwriting) Expense (to Earned Premium)
UWYR	Underwriting Income Ratio (to Earned Premium)
Auto_share	For the insurer group, the share of DWP coming from the Automobile Line of Business
CLNA_share	For the insurer group, the share of DWP coming from the Commercial Non-Auto Lines of Business
LLAER_diff	Differential of the group Loss and Loss Adjustment Ratio (to Earned Premium) compared to the industry, in a given year
growth_diff	Differential of the group DWP growth from the prior year compared to the industry, in a given year
simplified_channel	Distribution channel as identified using the (A.M. Best Company. 1993-2011) documentation

2.1.2 Econometric specification: the choice of quantile regression

Contrary to most of the existing literature examining cost efficiency in the American P/C insurance industry[18], we will not use either Ordinary Least Squares or Weighted Least Squares regression to study the effect of covariates on variables of interest. The main reason why we are

[18] (Shi and Frees 2010) being a notable exception.

choosing quantile[19] regression is that it will allow us to study how covariates change the distribution of the variable of interest. Ideally, we would prefer to provide a causal interpretation of the coefficients[20], but that may not always be possible. Provided that a direct or indirect causal link can be found, or at least imagined, a quantile regression treatment would allow us to identify which part of the distribution of the dependent variable is affected by the covariates. For example, as discussed in (Koenker and Machado, Goodness of Fit amd Related Inference Processes for Quantile Regression 1999, 1297), Chamberlain was able to find that union membership had significantly more effect for workers with lower wages compared to workers with higher wages. Other reasons why quantile regression may be preferred include (1) its robustness to outliers while maintaining high efficiency and (2) the ease with which transformed data can be used in estimation[21]. Also, fortunately, quantile regression also has a projection interpretation as a best linear predictor of the quantile of a conditional distribution.

There are three main routes to quantile regression. The first route[22] is quite convenient and practical when available and is based upon the Generalized Method of Moments. This method is only available when the covariates are discrete and data is abundant for each combination of covariates. The method basically consists of computing the quantile of interest of the dependent variables $y_\tau|\boldsymbol{x}$ for each combination of covariates and then running a Weighted Least Squares regression on the sample $\{(y_\tau|\boldsymbol{x}), \boldsymbol{x}\}_{\forall \boldsymbol{x}}$. The weights are computed as a function of the quantile τ, the proportion of observations that have combination of covariates $\boldsymbol{x}$, and the density of the residuals $\boldsymbol{\varepsilon}$. It is possible to stretch the application of the method when the data is continuous by discretizing the covariates and imputing a single value of $\boldsymbol{x}$ to the binned observations. Doing this requires that there is little variability in the covariates within a bin. Unfortunately, it is this condition that prevents us to use this simple yet powerful method for inference purposes. Nonetheless, as is exemplified in the tables below, to which we'll come back to later, this approach can be quite useful in data exploration, as it can allow us to quickly visualize how the distribution of a variable is affected by another variable. To facilitate this visual exploration, the author has used the conditional formatting function of Excel to make it more apparent that, in the first table, generally, the share of Commercial Lines Non-Auto line of business increases as the commission rate increases while, in the second table, the share of the Automobile lines of business generally increases when the commission rate decreases.

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[19] See the appendix for a refresher on how to compute quantiles in the univariate case.
[20] In (Koenker and Machado, Goodness of Fit and Related Inference Processes for Quantile Regression 1999, 1296-1297), the authors discuss quantile treatment effects.
[21] See (Koenker and Bassett, Regression Quantiles 1978, 39).
[22] See (Buchinsky 1994, 409).

Binned Prop. Comm. Non-Auto Curr. Year (%) (→) *vs.* Binned Comm. & Cont. Comm. Curr. Year (%) (↓)

Year	(All)

Row Labels	On-Level DWP Curr. Year % 0	10	20	30	40	50	60	70	80	90	100	Total On-Level DWP Curr. Year %
[00.00-01.00)	84.3%	2.0%	1.8%	1.9%	1.7%	0.9%	0.5%	0.1%	0.0%	0.2%	6.5%	100.0%
[01.00-05.00)	32.2%	43.5%	1.1%	6.9%	2.9%	1.0%	4.6%	1.6%	0.7%	1.0%	4.6%	100.0%
[05.00-10.00)	36.5%	22.2%	12.5%	5.1%	3.9%	12.8%	2.1%	1.6%	0.4%	0.5%	2.3%	100.0%
[10.00-12.50)	17.7%	54.8%	4.6%	10.4%	2.6%	8.8%	0.7%	0.1%	0.0%	0.1%	0.2%	100.0%
[12.50-15.00)	12.0%	6.6%	40.2%	5.9%	10.3%	11.8%	11.3%	1.5%	0.0%	0.3%	0.0%	100.0%
[15.00-17.50)	3.6%	2.2%	20.0%	20.9%	18.5%	18.3%	12.6%	3.3%	0.4%	0.1%	0.0%	100.0%
[17.50-20.00)	4.2%	3.9%	5.3%	46.6%	18.2%	13.7%	4.8%	1.8%	0.9%	0.6%	0.0%	100.0%
[20.00-30.00)	6.8%	5.2%	6.3%	9.5%	20.5%	18.0%	7.2%	13.6%	6.4%	4.6%	1.9%	100.0%
[30.00-99.99)	17.8%	8.3%	7.8%	11.5%	8.5%	16.1%	11.2%	5.4%	6.6%	3.8%	3.1%	100.0%
Grand Total	**20.2%**	**21.0%**	**12.2%**	**14.2%**	**9.4%**	**11.8%**	**5.7%**	**2.4%**	**1.0%**	**0.8%**	**1.4%**	**100.0%**

Binned Prop. Auto Curr. Year (%) (→) *vs.* Binned Comm. & Cont. Comm. Curr. Year (%) (↓)

Year	(All)

Row Labels	On-Level DWP Curr. Year % 0	10	20	30	40	50	60	70	80	90	100	Total On-Level DWP Curr. Year %
[00.00-01.00)	32.4%	2.0%	2.4%	0.4%	1.1%	1.7%	12.9%	28.4%	8.0%	8.8%	1.8%	100.0%
[01.00-05.00)	24.9%	3.8%	5.8%	4.9%	8.8%	3.9%	2.4%	2.8%	25.8%	16.1%	0.7%	100.0%
[05.00-10.00)	9.4%	4.8%	16.1%	5.8%	7.6%	0.6%	4.5%	26.6%	11.0%	0.3%	13.3%	100.0%
[10.00-12.50)	2.5%	2.7%	7.6%	8.4%	3.7%	2.5%	28.2%	41.2%	1.3%	0.4%	1.4%	100.0%
[12.50-15.00)	4.8%	11.8%	13.8%	12.6%	4.2%	17.1%	23.3%	9.1%	1.0%	0.9%	1.4%	100.0%
[15.00-17.50)	3.3%	13.4%	19.4%	20.6%	9.7%	22.5%	6.6%	0.6%	0.6%	2.8%	0.7%	100.0%
[17.50-20.00)	3.8%	8.6%	9.6%	15.1%	43.5%	10.9%	2.7%	1.1%	0.8%	3.3%	0.5%	100.0%
[20.00-30.00)	16.9%	29.3%	18.3%	10.1%	7.9%	6.7%	3.2%	1.8%	1.8%	2.3%	1.7%	100.0%
[30.00-99.99)	30.2%	28.7%	15.8%	7.5%	2.7%	2.7%	1.7%	0.9%	3.1%	3.7%	3.1%	100.0%
Grand Total	**9.5%**	**9.3%**	**12.4%**	**10.6%**	**10.4%**	**8.4%**	**11.9%**	**16.3%**	**5.0%**	**3.0%**	**3.2%**	**100.0%**

