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Author(s): Kenneth F. Kroner and Douglas S. West
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Kenneth F. Kroner
Douglas S. West

ABSTRACT

This article modifies the Carlson and McAfee model of price dispersion to allow for screening. It is argued that only large insurers will be able to screen effectively and that they should insure fewer high-risk drivers and have lower loss costs as a result. We examine the relationship between firm size and loss costs using automobile insurance data for Alberta for the years 1978 through 1981. The relationship between cars insured per firm and loss costs per car insured is significant and is represented by a parabola, as expected, for four out of the five largest driver classes in Alberta.

Introduction

Since Stigler's (1962) seminal article on information in the labor market, economists have studied screening. Most of this literature has examined screening in the context of a firm's hiring decision. That is, firms cannot perfectly observe the productivity of their workers prior to hiring them, but they can attempt to screen out less productive workers if they know that some observed attribute (e.g., schooling) is highly correlated with productivity.

There has been a great deal of empirical work on educational screening (see Riley, 1979, for a review). More recently, the relationship between firm size and screening has come under closer scrutiny (see, e.g., Garen, 1985; Barron, Bishop, and Dunkelberg, 1985; and Barron, Black, and Loewenstein, 1987). There are, however, other contexts in which firms might engage in screening, an important one being an insurance market.[1] In an insurance market, firms

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Kenneth F. Kroner is Associate Professor in the Department of Economics, University of Arizona. Douglas S. West is Professor in the Department of Economics, University of Alberta. The authors thank Lawrence White and two anonymous referees for their many helpful comments. They also thank the S. S. Huebner Foundation for Insurance Education at the Wharton School of the University of Pennsylvania and the Social Sciences and Humanities Research Council of Canada for their financial support.

[1] This observation was also made by Joskow (1973, p. 405). Ippolito (1979) discusses how insurance agents attempt to determine the desirability of insuring each risk within stated categories by interviewing their applicants for insurance.

must confront individuals who are good risks and individuals who are bad risks, but they cannot directly observe the riskiness of a given individual. Rather, they can attempt to use information on the observed attributes of individuals to determine riskiness and on that basis insure only the individuals perceived to be good risks, leaving the bad risks to be insured by other firms or by an assigned risk plan.[2] If only certain firms successfully screen out bad risks, these firms would have lower loss costs and lower premiums for a given insurance policy than other firms. Thus, price dispersion in automobile insurance, which Dahlby and West (1986) found to be consistent with a model of costly consumer search, can also be consistent with differential screening.

This article follows Dahlby's (1988) modification of the Carlson and McAfee (1983) model of price dispersion to allow for screening. Unlike Dahlby, however (but consistent with Barron, Bishop, and Dunkelberg, 1985), effective screeners are predicted to consist primarily of large firms, and they should insure fewer high-risk drivers and have lower loss costs as a result. We examine the relationship between firm size and loss costs using automobile insurance industry data for Alberta for the years 1978 through 1981. The empirical results generally support the implications of the theory. In particular, the relationship between cars insured per firm and loss costs per car insured is significant and is represented by a parabola, as expected, for four out of the five largest driver classes in Alberta.

The next section briefly reviews the Carlson and McAfee model and presents an extension that incorporates screening. The testable implications relating to screening are also derived. In the subsequent section, we describe the data that are used in the tests for screening, and some descriptive statistics are presented. Then we discuss the empirical results and, finally, provide a summary and some concluding remarks.

Screening in a Model of Price Dispersion

This study's tests for screening in an automobile insurance market are based on an extended version of the Carlson and McAfee (1983) model of price dispersion.[3] Assume that there are J driver classes, j = 1, 2,..., J, defined on the basis of some easily observed characteristic of a driver, such as age or sex. (Since the following analysis applies to each driver class, the j subscript will be suppressed.) There are M consumers, and each consumer has one car that must be insured. There are N firms, indexed i = 1, 2,..., N, and firm i's premium is z_i, with $z_1 \leq z_2 \leq ... \leq z_N$. The probability that a consumer will observe firm i's premium after engaging in one unit of search is 1/N. This implies sampling with replacement. Assuming that consumers know the distribution of

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[2] Assigned risk plans were established to provide some basic minimum insurance coverage to those drivers who were refused coverage in the voluntary market (see Joskow, 1973, pp. 406-407).

[3] The Carlson and McAfee model has previously been applied to the automobile insurance market by Dahlby and West (1986).

premiums and use a sequential reservation price search strategy and that the distribution of search costs across consumers is uniform over the interval [0,2Y], Carlson and McAfee have shown that the demand curve facing firm i is

$$q_i^d = \frac{M}{N}\left[1 - \frac{z_i - R_i}{2Y}\right], \tag{1}$$

where q_i^d = the quantity demanded from firm i,
R_i = the average premium charged by all firms other than i, and
Y = the average cost of a price search.

The ith automobile insurer engages in screening by insuring only those drivers with expected loss costs less than its screening standard θ_i. The screening standard θ_i is treated as exogenous since most of the firms selling automobile insurance in one jurisdiction (e.g., Alberta) also sell insurance in other jurisdictions, and the θ_i for a given jurisdiction is presumably dictated by the head office. (The interest in this study also centers on the ability of a firm to implement a given screening standard rather than on the choice of the standard itself.) If a firm chooses not to screen, its θ_i is infinite. It is assumed that the distribution of expected loss costs per car insured is f(c), $0 < c < \infty$. The corresponding cumulative distribution function is F(c), and the mean of c is μ.