A second route[23] to quantile regression uses the Generalized Method of Moments to solve the moment condition

$$\sum_{i=1}^{n}\left(\left((I\{y_i \leq \boldsymbol{\beta}^{\tau}\boldsymbol{x}_i\} - \tau)\boldsymbol{x}_i\right)'\left((I\{y_i \leq \boldsymbol{\beta}^{\tau}\boldsymbol{x}_i\} - \tau)\boldsymbol{x}_i\right)\right) = \mathbf{0} \qquad (2.1.2.1)$$

where τ is the quantile of interest, $\boldsymbol{\beta}^{\tau}$ is a vector of coefficients, $I\{\cdot\}$ is the indicator function, and n is the number of observations. Using this approach, the coefficients and standard errors can be computed using the standard Generalized Method of Moments machinery[24]. Finally, one can minimize the criterion function

$$S(\boldsymbol{\beta}^{\tau}) = \sum_{i=1}^{n}\left((1-\tau)|y_i - \boldsymbol{\beta}^{\tau}\boldsymbol{x}_i| I\{y_i \leq \boldsymbol{\beta}^{\tau}\boldsymbol{x}_i\} + \tau|y_i - \boldsymbol{\beta}^{\tau}\boldsymbol{x}_i| I\{y_i \leq \boldsymbol{\beta}^{\tau}\boldsymbol{x}_i\}\right) \quad (2.1.2.2)$$

by setting $\widehat{\boldsymbol{\beta}}^{\tau} = arg\min_{\boldsymbol{\beta}^{\tau}} S(\boldsymbol{\beta}^{\tau})$. This approach requires the implementation of a linear programming algorithm and is best done with a computer or vector algebra system. It is important to note that the $arg\min_{\boldsymbol{\beta}^{\tau=0.50}} S(\boldsymbol{\beta}^{\tau=0.50})$ is generally not the set of coefficients that return the

23 (Hansen 2011, 169-173) makes an introductory presentation of median and quantile regressions that is appropriate for mathematically inclined actuaries.
24 See, for example, (Hansen 2011, 108-114, 134-145).

conditional mean, or the Best Linear Prediction[25] of the conditional mean, but rather the conditional median, or the Best Linear Prediction of the conditional median. Actuarially speaking, that is generally an undesirable feature of quantile regression as the quantity of actuarial interest is very often the conditional mean itself. In this case, however, as we are not so much interested in the changes in conditional mean but in the changes of the distribution itself, this disadvantage of the quantile regression has no force.

For our purposes, we have chosen to use the rq implementation of quantile regression available in the R statistical software[26]. So doing, we have a choice of three possible ways to compute standard errors (SE) that don't assume that the error terms are independent and identically distributed or use a computation intensive bootstrap algorithm. One of the methods is based on (Koenker and Machado, Goodness of Fit amd Related Inference Processes for Quantile Regression 1999) but does not return p-values, but only a confidence interval. One of the methods is based on the more traditional "sandwich" form for standard errors but is computationally unstable on the considered data, as it regularly returns message errors. Finally, the here preferred method, "*ker*", is based on (Newey and Powell 1990, 302) and implements a non-parametric kernel estimation algorithm to compute the density of ε at the appropriate points, as required by theory.

In the quantile regression tables found below, the models were estimated for five quantiles: the $10th, 25th, 50th, 75th, 90th$ percentiles. In all cases, the models are separately estimated for the sake of convenience[27].

For the purposes of the current analysis, quantile regressions were computed using Direct Written Premium as weights[28]. Weights were introduced not for the sake of statistical efficiency, but for the purpose of better reflecting the impact of relative efficiency on the public and, most importantly, the insureds.

Also, again, contrary to most of the existing literature on the subject of cost efficiency in the P/C insurance market[29], we make use of the panel structure of the data. We use it only when it comes time to understand the drivers of the Loss and Loss Adjustment Expense Ratio and of Direct Written Premium growth. For these two dependent variables as opposed to the underwriting

[25] Depending on whether one wants to interpret the model as a regression or as a projection.
[26] See (R Documentation n.d.).
[27] Joint estimation of multiple quantiles is certainly feasible and relatively simple to implement using specifications based on the Generalized Method of Moment. One of the usefulness of joint estimation is to allow tests of equality of coefficients across quantiles. As this is not of interest to us here, it seems acceptable not to undertake joint estimation.
[28] Although quantile regression using insurer-years as weights were also computed. The results were generally similar and can be made available upon request to the author.
[29] (Shi and Frees 2010) and (Hecht 1999) being notable exceptions.

expense ratio, it is apparent that there are material year to year fluctuations and it is best to first neutralize the year effect before attempting a regression.

Year	Loss and LAE Ratio (%)	Expense Ratio (%)	DWP Growth (%)
1992	75.2	41.1	
1993	66.8	40.2	6.5
1994	68.6	41.5	1.0
1995	65.7	42.3	0.7
1996	65.4	40.4	5.6
1997	60.4	42.1	6.9
1998	63.1	41.8	5.2
1999	65.1	***46.3 ****	5.9
2000	67.8	40.8	1.5
2001	75.1	***44.3 *****	9.8
2002	68.3	40.4	17.8
2003	61.6	39.5	9.4
2004	59.9	39.1	3.8
2005	61.5	39.4	2.2
2006	53.2	40.0	4.1
2007	55.7	39.7	0.9
2008	65.4	39.7	-0.4
2009	59.3	40.7	-1.8
2010	61.1	41.7	1.5

When the insurer groups that make up 95% of DWP are used, the starred numbers are:
* 42.2
** 42.6

Note, however, that we do not otherwise really make use of the panel structure of the data for quantile regression and use all data as if it all came from one large cross-section because of the following rationale. Take the underwriting expense ratio as an example. In this case, for 80% of the Earned Premium available in the study, the year-to-year variability of the underwriting expense ratio is 5.7% or less, while the inter-group (all years combined) underwriting expense ratio has a standard deviation of 12.8%. This provides an indication that the expense ratio of the current year is largely determined by the expense ratio of the prior year for most insurer groups, especially under normal operations. This is *a priori* plausible because expenses, as opposed to losses, are largely in the control of the insurer and are subject to internal controls. Since we are interested in what features of the insurer drive the level of the underwriting expense ratio, since the level is approximately constant for most insurers under most circumstances, and since the features we'll be considering are also largely constant through time for most insurer groups, this justifies treating the entire dataset as being generated by one cross-section. This rationale applies also when we're considering the commission rate, and the Commercial Non-Auto and Automobile lines of business share of premium.

2.1.3 The Commission and Contingent Commission Ratio as a Proxy for the Distribution Channel

One of the key variables that have been examined in the literature concerning the cost efficiency of P/C insurers has been the distribution channel. In sub-sections 2.1.4 and 2.1.5, we will discuss and validate the historical findings.

As noted above, the exact distribution channel of insurers is only known for 732 insurer-years. Taking into account the size of the full database, it is apparent that it is desirable to identify a proxy for the distribution channel so as to enable us to use the full database when results not dependent on the exact knowledge of the distribution channel are required.

Target Variable:	CCCR_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	2.420	0.4%	6.440	7.3%	10.830	0.0%	11.470	0.0%	14.290	0.0%
agency	7.320	0.0%	6.320	8.1%	4.800	0.0%	6.210	0.0%	5.460	0.0%
mixed	-0.310	80.7%	-4.030	28.3%	-3.530	0.1%	-2.790	0.2%	-5.290	0.0%
reinsurer	0.320	93.0%	-3.470	48.6%	2.840	0.0%	2.200	0.0%	-0.620	61.5%

As can be seen in the table above, agency writers, that do not distribute their insurance products directly to consumers, tend to have a higher Commission and Contingent Commission Ratio. This conclusion can be reached by examining the coefficients associated with the agency indicator variable for the quantile regression for the different quantiles: the coefficients are all positive and significant (as their p-value are all under 1%). This suggests that for the $10th, 25th, 50th, 75th,$ and $90th$ percentiles, the (DWP weighted) Cumulative Distribution Function of the $CCCR\_minus\_0$ variable for agency writers lies to right than the one for direct (non-agency, non-mixed, non-reinsurer) writers.

This is unsurprising because they are using external and independent parties to distribute their products. They will tend to have to compensate these parties in commissions more so than they would an employee. The difference arises because of the difference in the situation between an insurer and its brokers *versus* an insurer and its employees. In the case of a salaried workforce, while it is necessary to maintain incentive compatibility and offer a compensation package that rewards the employee for acting in the interest of the insurer, employees generally desire a significant portion of their compensation to be fixed and not subject to risk. This can be contrasted with the situation of an external contractor that is not salaried. Thus, it is not surprising to see that commissions are higher when insurers distribute through brokers. This leads us to formulate the following rule-of-thumb: as the CCCR of an insurer goes up, the likelihood that the insurer is a direct writer goes down.

2.1.4 Cost efficiency of direct writers

One of the key findings of the historical literature concerning itself with the cost efficiency in the P/C insurance industry is that, in the USA, direct writers tend to be more efficient than agency writers that distribute their products through independent brokers[30]. The table below illustrates that, for insurers that are in the upper half of the distribution of expenses conditional on their known distribution channel, insurers that distribute through independent brokers tend to have a higher underwriting expense ratio. A similar phenomenon can be found when we use the proxy variable CCCR as a predictor of the expense ratio.