The question arises as to how firms implement their exogenously determined screening standards. Implementation of a screening standard requires that firms estimate the expected loss cost of a given driver. This could be done in a formal way, as suggested by Boyer and Dionne (1989), who found that the probability of an accident could be estimated for Montreal drivers using data on driver characteristics, such as age and sex, and data on past experience, including number of demerit points, license suspensions, and previous accidents. However, firms would have to be large to collect enough driver-specific information to allow them to estimate the probability-of-accident regression. Boyer and Dionne themselves estimated a probability-of-accident probit regression using data from a sample of 19,013 randomly selected drivers from Québec. Their data were obtained from the Régie de l'Assurance Automobile du Québec (RAAQ), which is an insurer owned by the Province of Québec and provides the compulsory bodily injury insurance for Québec drivers. Presumably, private insurers would not have access to the same quality and quantity of data unless they are large.

The relationship between a firm's demand and θ_i is derived assuming that the firm can calculate the expected loss cost of each driver. The relationship is expected to hold, however, only for those driver classes in which firms insure a relatively large number of cars. These driver classes should generate sufficient loss cost data to enable firms to impose effectively a given screening standard.

It should be noted that all firms can engage in a minimum level of screening based on certain driver characteristics such as age, sex, and marital status.

Rating bureaus, such as the Insurers' Advisory Organization (IAO), report to their members loss data for categories defined by these driver characteristics, and these data help firms assess the risks of insuring various types of drivers. However, there is driver-specific information that rating bureaus do not collect that might assist a firm in assessing the riskiness of a given driver. Once again, large firms will have access to more of these data than small firms, and thus should be more effective screeners.

It is assumed that consumers complete their search over premiums before finding out whether the firms they have chosen will insure them. If a consumer's expected loss cost is greater than the chosen firm's screening standard, then the firm will refuse to insure the consumer, and the consumer will be insured through the assigned risk plan, which we define to be firm N. This assumption is made for the purpose of analytical tractability. Without this assumption, each firm's size would depend on *all* other firms' screening standards. The assumption would also be reasonable if, as Joskow (1973, p. 407) suggests was the case after 1969, insurance agents are permitted to charge commissions on the full premium quoted by the assigned risk plan. In other words, insurance agents could make more money by getting insurance for their clients through the involuntary market than through the voluntary market because of the higher premiums quoted in the former. Furthermore, Grabowski, Viscusi, and Evans (1989) suggest that if regulators keep average premiums below competitive equilibrium levels, insurers could respond in part by placing marginal risks in the assigned risk pool. Their results show that regulation does have the expected positive and statistically significant effect on the size of the voluntary market. (As noted below, Alberta has a prior approval regulatory mechanism.)

On the assumption of a random search by consumers, only the fraction $F(\theta_i)$ of the consumers that choose the screening firm will actually be insured by firm i; the others will be rejected.[4] Furthermore, it is assumed that there is a large number of firms, so that R_i can be approximated by $\bar{R}$ for all i, where $\bar{R}$ is the average premium in the market. The implication of these assumptions is that each firm's demand curve depends on its own screening standard, θ_i, given consumer search costs and processes. The relationship between q_i^* and θ_i will be the same for all firms. Firm i's demand curve is

$$q_i^d = \frac{M}{N} F(\theta_i)\left(1 - \frac{z_i - \bar{R}}{2Y}\right). \tag{2}$$

Note that, as θ_i approaches infinity, this demand converges to the Carlson and McAfee (no screening) demand curve.

[4] The assumption of random search helps to ensure analytical tractability of the model. It could be assumed that Y and c are correlated, which implies that search is not random. However, this would not affect any of the essential features of the model.

Firms that screen and only accept the lower risks will have lower expected loss costs than nonscreening firms. By finding the density of c, given that c is less than θ_i, and taking the expectation of this density, one obtains

$$c(\theta_i) \equiv c_i \equiv E(c|c<\theta_i) = \frac{1}{F(\theta_i)}\int_0^{\theta_i} cf(c)dc. \quad (3)$$

Note that, as expected, $c(\theta_i)$ is equal to zero if θ_i is zero, less than μ for all θ_i greater than zero, and equal to μ if θ_i approaches infinity. The parameter μ can be interpreted as the expected loss costs of all firms.

In practice (and in equilibrium), firms' premiums will be proportional to expected loss costs, so that

$$z_i = tc(\theta_i). \quad (4)$$

This conjecture is motivated by the fact that many jurisdictions (Alberta being one) employ a prior approval regulatory mechanism. According to Joskow (1973, pp. 394-395), under a prior approval regulatory system, rates are established so as to yield a particular rate of return on premiums collected. (Investment income is not included as revenue.) With a five percent rate of return, P_i equals $A_i/(1\text{-}0.05\text{-}E)$, where A_i is a measure of historical losses (or perhaps an estimate of expected losses) for this territory and class, E is a measure of historical operating and production expense ratio, and P_i is equal to total premiums for a particular territory and class.[5]

Substituting equations (3) and (4) into equation (2) yields the following equation:

$$q_i^* = \frac{M}{N}F(\theta_i)\left[1+\frac{\bar{R}}{2Y}\right]-\frac{M}{N}\frac{t}{2Y}\int_0^{\theta_i} cf(c)dc. \quad (5)$$

This equation captures the relationship between the cars insured by firm i and the screening standard. Note that M, N, μ, t, and Y are all parameters, and $\bar{R}$ is taken as given by firm i, so q_i^* is a function of θ_i.