Target Variable:	ExpR_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	32.290	0.0%	36.040	0.0%	38.240	0.0%	41.690	0.0%	43.870	0.0%
agency	1.730	41.2%	0.600	60.5%	3.600	0.0%	4.130	0.0%	6.690	0.0%
mixed	-4.440	9.7%	-5.390	0.6%	-1.780	28.1%	-2.400	14.4%	-1.730	29.4%
reinsurer	2.460	70.8%	1.670	85.9%	2.570	0.3%	-0.880	38.4%	-3.060	0.1%

Target Variable:	ExpR_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	2.709	9.0%	8.993	0.0%	15.497	0.0%	21.368	0.0%	28.122	0.0%
CCCR_minus_0	1.942	0.0%	1.942	0.0%	1.942	0.0%	1.941	0.0%	1.941	0.0%

When examining the impact of distribution channel on the overall Underwriting Income Ratio, known agency writers seem to do as well as direct writers, as can be seen in the table below. When we use the proxy variable CCCR, the values become significant, but the scale of the coefficients become economically neglectable.

Target Variable:	UWYR_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-14.670	0.0%	-9.360	0.0%	-3.270	0.0%	1.670	26.5%	8.080	0.2%
agency	-4.720	7.2%	1.680	46.9%	1.880	14.3%	3.180	11.6%	2.490	36.7%
mixed	12.040	0.0%	9.530	0.6%	8.940	0.2%	20.970	0.0%	21.910	0.0%
reinsurer	-22.000	48.2%	2.120	39.5%	-3.970	0.6%	-8.910	0.0%	-4.370	74.1%

Target Variable:	UWYR_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-17.435	0.0%	-8.230	0.0%	-2.264	0.0%	3.873	0.0%	10.265	0.0%
CCCR_minus_0	0.000	0.0%	-0.001	0.0%	-0.001	0.0%	-0.001	0.0%	-0.001	0.0%

This finding of greatest efficiency of the direct channel has lead some actuaries, like Sholom Feldblum, to criticize the agency way of distributing insurance[31]. Part of the expense advantage that

[30] Findings found, for instance, in (Cummins and VanDerhei 1979), (Barrese and Nelson 1992), (Berger, Cummins and Weiss 1997).

[31] "Independent agency companies pay level commissions, such as 15% or 20% of premium, in all years. The level commission structure is needed because the agent "owns the renewals" (National Fire Insurance case of 1904). (…) A

direct writers have built comes from early adoption of improved technology related to collection of premium[32]. However, part of the reason of the persistence of the broker distribution channel may well be due to the fact that brokers undertake value-added activities for the insureds[33].

2.1.5 Relative strength of agency writers in Commercial Lines

Another key finding of the historical literature concerning itself with the cost efficiency in the P/C insurance industry is that insurers that distribute through brokers tend to be more present in the Commercial Lines Non Auto lines of business in the USA. On the flip side, as is demonstrated in the second table below, direct writers tend to write more of the Automobile line of business. Unfortunately, as can be seen in the two tables of Appendix B, when the proxy variable CCCR is used, the findings are not conclusive; however, note that these relationships were visually explored in section 2.1.2 and the findings were supportive of historical findings. In this particular case, the results from the historical literature can be said to be confirmed by the current data.[34]

Target Variable:	CLNA_share_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	3.688	0.0%	4.938	0.0%	5.690	0.0%	13.253	0.0%	23.501	0.0%
agency	7.283	20.8%	22.453	0.0%	36.212	0.0%	39.161	0.0%	36.852	0.0%
mixed	-1.406	74.3%	-2.434	58.8%	8.478	18.1%	45.581	0.0%	40.978	0.0%
reinsurer	5.417	72.7%	11.532	63.1%	18.386	0.0%	10.823	0.4%	0.575	82.2%

[35]

Target Variable:	Auto_share_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	38.837	0.0%	60.339	0.0%	67.754	0.0%	71.158	0.0%	76.754	0.0%
agency	-30.431	0.0%	-43.543	0.0%	-42.274	0.0%	-27.844	0.0%	-10.664	16.6%
mixed	-38.837	0.0%	-60.339	0.0%	-7.530	30.4%	-1.756	78.0%	-3.453	60.8%
reinsurer	-33.935	46.0%	-46.661	41.2%	-17.384	0.0%	-20.788	0.0%	7.989	79.9%

lower commission in renewal years would induce the agent to move the policy to a competing insurer and obtain a "first year" commission.
The level commission structure does not reflect the actual incidence of acquisition expenses, since agents spend more effort writing new policies than renewing existing policies. **Because of this (and other reasons), many economists consider the independent agency system to be inefficient**. In the personal lines of business, direct writers are steadily gaining market share, and the level commission structure is becoming less important. As the asset share pricing model shows, a level commission structure works well for risks that terminate quickly. It works poorly for risks that endure with the carrier. " (Feldblum 1996, 205-206) [my emphasis]

32 See, for example, (Gron 1998, 410).

33 For example, see (Cummins and Doherty 2006, 361).

34 A potential explanation for the seemingly contradictory results could, in part, emanate from smaller insurers that choose to focus on a particular sub-market. To be competitive, they are more likely to distribute directly without having to pay commissions or they may use a broker that receives a lower commission rate because of the economies of scale that could accrue on the brokerage side.

35 Even though the "CLNA_share_minus_0" and "Auto_share_minus_0" variables are fundamentally variables that lie on a bounded [0,1] support, the author feels it is acceptable in this case to use quantile regression as it has been presented because the intent is only to show the existence of an association.

One way to rationalize this finding is to notice that some of the key roles of brokers are more valuable for insured businesses compared to insured individuals. Among these roles, one can think of the assistance the broker provides the insured in identifying the required coverages, of the matching of the insured with the insurer based on the insurer's appetite, of the risk 'branding' of the insured helping insurers to circumvent informational asymmetries in the insurance market, of the assistance that the broker provides the insured in the claiming process, *etc.*[36]

One of the ways to justify the continued coexistence of both distribution channels, direct and broker distributed, in both Personal and Commercial Lines of business is to note that different customers have different ways to shop for insurance. Some insureds that have high search costs prefer to take advantage of brokers to "avoid searching" by themselves.[37]

2.1.6 Ignored dimensions: geographic concentration, reinsurance usage, ownership form

Before moving to the exploration of the cost structure in the Canadian P/C insurance industry, the author wishes to complete the review of the historical literature. The items noted here are items that the author would be willing to stipulate without seeking further evidence and thus be willing to keep the items as part of the research blind spot. Fortunately, work has been done to gather evidence to support the findings.

First, some authors have considered the effect of geographic concentration on the cost structure of American P/C insurers. For the moment, suffice it to note that insurers more geographically diversified in the USA tend to be significantly bigger insurers, as can be seen from the table below where the Herfindahl Index has been computed as $\sum_{i=1}^{S} m_i^2$, where S is the number of states/territories found in total Direct Written Premium exhibits for the period from 2002 to 2010, and m_i is the proportion of the total Direct Written Premium that the insurer writes in state/territory i. The period 2002 to 2010 was selected by way of convenience. The results are highly similar for any given chosen year.

[36] See (Regan and Tennyson, Agent Discretion and the Choice of Insurance Marketing System 1996), (Kim, Mayers and Smith 1996), (Regan, An Empirical Analysis of Property-Liability Insurance Distribution Systems: Market Shares Across Lines of Business 1998), and (Cummins and Doherty 2006).
[37] See (Posey and Yavas, A Search Model of Marketing Systems in Property-Liability Insurance 1995, 669).

Second, some authors have inquired about the reinsurance cost portion of the underwriting expense. Mayers and Smith (1990) find that bigger insurers tend to purchase less reinsurance. In a follow up study, Cole and McCullough (2006) find that the demand for domestic reinsurance decreases as the size of the insurer increases, but the demand for foreign reinsurance increases as the size of the insurer increases.

Finally, Regan and Tzeng (1999) found and justify that the ownership structure of the insurer is related to its distribution channel. In particular, they found that the stock owned insurers tend to more commonly associate with the broker distribution channel. They find that:

> [c]ontrolling for ownership form as an exogenous variable, the authors find that independent agency insurers are likely to be associated with stock ownership, are characterized by higher liabilities relative to surplus, and are more likely to specialize in complex lines of business. (...) When ownership form is treated as an endogenous variable, however, no significant relation exists between ownership form and distribution system. This suggests that these elements are related, but only indirectly through the effect of risk and complexity. (Regan and Tzeng, Organizational Form in the Property-Liability Insurance Industry 1999, 253)

In short, there is a substantial body of work that demonstrates that some characteristics of the insurer are correlated with features of insurers that are of interest to us here.

2.2 The Cost Structure of the Canadian P/C Insurance Industry

Kelly and Kleffner (2006) conducted a study similar to the studies documented and reproduced in section 2.1 for the Canadian industry, but found quite surprising results. In effect, they found that, in the Canadian insurance P/C industry, direct writers do not enjoy a cost efficiency advantage like they do in the American P/C insurance industry, and direct writers do not dominate Personal Lines, although insurers that distribute through brokers have lost some market shares in Personal Lines.

Extracted from Table 2 of (Kelly and Kleffner 2006, 57)					
	Canadian writers 1995-2003				
Mean	Entire sample	Multiple-channel writers	Commodity writers	Exclusive writers	Agency writers
UWE / NPW	35.59%	34.30%	36.31%	35.58%	35.68%
(UWE + LAE) / NPW	44.91%	44.13%	43.14%	43.70%	45.54%

Extracted from Table 1 of (Kelly and Kleffner 2006, 56)				
	Personal Lines		Commercial Lines	
	1995	2003	1995	2003
Multiple-channel writers	9.55%	6.65%	13.54%	9.80%
Exclusive writers	15.33%	16.64%	4.92%	6.79%
Agency writers	67.30%	63.75%	77.44%	76.52%
Commodity writers	7.82%	12.95%	4.10%	6.89%

They also extract other statistics. First, contrary to the American P/C insurance industry direct and broker insurers have fairly similar commission rates. Second, like in the USA direct writers invest more in Electronic Data Processing expenses than broker insurers. Third, just like in the USA, direct writers tend to write less complex business than broker insurers.

Extracted from Table 4 of (Kelly and Kleffner 2006, 65)						
	Canadian writers 1995-2003				U.S. Insurers 1980-1998	
	Multiple-channel writers	Commodity writers	Exclusive writers	Agency writers	Exclusive writers	Agency writers
Commissions / DPW	12.67%	10.73%	15.08%	15.94%		
Advertising Ratio	0.44%	29.34%	3.40%	0.52%	0.32%	0.14%
EDP Ratio	0.84%	6.10%	1.42%	0.95%	1.19%	1.01%
Complexity Ratio	46.51%	38.12%	30.26%	48.79%	16.73%	41.39%

This leads us to reconsider the validity of the theory that supported the rationalizations of the market structure in the USA, as these theories are equally valid for the Canadian market. The authors believe that the smaller scale of the Canadian P/C insurance landscape is the key to understanding the different industry structures between the two markets. They point particularly towards the relative size of the Automobile market that is smaller in Canada due to increased governmental presence, to the decreased efficiency of mass advertising, and to the decreased efficiency of investment in information technology. We will further explore these in subsequent sections using the NAIC data.

2.3 Ignored Collinearity

While the historical literature has recognized that there are economies of scale in the P/C insurance industry, it was never recognized to be the leading driver of the magnitude of the expense ratio. The hope of the author is to establish that economies of scale are the principal force that leads to a decreased underwriting expense ratio. If that is established, the author has to explain why some insurers get to be significantly bigger than others. In the mean time, let us reconsider the findings from sub-section 2.1. First, examining the table below, it is highly probable that the distribution channel is materially correlated with the size of the insurer, as the upper half of the CCCR distribution decreases as insurer size increases. While, on the lower half of the distribution, insurer size seems to increase the CCCR, it does so with smaller values, such that the net effect is an increased likelihood to be a direct insurer conditional on being a large insurer and *vice versa*. So, if a regression was conducted using both the distribution channel and insurer size as covariates, due to the collinearity of insurer size with the distribution channel, it would be unclear what is the marginal contribution of insurer size for the coefficient relating to the direct writer indicator variable.

Target Variable:	CCCR_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-20.569	0.0%	-8.530	6.8%	40.578	0.0%	62.600	0.0%	127.141	0.0%
log10_DWPt_onl_minus_0	2.416	0.0%	1.751	0.0%	-2.748	0.0%	-4.661	0.0%	-10.658	0.0%

Before moving to section 3, where we will attempt to establish the importance of economies of scale in the P/C insurance industry, let us examine the large impact that insurer size has on the underwriting expense ratio of P/C insurers.

Target Variable:	ExpR_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-0.343	91.1%	35.109	1.2%	62.365	0.0%	82.600	0.0%	129.270	0.0%
log10_DWPt_onl_minus_0	3.247	0.0%	0.078	95.8%	-2.227	0.0%	-3.849	0.0%	-8.141	0.0%

3. ECONOMIES OF SCALE IN THE P/C INSURANCE INDUSTRY

In this section, we will set up what we believe to be the key of the resolution of the puzzle: economies of scale. First, we will demonstrate why we believe economies of scale play a critical role in the structure of the P/C insurance industry. Second, we will discuss the potential sources of economies of scale. Third, we will explore what are potential drivers of size and/or growth. Finally, we will explore the consequences of growth.

3.1 Signs of the Presence of Economies of Scale

As is noted in the finance and accounting literatures[38], the seeking of operational synergies can be a driving force behind Mergers and Acquisitions[39]. The argument can be extended to industry consolidations and, as a matter of fact, the American P/C insurance has been the subject of a major consolidation in the last 20 years[40].

In the tables below, "H.I." denotes the Herfindahl Index of the American P/C insurance industry. The columns "t" and "t^2" refer to a quadratic parametric model that is fitted to the values of interest. Ordinary Least Squares was used to fit the quadratic model. OLS is sufficient here because we are only looking for a Best Linear Predictor and we are not attempting to provide any causal or structural interpretation for the parameters.

Total: Total USA P/C Industry

Top 5	t	t^2	Year	Actual	Predicted
β(·)	9.20E-04	2.85E-05	1992	30.9%	30.9%
se(·)	1.33E-03	5.92E-05	2001	30.6%	32.1%
t-value	0.69	0.48	2010	33.0%	33.7%
Top 10	t	t^2	Year	Actual	Predicted
β(·)	2.64E-03	9.18E-05	1992	42.8%	42.1%
se(·)	1.40E-03	6.22E-05	2001	44.8%	45.5%
t-value	1.88	1.48	2010	49.5%	50.5%
Top 20	t	t^2	Year	Actual	Predicted
β(·)	5.66E-03	-7.17E-05	1992	57.6%	55.9%
se(·)	1.97E-03	8.72E-05	2001	61.0%	60.2%
t-value	2.88	-0.82	2010	62.8%	63.3%
H.I.	t	t^2	Year	Actual	Predicted
β(·)	-9.61E-05	9.92E-06	1992	3.0%	3.1%
se(·)	1.39E-04	6.16E-06	2001	3.1%	3.1%
t-value	-0.69	1.61	2010	3.3%	3.3%

Auto: Automobile

Top 5	t	t^2	Year	Actual	Predicted
β(·)	-6.78E-03	4.02E-04	1992	42.6%	43.1%
se(·)	1.42E-03	6.31E-05	2001	42.6%	41.7%
t-value	-4.77	6.37	2010	47.0%	46.8%
Top 10	t	t^2	Year	Actual	Predicted
β(·)	4.78E-03	1.39E-04	1992	50.9%	50.5%
se(·)	1.36E-03	6.05E-05	2001	57.7%	56.4%
t-value	3.51	2.29	2010	64.3%	64.6%
Top 20	t	t^2	Year	Actual	Predicted
β(·)	8.86E-03	-5.05E-05	1992	62.3%	61.8%
se(·)	1.07E-03	4.75E-05	2001	70.2%	69.2%
t-value	8.27	-1.06	2010	75.1%	75.8%
H.I.	t	t^2	Year	Actual	Predicted
β(·)	-1.93E-03	8.00E-05	1992	6.0%	6.2%
se(·)	4.26E-04	1.89E-05	2001	5.7%	5.4%
t-value	-4.54	4.23	2010	6.0%	5.9%