[5] The assumption that a firm's premiums will be proportional to expected loss costs has also been made by Harrington (1990) in his analysis of the relationship between voluntary and involuntary market rates and rate regulation. Grabowski, Viscusi, and Evans (1989) state that "If the insurance market were perfectly competitive, then equilibrium premium payments would equal expected losses plus the expenses necessary for servicing these losses efficiently (i.e., sales expenses, loss adjustment expenses, etc.) plus a return that adequately compensates insurers for risk bearing." Hence, in equilibrium, they have $P_{ij} = 1/(1\text{-}e_{ij}\text{-}r_{ij})$, where P_{ij} = premiums in state i for category j drivers, L_{ij} = expected losses to insurers in state i for category j drivers, e_{ij} = other insurance expenses in state i for category j drivers, and r_{ij} = competitive return for risk bearing in state i for category j drivers. Grabowski, Viscusi, and Evans argue that, if regulation reduces average premiums below competitive levels, insurers will receive a lower return, perhaps causing firms to reduce quality and service levels (including placing marginal risks in the assigned risk pool). Furthermore, if premiums fail to cover costs in the long run, firms can request regulatory approval for higher premiums, or they can stop selling insurance in the jurisdiction.

Differentiating equation (5) with respect to θ_i gives

$$\frac{dq_i^*}{d\theta_i} = \frac{M}{N} f(\theta_i)\left[1 - \frac{t\theta_i - \bar{R}}{2Y}\right]. \tag{6}$$

From equations (5) and (6), it is clear that firm size is zero if $\theta_i = 0$ and rises to its maximum value when $\theta_i = \frac{2Y + \bar{R}}{t}$, then falls to a horizontal asymptote of $\frac{M}{N}$.[6]

Equation (5) can be plotted for selected values of $\bar{R}$, μ, M, N, t, and Y if one makes some assumptions with respect to the distribution of expected loss costs. In Figure 1, it is assumed that the distribution of expected loss costs per car insured is exponential, with parameter μ:

$$f(c) = \frac{1}{\mu} e^{-\frac{c}{\mu}} \qquad c > 0.$$

$\bar{R}$ is set equal to the average premium charged in urban Alberta by the 24 firms in the sample (i.e., total premiums collected divided by total cars insured), μ is set equal to the average loss cost per car insured for the 24 firms in the sample, M is the total cars insured by the N firms in the sample, t is equal to total premiums collected divided by total losses, and Y is set equal to 30, which is close to the mean search costs of drivers in class 01 in 1980 estimated by Dahlby and West (1986, p. 429). Reading from right to left, the relationship implies that a screening firm will be larger than a nonscreening firm (i.e., one whose size is M/N) until the screen becomes so stringent that its size is reduced below M/N. Screening allows the firm to reduce its expected loss cost and hence its premiums, which increases q_i until θ_i equals $(2Y+\bar{R})/t$. Beyond this point, increasing the toughness of the screen reduces q_i.

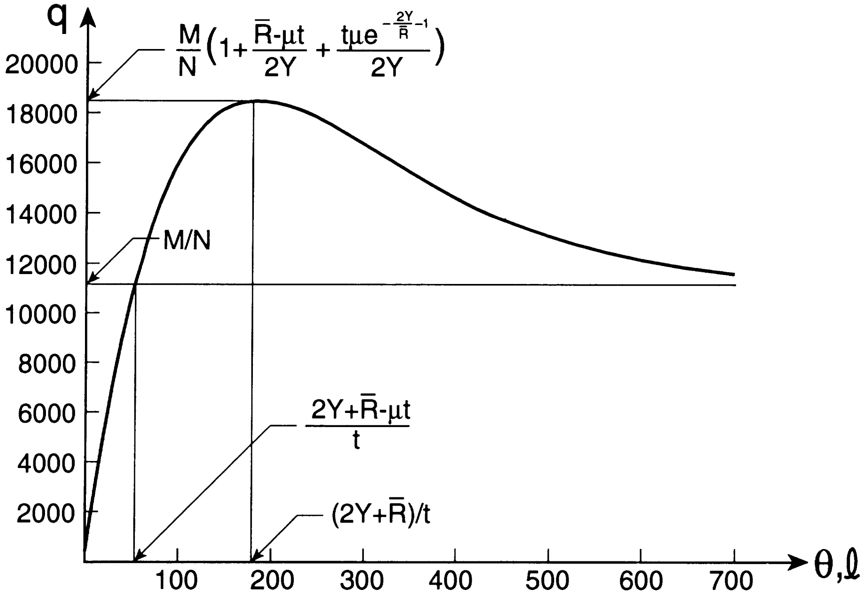
Dahlby (1988) expected screening firms to have three characteristics: low loss costs, low premiums, and relatively low market shares. In Figure 1, these firms would be of a size below M/N and thus be very stringent screeners.

[6] Instead of assuming that t is a constant, it could be assumed that $t_i = t(\theta_i)$. Then equation (5) is unchanged except that t is now $t(\theta_i)$. The derivative in equation (6), $dq_i^*/d\theta_i$, becomes

$$\frac{dq_i^*}{d\theta_i} = \frac{M}{N} f(\theta_i)\left[1 - \frac{\theta_i t(\theta_i) - \bar{R}}{2Y}\right] - \frac{M}{N}\,\frac{t'(\theta_i)}{2Y}\int_0^{\theta_i} cf(c)\,dc.$$

Assuming that $t' \le 0$, $t'(\infty) = 0$, and $t^* \le t(\theta_i) < \infty$, then making t a function of θ_i will yield the same general shape of the q_i^* function. It starts at zero, rises to a maximum, and falls to a horizontal asymptote of $\frac{M}{N}$. The θ_i that maximizes q_i^* can no longer be computed. It is known, however, that the new maximum will be to the right of the old maximum if the markup in the old model was t*.

Figure 1
The Relationship Between Size and Screening



Note: Θ = the screening standard, ℓ = loss cost per car insured, and q = the number of cars insured. The distribution of expected loss costs is given by $f(c) = \frac{1}{\mu}e^{-\frac{c}{\mu}}$, $c>0$. $\bar{R}$ = 160.37 = the average premium charged by all firms in the sample, μ = 126.48 = average loss cost per car insured for the 24 firms in the sample, M = 265,688 = the number of cars insured by the 24 firms in the sample, N = 24 = the number of firms in the sample, t = 1.268 = total premiums collected divided by total losses, and Y = 30 = average cost of a price search by drivers in Class 01 in 1980, estimated by Dahlby and West (1986).

However, this assumes that they can estimate expected loss costs. If firms are too small, they will not have sufficient information with which to screen effectively. They will be unable to implement their screening standards and would experience low loss costs either by chance or if they are able to exploit information (e.g., loss cost data or data on other screening variables) acquired from external sources. Furthermore, small firms will be unable to use their own loss experience to justify their premiums to the regulator in a prior approval system. Rather, they will set premiums recommended by the rating bureau to which they belong (in Alberta, this is the IAO) and that are approved by the regulator.[7] IAO-recommended premiums are among the highest premiums charged by firms in a given year. Therefore, one would actually expect some small firms to have high premiums and high expected loss costs and to avoid

[7] Dahlby (1988) and Danzon (1983) have both pointed out that small firms tend to be members of rating bureaus like the IAO.

insuring high-risk drivers. As a consequence, one would expect more noise in the size-loss cost relationship for small firms than for large firms. Larger firms are expected to be more effective screeners and to achieve lower loss costs, and this expectation is reflected in the equation estimated below.[8]

Data

The data used in this article were originally collected for Dahlby and West (1986), although they did not make use of the firm-specific loss cost data available for some firms for some years. They collected data on bodily injury and property damage (BIPD) premiums and cars insured in Alberta for the period 1974 through 1981 from the Alberta Automobile Insurance Board. In Alberta, BIPD insurance is compulsory, and premiums are regulated by the Insurance Board under a prior approval regulatory system. Data were collected on 54 insurers in 1974 and 61 insurers in 1981, and these companies accounted for 83.2 percent and 93.5 percent, respectively, of the automobile insurance written in Alberta. Policies represented \$50,000 coverage from 1974 to 1977 and \$100,000 coverage between 1978 and 1981, and the premiums collected were those in effect on June 30 of each year. BIPD premiums are set according to driver class, of which there are 14, driving record (zero, one, two, three, or five years claim-free driving), and three rating territories. Territory 1 is urban and includes Edmonton and Calgary, and the other two territories are rural.

Table 1 shows the driver class definitions and proportions of cars insured in Territory 1 in 1981.[9] As shown in Table 1, driver classes are defined in terms of age, sex, marital status, and how the car is to be used. These classes are associated with different risks, and, because loss cost information on an aggregate basis is available to all firms, all firms can engage in some minimal level of screening. However, within each class, there will also be a distribution of risks, and one would expect large firms to generate the loss cost data necessary to screen risks within driver classes. Classes 01 and 02 are the largest, with over 70 percent of all cars insured. Evidence of screening should be found for these classes. Other classes for which evidence of screening might be obtained are 03, 07, and 19 since they each have over four percent of cars insured. The next section estimates an econometric model for each driver class in order to determine whether the data are consistent with screening within driver classes.

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[8] With respect to differences in screening ability between direct writers and agency firms, Joskow (1973) suggested that direct writers would be more effective screeners than agency firms. This implies that direct writers should be closer to the size implied by theory, that is, equation (5) should hold more accurately for direct writers than for other firms. This implies a smaller error variance for direct writers (i.e., heteroskedasticity) which is accounted for in the estimation by using White (1980) standard errors.

[9] Because driver class 04 was dropped in 1981, it is not included in the empirical analysis.

Table 1
Definitions and Relative Sizes of Driver Classes in Alberta (1981)

Driver Class Definitions	*Proportion of Cars Insured in Territory 1*
Pleasure—No males under 25, no unmarried males ages 25-29 who are principal operators, no female operators under 25, no unmarried female occasional operators under 25	
Class 01—No driving to work; annual mileage of 10,000 or less; two or fewer operators per automobile who have held valid operator licenses for at least the past three years	0.36680
Class 02—Drive to work ten miles or less one way permitted; unlimited annual mileage; two or fewer operators per automobile	0.33780
Pleasure—No males under 25; no female principal operators under 25	
Class 03—Drive to work over 10 miles permitted; unmarried female occasional drivers under 25 may drive; no unmarried male principal operators ages 25-29	0.04350
Class 04[a]—Unmarried male principal operator age 25 through and including age 29; no male driver under age 25	—
Pleasure or Business	
Class 06—Occasional male driver use—male under 25 (the principal operator insures the automobile for use by all other drivers under class 01, 02, 03, 04, or 07)	0.02120
Class 07—Business primarily; no male drivers under age 25	0.53500
Principal operators under 25 years of age	
Married male	
Class 08—ages 20 and under	0.00170
Class 09—ages 21, 22, 23, and 24	0.02160
Unmarried male	
Class 10—ages 18 and under	0.01440
Class 11—ages 19 and 20	0.02210
Class 12—ages 21 and 22	0.02830
Class 13—ages 23 and 24	0.02690
Female—married or unmarried	
Class 18—ages 20 and under	0.02230
Class 19—ages 21, 22, 23, and 24	0.04040