CLNA: Commercial Lines Non-Auto

Top 5	t	t^2	Year	Actual	Predicted
β(·)	1.57E-02	-5.07E-04	1992	25.2%	24.5%
se(·)	2.75E-03	1.22E-04	2001	30.0%	32.7%
t-value	5.69	-4.16	2010	31.5%	32.6%
Top 10	t	t^2	Year	Actual	Predicted
β(·)	1.63E-02	-5.50E-04	1992	39.8%	39.3%
se(·)	2.44E-03	1.08E-04	2001	45.4%	47.5%
t-value	6.67	-5.07	2010	46.1%	46.9%
Top 20	t	t^2	Year	Actual	Predicted
β(·)	1.09E-02	-3.89E-04	1992	59.3%	56.6%
se(·)	3.12E-03	1.38E-04	2001	62.0%	61.9%
t-value	3.50	-2.81	2010	59.9%	60.9%
H.I.	t	t^2	Year	Actual	Predicted
β(·)	1.97E-03	-6.90E-05	1992	2.6%	2.3%
se(·)	5.02E-04	2.23E-05	2001	2.8%	3.3%
t-value	3.93	-3.10	2010	2.9%	3.1%

PLNA: Personal Lines Non-Auto

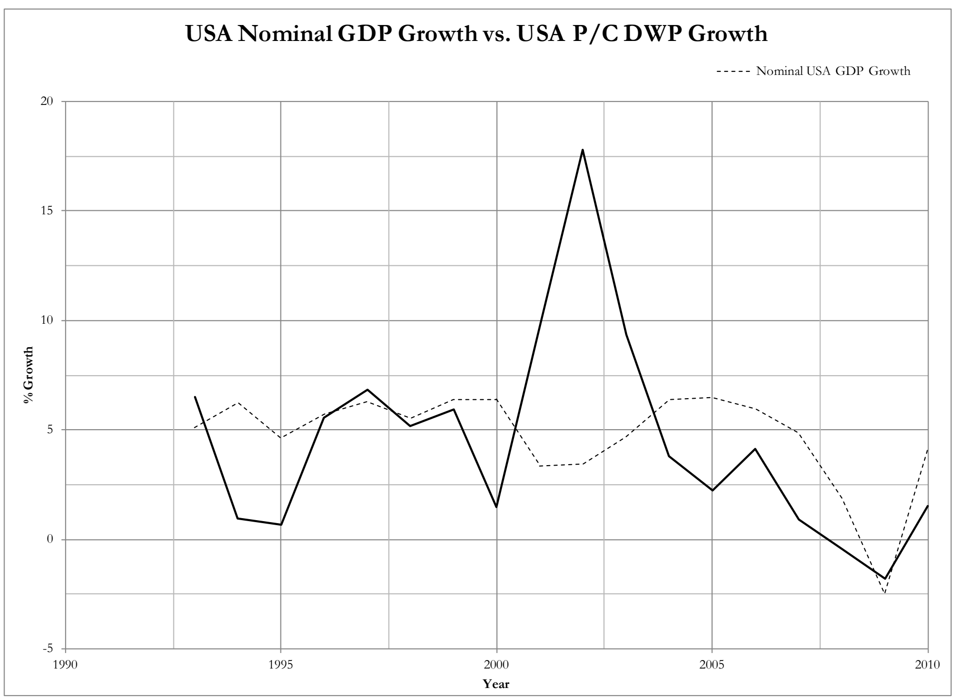
Top 5	t	t^2	Year	Actual	Predicted
β(·)	8.26E-03	-4.76E-04	1992	42.3%	42.7%
se(·)	3.14E-03	1.39E-04	2001	48.4%	44.5%
t-value	2.63	-3.41	2010	40.2%	38.7%
Top 10	t	t^2	Year	Actual	Predicted
β(·)	1.01E-02	-4.24E-04	1992	51.9%	51.8%
se(·)	3.15E-03	1.40E-04	2001	60.0%	55.9%
t-value	3.19	-3.03	2010	54.5%	53.2%
Top 20	t	t^2	Year	Actual	Predicted
β(·)	1.13E-02	-4.56E-04	1992	64.5%	64.1%
se(·)	2.46E-03	1.09E-04	2001	72.4%	68.9%
t-value	4.58	-4.18	2010	67.1%	66.3%
H.I.	t	t^2	Year	Actual	Predicted
β(·)	1.39E-04	-5.53E-05	1992	6.5%	6.7%
se(·)	8.80E-04	3.90E-05	2001	7.1%	6.2%
t-value	0.16	-1.42	2010	5.1%	4.8%

While it is apparent that the over American P/C industry has been consolidating in the last 20 years, it is also clear that the line of business that is the main source of the consolidation has been

[38] See, for example, (Grinblatt and Titman 2002, 699-701), (Palepu and Healy 2008, 11-1,11-2).
[39] See, for example, (Intact Financial Corporation 2011).
[40] See, for example, (Cummings n.d.).

the Automobile line of business. While the Commercial Lines Non-Auto has been the subject of some consolidation, it has been counter-balanced by the Personal Lines Non-Auto which has seen no increase in concentration and has also been increasing in importance in the last 20 years as a proportion of DWP[41].

The question then becomes one where we need to inquire about channels of growth for insurers. One possibility is that insurers are growing because the overall market is expanding. Based on the graph below, this is highly unlikely as the American P/C insurance industry seems saturated. Another source of growth could be from insurers forming a combine that forces prices up. While it is not easy to disprove that theory using archival data, like what is used here, the possibility will be rejected on the assumption that an insurance cartel would have likely lead to a 'major' class action against insurers and this class action has not been observed. We've already discussed the possibility of growth through Mergers and Acquisitions[42]. Unfortunately, it is not easy in the NAIC data to observe Mergers and Acquisitions activity. Finally, growth can occur organically. For example, this seems to be the current preferred growth channel of Progressive (The Progressive Corporation 2010).



Next, we will inquire about what are the potential sources of economies of scale.

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41 From about 10% of overall DWP in 1992 to about 20% in 2010.

42 We are here mainly focusing on horizontal integration within the P/C insurance industry. Note however that vertical integration (*e.g.* insurers merging with/acquiring brokers, insurers forming strategic alliances with service providers, *etc.*) could also be considered.

3.2 Potential Sources of Economies of Scale

To better understand how large insurers can create a cost competitive advantage for themselves, we will explore some working hypotheses regarding economies of scale in the market for the manufacturing and distribution of financial products.

First, in the insurance industry, like in many financial sub-industries, the acquisition, processing, interpretation and usage of information is subject to economies of scale. Take the example of creating a report for a sub-portfolio and using the information discovered with the report to affect pricing strategy by implementing a rate change through the rating systems. In the considered example, the cost of labor required is quite possibly sub-proportional to the number of insureds in the sub-portfolio, while it is most probably an increasing function of the size of the portfolio.

Second, the viability of e-commerce investment in the financial sector is largely a function of the proportion of clients, or more generally affected stakeholders, that actually adopt the technology that saves costs to the financial firm. In the case of the P/C insurance industry, an investment in a Broker Management System or web quoting engine will likely only be a positive net present value project if brokers or clients adopt the technology. Like (Allen, Clark and Houde 2008) argue, less competitive markets and more dominant firms within the market tend to favor massive adoption of cost saving technology.

Third, a larger insurer can be in a much better position to influence prices in the market for repair goods, through the exercise of monopsony power. As (Nell, Richter and Schiller 2009, 350) note: "[t]aking the problems associated with incomplete insurance contracts into account, only institutional arrangements can increase welfare beyond a third-best situation. Especially the vertical integration of insurance and repair markets maybe an appropriate approach."

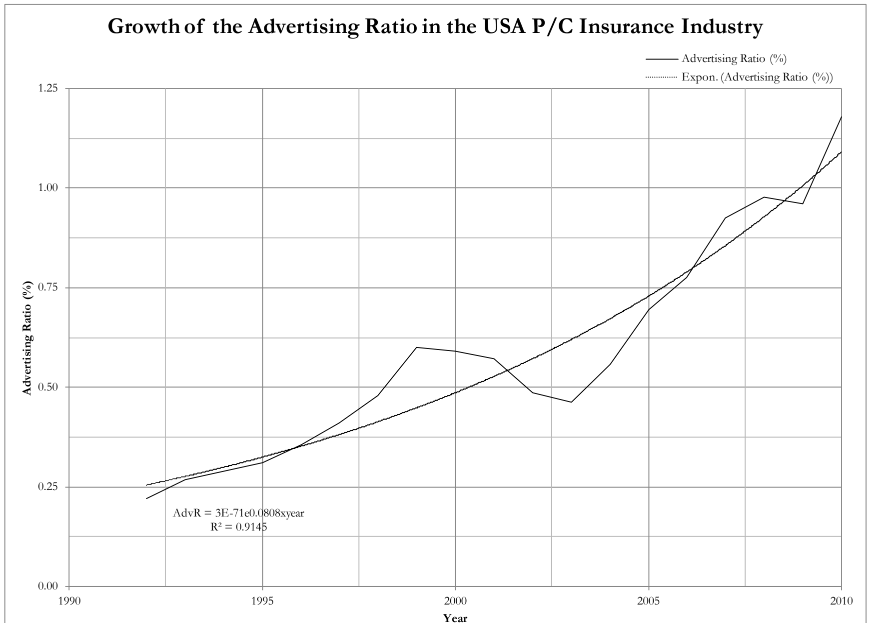
Fourth, more generally, insurer size may be associated with market power in the many markets insurers need to engage in, like the labor market.