Source: Driver class definitions were obtained from the Insurance Bureau of Canada, *Automobile Insurance Experience* (Green Book). Proportions of cars insured were calculated from unpublished data provided by the Insurance Bureau of Canada.

[a] Driver class 04 was dropped in 1981. Prior to 1981, approximately 2 percent of cars insured were in this class.

To conduct the test for screening, data are required on the number of cars insured by firm and by driver class, and the associated loss costs. Complete data on cars insured and losses were available for 15 firms in Territory 1 covering the period 1979 through 1981 and for nine other firms covering the three-year period 1978 through 1980. Because any one year's loss cost experience could be anomalous and distort the true underlying long-run loss cost of the firm (especially the smaller firms), the regression analysis of the next section uses the average loss cost and average number of cars insured over the available three-year period.

The 24 firms in the sample represent 22 percent of the 111 firms that sold BIPD insurance in Alberta in 1981. They were also responsible for 44.6 percent of the net premiums written in that year. The sample is thus weighted toward the larger firms, since these are the ones that tended to report detailed loss cost data to the Alberta Automobile Insurance Board. Only three of the firms in the sample used premiums recommended by the IAO. The other firms were large enough to seek approval for their premiums based on their own loss cost experience.

Loss cost data are also available by driving record (i.e., zero, one, two, three, and five years of claim-free driving). Although ideally one would like to conduct separate tests of the model for each driving record within each driver class, there are too few observations in the zero, one, and two years of claim-free driving categories to run separate regressions. Therefore, these categories have been aggregated with the three years of claim-free driving category, and separate tests are run for the five-year and zero-to-three year categories.[10]

Table 2 contains descriptive statistics on cars insured (q) and loss costs per car insured (ℓ). The number of observations, mean, median, standard deviation, and maximum value of each variable are reported by class and driving record. (Class 015 is the five-year claim-free driving record in driver class 01, class 013* is the zero, one, two, and three years of claim-free driving records in driver class 01, etc.). Note that the number of firms insuring drivers in a given class varies across classes and that some classes are very small (e.g., class 085 has about three cars insured per firm), while some are quite large (e.g., class 015 has over 3,400 cars insured per firm). Not surprisingly, the small classes do not yield results consistent with screening.

[10] The regression results for the three-year claim-free driving record category by itself differ somewhat from the results when the zero-, one-, two-, and three-year driving records are aggregated. However, the qualitative results only change for classes 09 and 12.

Table 2
Descriptive Statistics on the Number of Cars Insured (q) and the Loss Cost per Car Insured (ℓ)

Variable	*Class*	*Number of Firms*	*Mean*	*Median*	*Standard Deviation*	*Maximum*
q	015	24	3409.1	1293.0	4554.9	19491.0
ℓ	015	24	88.3	77.4	43.1	221.3
q	013*	24	646.6	291.7	855.1	3143.1
ℓ	013*	24	126.2	116.1	66.6	327.8
q	025	24	3039.3	1060.0	4522.5	19819.0
ℓ	025	24	103.2	94.5	45.2	188.6
q	023*	24	873.8	343.1	1344.9	5672.0
ℓ	023*	24	168.0	135.8	138.8	691.9
q	035	23	394.0	149.7	734.8	3527.3
ℓ	035	23	97.1	83.6	76.0	315.4
q	033*	23	130.5	48.0	194.2	797.3
ℓ	033*	23	128.0	121.4	98.6	452.9
q	065	21	39.7	4.7	75.3	305.3
ℓ	065	21	42.2	0.0	67.6	231.8
q	063*	22	173.9	79.3	193.8	633.0
ℓ	063*	22	96.1	44.4	142.7	550.4
q	075	24	476.2	225.7	669.1	2984.0
ℓ	075	24	88.9	85.7	39.4	158.2
q	073*	23	146.8	50.6	215.1	864.4
ℓ	073*	23	152.0	126.8	110.6	577.1
q	085	18	3.1	1.3	4.7	18.7
ℓ	085	18	74.2	0.0	236.0	996.5
q	083*	22	21.0	11.0	24.0	92.7
ℓ	083*	22	289.0	153.5	418.1	1614.7
q	095	23	156.7	54.3	205.4	819.7
ℓ	095	23	195.5	126.0	273.6	1303.0
q	093*	23	116.5	44.0	144.2	536.7
ℓ	093*	23	223.7	138.1	182.4	642.3
q	105	16	21.1	2.3	44.2	137.0
ℓ	105	16	223.0	43.0	493.7	1982.3
q	103*	23	144.6	78.7	169.2	608.7
ℓ	103*	23	634.2	350.6	650.7	2554.6
q	115	18	44.6	6.7	103.8	405.0
ℓ	115	18	265.5	35.6	509.2	2004.0
q	113*	24	183.1	51.7	214.9	700.3
ℓ	113*	24	272.1	250.0	170.4	674.5
q	125	22	124.3	35.7	148.3	532.3
ℓ	125	22	376.2	139.9	1023.7	4934.5
q	123*	24	145.7	51.0	182.4	702.6
ℓ	123*	24	337.5	197.7	555.3	2845.1