Finally, as argued in (Intact Financial Corporation 2010, 6), larger insurers may be in a better position to form predictive models of consumer profitability.

Next, we will separately consider advertisement.

3.3 Determinations of Size or Growth

Before going further, let us examine the evolution of the advertising ratio in the American P/C industry in the last 20 years. Clearly, there has been a large positive trend of increased advertising expenditures. This large trend makes the comparison that (Kelly and Kleffner 2006) make in table 4 not as enlightening as they intended it to be, as the covered periods are long and do not overlap for Canada and USA



Mass advertising can be an effective tool for reaching a large number of persons at the same time, but it has the disadvantage that many people that see it may not have been the target audience. Also, mass advertising can become quite expensive[43]. Therefore, it is unclear, in an *a priori* way that advertising is subject to increased efficiency as insurer size increases even if it is likely that advertising effectiveness increases as the size of the advertising campaign increases, if it is executed appropriately within a marketing strategy coherent with the business strategy.

At this point, we empirically examine the quantile effect of advertising, controlling for the share of the insurer premium that is written in the Automobile lines of business[44]. As can be seen below, current period advertising seems to be positively correlated with DWP growth. It is somewhat surprising to find that prior year advertising is negatively correlated with current year DWP growth differential, but the advertising ratio should be correlated from one year to the next for most insurers. Note that the positive effect of advertising seems to stem from the upper half of the DWP growth differential distribution. Note also that it is unclear that a causal interpretation can be made of the result, because it could be that insurers that intend to pull out of a market decide to stop advertising in that market.

43 See (Peter and Donnelly 2006, 111).
44 Automobile insurance being the line of business most likely to see efficacious advertising, as products are standardized, purchased by a very large portion of the population, and competitive.

Target Variable:	growth_diff_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-26.126	67.5%	-31.787	89.5%	-156.036	0.0%	-69.572	0.0%	-27.986	0.0%
Auto_share_minus_0	0.279	78.4%	0.403	90.8%	2.141	0.0%	0.758	0.0%	0.340	0.2%
AdvR_minus_0	27.358	88.2%	58.240	91.7%	727.757	0.0%	727.126	0.0%	726.822	0.0%
Auto_share_minus_0 x AdvR_minus_0	-0.397	90.0%	-0.851	92.3%	-10.312	0.0%	-8.504	0.6%	-7.478	0.0%

Target Variable:	growth_diff_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-64.199	0.0%	-22.828	0.0%	-3.579	38.3%	6.137	4.5%	10.760	2.6%
Auto_share_minus_0	3.660	14.1%	2.606	31.0%	1.911	35.0%	-0.265	91.0%	-3.871	0.3%
AdvR_minus_0	733.364	0.0%	733.090	0.0%	732.497	0.0%	731.650	0.0%	730.093	0.0%
Auto_share_minus_0 x AdvR_minus_0	-10.057	0.0%	-10.531	0.0%	-10.533	0.0%	-9.001	0.0%	-7.685	0.0%
Auto_share_minus_1	-2.895	22.9%	-2.326	37.4%	-1.909	35.5%	0.125	95.8%	3.785	0.4%
AdvR_minus_1	-781.725	0.0%	-785.164	0.0%	-728.863	0.0%	-632.275	0.0%	-442.559	0.0%
Auto_share_minus_1 x AdvR_minus_1	10.189	0.0%	11.049	0.0%	10.496	0.0%	8.067	0.0%	4.777	0.0%

Before moving back towards the larger picture of business strategy, we will explore the potential effects of growth and investment in information technology of the Loss and Loss Adjustment Expense ratio side of underwriting profitability.

3.4 Consequences of Growth

As has been observed and justified in (D'Arcy and Doherty 1990), because new businesses tend to receive lowballed prices in a market where there are *ex ante* informational asymmetries, one could potentially expect that insurers that are growing rapidly will first experience a deteriorating loss ratio that would improve over time. But, as we mentioned earlier, a larger insurer may be able to generate economies of scale in loss adjustment expenses as well as in the loss ratio, by being able to negotiate better prices in the repair goods market. It is therefore an empirical matter of which force is strongest and the following tables attempt to answer that question.

Target Variable:	LLAER_diff_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-11.980	0.0%	-5.930	0.0%	-0.480	12.6%	4.670	0.0%	9.370	0.0%
growth_diff_minus_0	0.000	0.0%	0.000	0.0%	0.000	0.0%	0.000	0.0%	0.000	95.3%
growth_diff_minus_1	0.000	96.4%	0.000	20.5%	0.000	64.1%	0.000	38.1%	0.000	1.6%

As is observed in the preceding table, the DWP growth differential seems to have little net impact on the LLAER differential.

Target Variable:	LLAER_diff_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	-11.919	0.0%	-5.891	0.0%	-0.351	60.0%	4.724	0.0%	9.443	0.0%
EquipR_minus_0	0.013	0.0%	-0.003	0.0%	-0.018	0.0%	-0.032	0.0%	-0.045	0.0%

The table found above was meant to serve the goal to explore the following working hypothesis: insurers that invest more heavily in information technology tend to be more sophisticated and disciplined than other insurers and are therefore experiencing a lower LLAER ratio than other insurers. Clearly, except for the 10th percentile, the working hypothesis is not infirmed by the data, although the economic significance of the coefficients associated with the $EquipR\_minus\_0$ term are not great.

4. BUSINESS STRATEGY

Before moving further, let's gather together the accumulated evidence. (1) The American P/C insurance industry has been consolidating in a material way in the last twenty years. (2) One way for the industry to consolidate is through Mergers and Acquisitions activities, and M&A activity has operational synergy as one of its key motivators. There is no *a priori* reason to believe that there is no similar motivation for insurers when they engage in organic growth; especially since we've identified potential sources of economies of scale. (3) When a one-way quantile regression of the underwriting expense ratio is run against P/C insurer size, larger insurers appear to have a lower expense ratio. (4) Insurer size is correlated with its distribution channel, as bigger American P/C insurer are more likely than average to distribute through the direct channel. (5) Provided that an insurer has chosen the broker distribution channel, Commercial Lines generally constitutes a larger portion of its book than it would otherwise be. Provided that an insurer has chosen the direct distribution channel, Automobile insurance generally constitutes a larger portion of its book than it would otherwise be. Both the Automobile and the Commercial lines of business have been consolidating; although the extent of consolidation has been much stronger in the Automobile lines of business. (6) Larger American P/C insurers tend to be much less geographically concentrated than average: their customer base is much larger and diversified geographically. (7) The Canadian P/C insurance market is not dominated by direct writers in Personal Lines insurance, that includes the Automobile line of business, and direct writers do not have an expense advantage. Let's add the following information. (8) In Canada, the P/C insurance has also been consolidating, but the consolidation has been lead by an insurer that mainly focuses on distributing its products through brokers[45].

The question can then be asked about what is the most likely dominant force leading to cost efficiency, given a business strategy. The historical answer from the P/C insurance efficiency literature, which was mainly written by Americans attempting to explain the structure of the American P/C insurance market, was that the distribution channel was the key driver of efficiency,

[45] "Proven acquisition strategy: We are an active acquirer in the industry, with 11 successful acquisitions since 1988. Our strategy focuses on fit, technological integration and increasing the profitability of the acquired book of business through our pricing, underwriting expertise and claims." (Intact Financial Corporation 2010, 6)

even while many noted that economies of scale were available. Assuming that the distribution channel was the driving force for efficiency, in Canada, direct writers should also be dominating in the sub-market in which they should naturally dominate: Automobile insurance. However, it is not the case. Plus, if the key force driving efficiency was the distribution channel, it would not provide a strong rationale for the material consolidation of the American P/C insurance industry.

If, instead, we suppose that economies of scale are the driving force behind cost efficiency in the P/C insurance industry, then (1) it is easy to rationalize the consolidation of the P/C insurance industry in Canada and in the USA and, (2) given that the distribution channel then becomes a secondary force, it not surprising to find that, in Canada, broker insurers do not have an expense disadvantage over direct writers, but that direct writers have nonetheless been gaining market shares.

Under this alternate rationalization, what has instead to be explained is why, in the USA, large P/C insurers are quite likely to choose a generic strategy of cost leadership while, in Canada, large P/C insurers are more likely to choose a generic strategy of differentiation?

Why do we say that large American insurers tend to prefer a cost leadership strategy? Cost leadership can be defined as "an integrated set of actions designed to produce or deliver goods or services with features that are acceptable to customers at the lowest cost, relative to that of competitors." (Hitt, et al. 2006, 147) The very motivation behind the direct distribution channel finds its roots in cost minimization. Historically, it has been expressed as direct insurers taking care of billing. More recently, it has expressed itself in large direct insurers pursuing initiatives related to usage of internet in the distribution of their products. Some of the cost savings technologies can have significant fixed costs associated with them and massive adoption of the technology can be a critical factor for success.

Why do we say that large Canadian insurers tend to prefer differentiation? Differentiation can be defined as a strategy designed "to produce or deliver goods or services (at an acceptable cost) that customers perceive as being different in ways that are important to them." (Hitt, et al. 2006, 153) Using Intact Financial Corporation as an example, we can see that the insurer intends to (1) be supportive of its broker sales force to provide clients with "customer choice, personalized service and trusted advice" (Intact Financial Corporation 2010, 6), (2) offer clients the choice of which distribution channel to use to approach the insurer, (3) offer superior claims service, and (4) use its scale advantage "to negotiate preferred terms with suppliers, priority repair service, quality guarantees and lower material costs." (Intact Financial Corporation 2010, 6) Similar examples could be found for other large Canadian P/C insurers.

Under both these generic business strategies[46], large insurer size is (1) possible and (2) useful. The way insurer size is used differs under the differentiation and the cost leadership strategies differ: under cost leadership, insurer size is used to channel economies of scale in reduced prices leading to further growth; under differentiation, insurer size is used to allow the insurer to offer more differentiating features (because the consumer pool increases) while not having prices explode (because of economies of scale).

It is worthy to note that, under both the differentiation and the cost leadership strategies, mass advertising and investment in information technology are sensible because, under both generic strategies, economies of scale help render the strategy more effective and efficient. Assuming that a properly strategized and executed advertising campaign actually favors growth, advertising helps insurers create economies of scale. Also, we saw that investment in information technology is likely to be associated with sophistication in the costing and pricing of insurance contracts, and pricing sophistication is necessary under both differentiation and cost leadership.

We can formulate two working hypotheses for why the American and the Canadian P/C insurance markets have evolved differently. As noted in (Kelly and Kleffner 2006, 66), in Canada, available premium in the Automobile line of business, historically favored by direct writers, is much smaller than in the USA because (1) the population is much smaller to start with, but also because (2) Automobile insurance is handled, at least in part, by government insurers in many provinces. As available economies of scale for direct writers are less important, it did not favor the growth of that distribution channel. Another working hypothesis would say that broker insurers in Canada found itself facing an insurance brokerage industry that was not as concentrated as in the USA and was therefore better able to embark brokers in the use of cost saving technology. The motivation for the second working hypothesis stems from noting that the American insurance brokerage is quite concentrated[47], and from noting that some large Canadian insurers work quite intensively with brokers to help them in their endeavors. Supporting evidence needs to be sought to support both working hypotheses.

5. CONCLUSION

We've identified two fatal flaws of the historical literature concerning itself with the cost efficiency P/C insurance market. One, we've identified that the historical literature has neglected the effect of collinearity when interpreting the results of regressions relating to the drivers of the underwriting expense ratio. Two, we've identified that the historical literature has neglected the

46 Generically speaking, both differentiation and cost leadership can be distinguished from a focus strategy where the firm focuses on "the needs of a particular competitive segment." (Hitt, et al. 2006, 159)
47 See (Cummins and Doherty 2006, 363-367).

possible effectiveness of the differentiation generic business strategy in the P/C insurance market. So doing, we've been lead to place economies of scale at the heart of a successful business strategy for insurers that do not choose the focus generic business strategy; thus, displacing the choice of distribution channel as subordinate to the choice of the generic business strategy.

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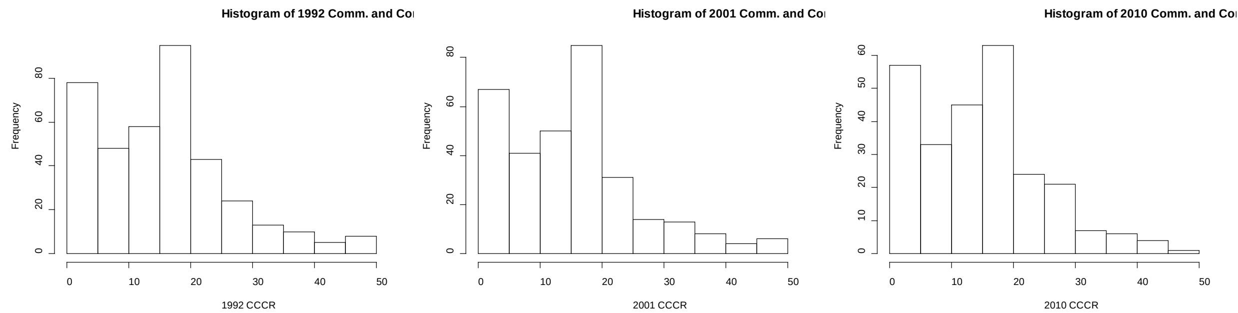
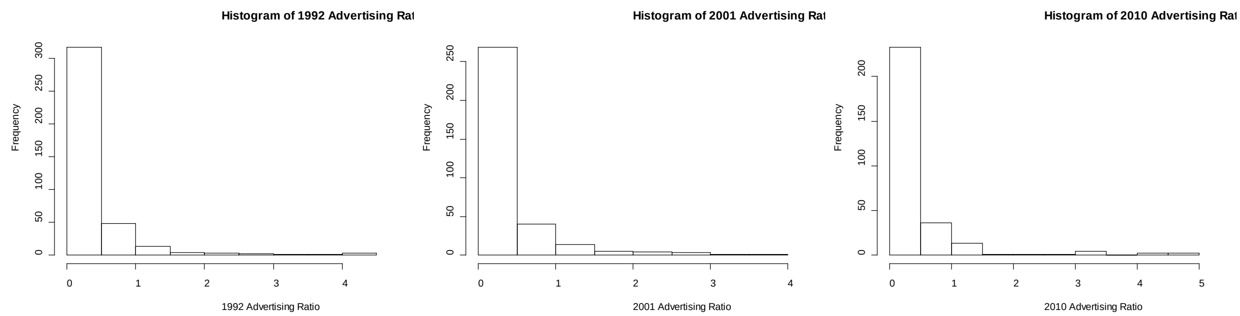
Appendix A: Histograms of other key variables

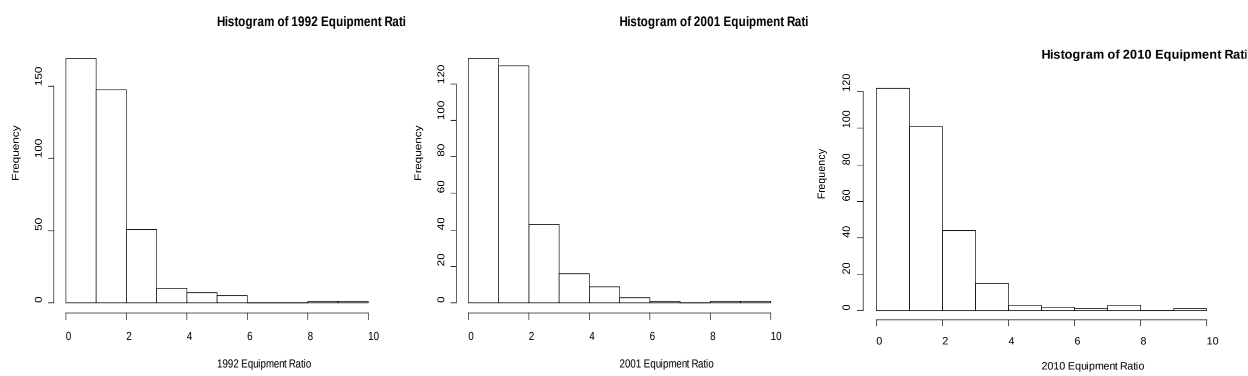
Commission and Contingent Commission Ratio