(continued)

Table 2 (continued)

Variable	*Class*	*Number of Firms*	*Mean*	*Median*	*Standard Deviation*	*Maximum*
q	135	23	145.1	35.3	168.0	576.3
ℓ	135	23	212.2	121.2	218.5	694.0
q	133*	22	109.1	52.7	130.9	495.3
ℓ	133*	22	162.4	135.8	120.9	349.8
q	185	22	29.8	4.3	60.8	258.0
ℓ	185	22	99.9	26.4	211.6	974.3
q	183*	24	188.7	129.6	200.5	588.7
ℓ	183*	24	200.5	180.8	143.7	735.0
q	195	23	207.4	97.0	239.6	929.3
ℓ	195	23	112.8	93.2	72.1	289.2
q	193*	24	165.6	64.7	190.0	662.3
ℓ	193*	24	128.5	109.5	97.1	396.8

Note: An asterisk on a driver class indicates that that class contains the zero, one, two, and three years of claim-free driving records; those classes without asterisks contain only the five years of claim-free driving records. See Table 1 for driver class definitions.

Estimation and Results

Equations (2), (3) and (4) imply the following system of simultaneous equations:

$$q_{ij} = \alpha_{0j} + \alpha_{1j}z_{ij} + \alpha_{2j}\theta_{ij} + \alpha_{3j}\theta_{ij}^2 + \varepsilon_{1ij} \quad (7)$$

$$z_{ij} = \beta_{0j} + \beta_{1j}q_{ij} + \beta_{2j}L_{ij} + \varepsilon_{2ij} \qquad j = 015, 013*, \ldots, 195, 193* \quad (8)$$

$$L_{ij} = \delta_{0j} + \delta_{1j}\theta_{ij} + \delta_{2j}\theta_{ij}^2 + \varepsilon_{3ij} \quad (9)$$

where q_{ij} = the number of cars insured by firm i in risk class j,
θ_{ij} = the screening standard employed by firm i in risk class j,
z_{ij} = the premium charged by firm i in class j,
L_{ij} = the loss cost per car insured of firm i in class j relative to the market,
ε_{1ij}, ε_{2ij}, and ε_{3ij} = disturbance terms, and

an asterisk on a risk class indicates that it includes zero, one, two, and three years of claim-free driving. The three endogenous variables in the system are q_{ij}, z_{ij}, and L_{ij}, and the exogenous variables are θ_{ij} and θ_{ij}^2. Equation (7) follows from equation (2) and states that the number of cars insured is a linear function of premiums and a nonlinear function of the screening standard. Equation (8) follows from equation (4), except that z_{ij} has been made a function of q_{ij} since larger firms are expected to be more effective screeners and therefore charge lower premiums.[11] Equation (9) is based on equation (3) and states that loss costs relative to the market are a nonlinear function of the screening standard.

Equations (7) and (9) are underidentified. However, the parameter estimates of the structural model are not of interest in this study. Rather, interest is centered on the effect of screening on firm size. This can be obtained from estimating the following reduced form equation that corresponds to equation (5) from the theory:

$$q_{ij} = \gamma_{0j} + \gamma_{1j}\theta_{ij} + \gamma_{2j}\theta_{ij}^2 + \varepsilon_{ij} \qquad j=015,013*,\ldots,195,193*. \tag{10}$$

The screening standard employed by the firm is θ_{ij}, which is defined as the maximum expected loss cost that a firm will accept. The screening standard θ_{ij} is not observed, but if a firm has a low θ_{ij}, and is large enough to implement its screening standard, then its loss costs are expected to be low. Therefore, the relationship between q_{ij} and θ_{ij} can be estimated by using observed loss cost per car insured, ℓ_{ij}, as a proxy for θ_{ij}.[12]

Equation (10) is estimated for each risk class separately using ordinary least squares (see Table 3). The t-statistics are calculated using robust standard errors (see White, 1980) in order to account for the heteroskedasticity that is present in the data. The results show that the relationship between q_{ij} and ℓ_{ij} is significant and shaped like a parabola for four of the five largest driver classes (i.e., classes 01, 02, 03, and 19). This result supports the theory, given that firms are expected to be able to screen when they have sufficient loss cost data. Figure 2 illustrates for class 03 drivers how closely the estimated rela-

[11] That premiums are a function of losses relative to the market follows from the fact that Alberta has a prior approval regulatory system. Under this type of premium regulation, according to Joskow (1973), rating bureaus are usually authorized to make and file rates, rate changes, rating schedules, etc., for their member and subscriber companies. (This is the case in Alberta. See Section 343 of Alberta's Insurance Act.) Insurers not wishing to use the bureau rates could file deviated rates for one or more classes of insurance or they could submit an independent filing. With respect to deviations, the deviating company has to justify its rate deviations by showing that its reduced rates are justified by lower costs than for the industry as a whole. Ippolito (1979) and Smallwood (1975, pp. 247-248) also discuss the rate deviation procedure and the requirement that firms justify lower rates on the basis of lower costs.

[12] This choice of a proxy will generate a simultaneous equation bias if the observed losses are endogenous. However, because we cannot obtain data on θ_{ij}, there appears to be no solution to this problem in our case. Still, if firms are successful screeners, the screening standard should be quantitatively similar to loss costs per car insured; if they are not successful screeners, the estimated model using ℓ_{ij} as a proxy for θ_{ij} should be rejected.

As noted by a referee, direct writers are known for lower operating expenses, and thus lower premium mark-ups relative to expected losses. This implies that insurance premiums will depend on whether an insurer is a direct writer or agency firm, holding L_{ij} fixed, and firm size will be affected as a result. To assess the impact of direct writing on the relationship between firm size and screening, the reduced form equation (10) should be estimated separately for direct writers and agency firms. However, data limitations do not permit these separate regressions to be estimated. Deleting the direct writers leads to results that are qualitatively the same as the results reported in Table 3.

Table 3
Estimates of the Cars Insured—Loss Cost Regression

Class	*Intercept*	ℓ_{ij}	ℓ^2_{ij}	*MAX*	*Threshold*
015	1775.70	49.053	-0.2817	87.08	2
	(0.81)	(1.42)	(-2.05)		
013*	202.10	8.648	-0.03205	134.91	2
	(1.01)	(2.32)	(-2.50)		
025	560.82	74.967	-0.41713	89.86	1
	(0.49)	(2.34)	(-2.38)		
023*	151.07	7.583	-0.01181	321.11	3
	(0.67)	(2.43)	(-2.65)		
035	24.81	8.188	-0.02847	143.81	2
	(0.31)	(2.61)	(-2.49)		
033*	9.63	1.712	-0.00383	223.54	2
	(0.40)	(2.91)	(-2.82)		
065	23.75	0.706	-0.00226	156.36	3
	(2.05)	(1.03)	(-0.62)		
063*	123.36	1.225	-0.00234	261.30	1
	(2.35)	(1.10)	(-1.18)		
075	13.00	10.164	-0.04689	108.40	2
	(0.13)	(1.44)	(-0.90)		
073*	43.21	1.179	-0.00217	271.54	1
	(0.54)	(1.29)	(-1.58)		
085	2.60	0.033	-0.00003	495.52	3
	(3.22)	(0.83)	(-0.083)		
083*	8.55	0.089	-0.00005	839.96	2
	(2.14)	(2.88)	(-2.64)		
095	181.91	-0.112	-0.00003	N.A.	2
	(2.60)	(-0.31)	(-0.012)		
093*	29.41	0.928	-0.00147	315.20	2
	(0.72)	(2.13)	(-2.27)		
105	15.00	0.085	-0.00005	917.53	1
	(1.19)	(0.82)	(-0.90)		
103*	24.94	0.383	-0.00016	1192.34	3
	(0.59)	(2.27)	(-2.62)		
115	3.50	0.380	-0.00019	1002.01	1
	(0.37)	(2.84)	(-2.64)		
113*	-31.37	1.2384	0.00121	512.07	3
	(-0.96)	(2.99)	(-1.76)		
125	106.03	0.154	-0.00003	2218.69	1
	(2.13)	(0.62)	(-0.71)		
123*	95.89	0.282	-0.00011	1274.20	3
	(1.70)	(0.96)	(-1.13)		
135	4.39	1.446	-0.00183	394.89	2
	(0.11)	(3.12)	(-2.39)		
133*	-3.79	2.294	-0.00559	205.10	3
	(-1.37)	(2.70)	(-2.35)		

(continued)

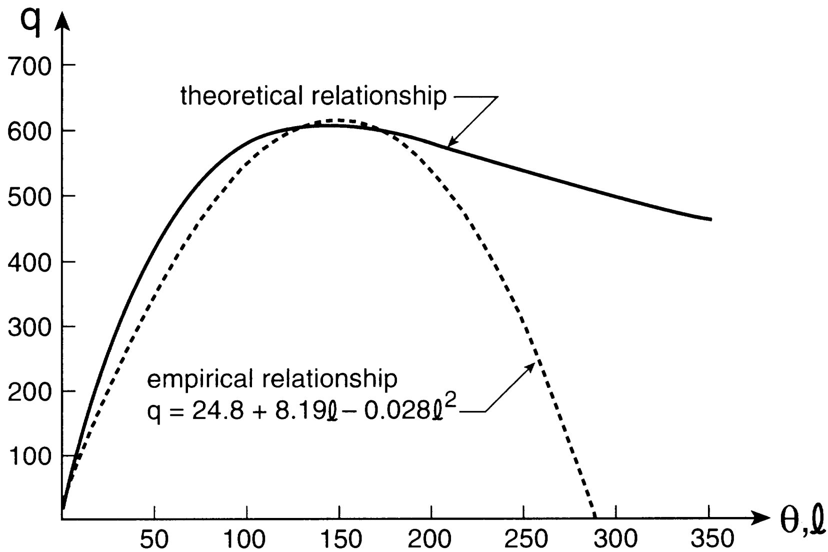
Table 3 (continued)

Class	*Intercept*	ℓ_{ij}	ℓ^2_{ij}	*MAX*	*Threshold*
185	17.46	0.293	-0.00032	457.96	3
	(1.81)	(1.69)	(-0.176)		
183*	23.00	1.454	-0.00210	346.62	2
	(0.50)	(3.01)	(-3.55)		
195	80.60	2.571	-0.00922	139.39	1
	(0.70)	(1.60)	(-1.94)		
193*	-5.71	2.839	-0.00757	187.44	3
	(-0.16)	(3.52)	(-3.55)		

Note: T-statistics are in parentheses. The variable ℓ_{ij} is the loss cost per car insured by firm i in class j. The dependent variable in the regression is the number of cars insured by firm i in class j. The MAX column reports the ℓ that maximizes q based on the estimated model. The Threshold column indicates the number of small firms (i.e., the five firms insuring less than 750 cars per year) appearing in the "left tail" of the parabola (i.e., the seven lowest loss costs of the firms in the regression). An asterisk on a driver class indicates that that class contains the zero, one, two, and three years of claim-free driving records; those classes without asterisks contain only the five years of claim-free driving records. See Table 1 for driver class definitions.