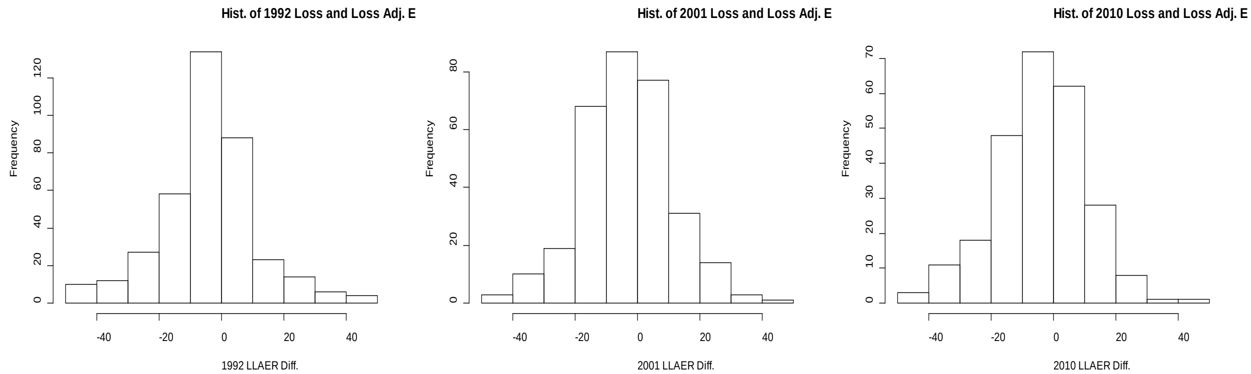
Advertising Ratio



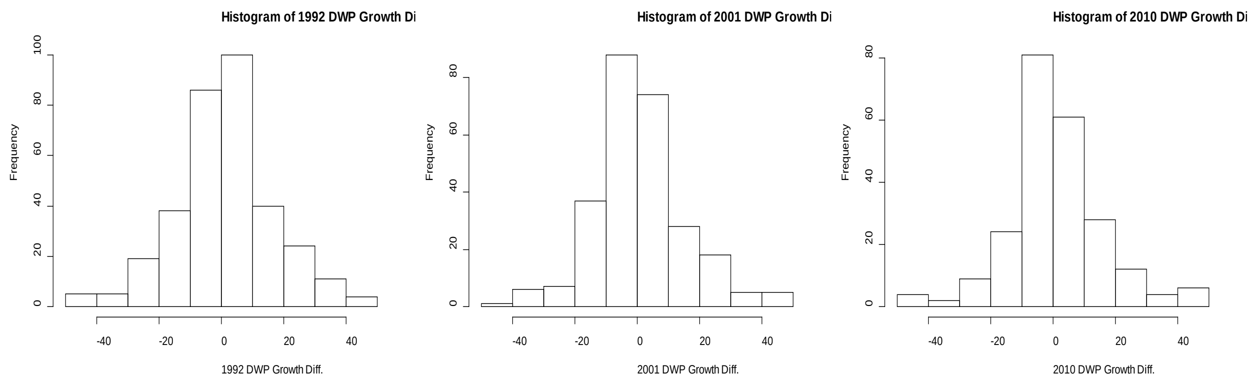
Equipment Ratio



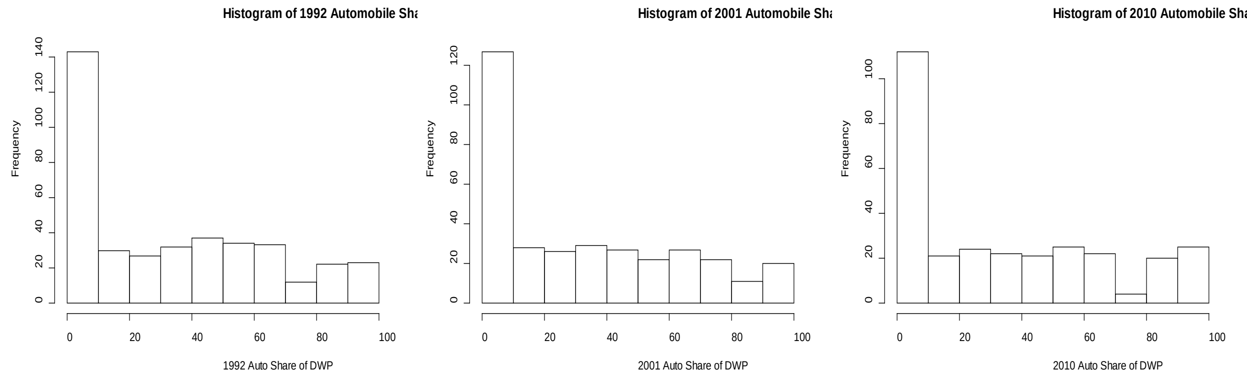
Loss and Loss Adjustment Ratio Differential to the Industry



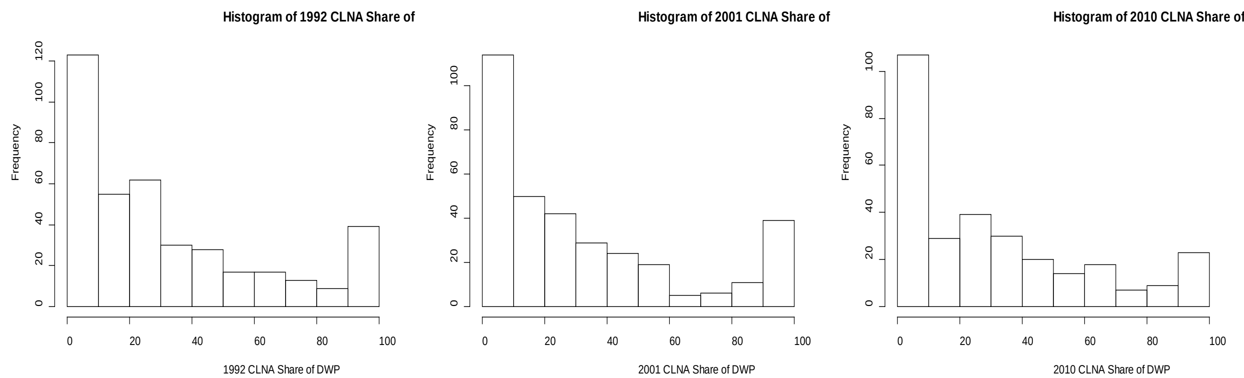
Direct Written Premium Growth Differential to the Industry



Automobile Share of Premium



Commercial Lines Non-Auto Share of Premium



Appendix B: Other quantile regression results

Target Variable:	CLNA_share_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	2.283	0.0%	5.563	0.0%	22.937	0.0%	43.585	0.0%	55.779	0.0%
CCCR_minus_0	0.000	0.0%	0.000	0.0%	-0.001	0.0%	-0.001	0.0%	-0.002	0.0%

Target Variable:	Auto_share_minus_0									
Percentile	10th		25th		50th		75th		90th	
DWP Weights; S.E.: "ker" Method	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
intercept	5.469	0.0%	18.988	0.0%	41.609	0.0%	67.454	0.0%	76.172	0.0%
CCCR_minus_0	0.000	0.0%	-0.001	0.0%	-0.001	0.0%	-0.002	0.0%	-0.002	0.0%

Appendix C: Quantiles in the univariate case

To better understand the second and third approach to quantile regression mentioned in section 2.1.2 "Econometric specification: the choice of quantile regression", we will recall how to compute quantile in the univariate case. Let us focus on the median. There are three ways to compute the median. One, one can plot the Cumulative Distribution Function of a random variable and find the point x for which $F_X(x) = 0.50$. Two, one could find the point m for which the quantity

$$\int_{-\infty}^{+\infty} |x - m| dF_X(x)$$

, or the absolute deviation from m, is minimized. Third, one could solve the following equation for m:

$$\int_{-\infty}^{+\infty} (I\{x \leq m\} - 0.5) dF_X(x) = 0$$

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Biography of the Author

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