Figure 2

Theoretical and Empirical Relationships for Class 035



Note: Θ = the screening standard, ℓ = loss cost per car insured, and q = the number of cars insured. The theoretical relationship was plotted assuming that the distribution of expected loss costs is exponential: $f(c) = \frac{1}{\mu} e^{-\frac{c}{\mu}}$, c>0. $\bar{R}$ = 135.36 = the average premium charged by all firms in the sample, μ = 94.47 = average loss cost per car insured for the 23 firms in the sample, M = 9,063 = the number of cars insured by the 23 firms in the sample, N = 23 = the number of firms in the sample, and Y = 30 = average cost of a price search by drivers in Class 01 in 1980, estimated by Dahlby and West (1986).

tionship is to the theoretical relationship based on parameter values calculated from class 03 driver data.

With respect to the smaller classes, as expected on the basis of Boyer and Dionne (1989), the results are mixed. The results for classes 11, 13, and 18 support the theory even though they contain only 2.2, 2.7, and 2.2 percent of cars insured in 1981, respectively. Classes 08, 09, and 10 yield mixed results in that the aggregated driving records support the theory, while the results for the five years of claim-free driving record do not. Classes 08, 09, and 10 have 0.2, 2.1, and 1.4 percent of cars insured in 1981, which makes them the smallest driver classes. Results for classes 06 and 12 are not significant, and both classes are relatively small.

The MAX column of Table 3 reports the ℓ that maximizes q based on the estimated model. To the left of MAX, increasing screening reduces firm size; to the right of MAX, reducing the stringency of the screen also reduces firm size. For the five largest driver classes, the MAX for the five-year claim-free driving record is less than the MAX for the zero to three years of claim-free driving record. In other words, the low-risk driver class/driving record drivers have lower losses on average. Also, the high-risk classes have higher MAXs in general. For example, class 125 has a MAX of 2,218.69 whereas class 015 has a MAX of 87.08. These results follow from the fact that, theoretically, MAX=(2Y+R)/t, so as R decreases, which it does for lower risk driver classes and driving records, MAX is expected to decrease.

The Threshold column of Table 3 indicates the number of "small" firms (i.e., the five firms insuring less than 750 cars per year) appearing in the "left tail" of the parabola (i.e., the seven lowest loss costs of the firms in the regression). While few small firms are expected to be found in the left tail because they lack the loss experience data to implement a screening standard, some very small firms might appear there by chance or if they are able to screen on the basis of information acquired from external sources. There are in fact one to three small firms in the left tail of the parabola for each driver class. Thirty-four of the 54 tail observations can be attributed to firms that insured less than ten drivers in the class and happened to experience no claims.

To account for the possibility that the residuals from the ordinary least squares regressions might be correlated across equations, the equations behind Table 3 were reestimated using a seemingly unrelated regression model. The results were similar.[13] However, because classes 085, 083*, 105, 103*, 115, and 113* are so small that only 11 firms insure in all these classes, these six equations had to be eliminated from the model, leaving a seemingly unrelated regression model with 20 equations and 21 observations per equation. To summarize the results, only the equations for classes 013* and 095 gave coefficients of the wrong sign, and of the remaining 18 equations, only class 075 gave insignificant results. Also, the screening standards that maximized firm size were very close to those implied by the ordinary least squares regressions. In fact, only four of the 20 classes gave MAX values that deviated by more than 10 percent from those implied by the ordinary least squares results. So the

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[13] The results are available from the authors.

conclusion from the seemingly unrelated regression model is the same as that from the ordinary least squares model--in general, the large classes provide support for the theory, while, as expected, nothing can be said about the small classes.[14]

Conclusion

This article has tested one of the principal implications of a simple model of screening in an automobile insurance market: that large firms will be more effective screeners than small firms. The Carlson and McAfee model of price dispersion was modified to allow for screening, and this permitted a derivation of the relationship between cars insured by a firm and the stringency of the screen (i.e., the expected loss costs above which a firm will not insure a driver). Although the theory suggests that some screening firms will be relatively small if they can estimate a driver's expected loss cost, it is argued that large firms are in a better position to generate sufficient firm-specific data to allow them to estimate expected loss cost. This prediction is tested by conducting a regression analysis of cars insured (i.e., firm size) and loss costs per car insured for different driver classes in urban Alberta. A parabola-shaped relationship is expected between these two variables for the larger driver classes, and the empirical results are generally consistent with our expectations.

Thus, the results on firm size and screening are consistent with those obtained by Barron, Bishop, and Dunkelberg (1985) and Barron, Black, and Loewenstein (1987), who also found that larger firms were more extensive screeners. And just as screening firms were found to pay higher wages in the Barron et al. studies, perhaps because screeners hire more able workers, larger (screening) insurers tend to charge lower premiums, perhaps because they achieve lower loss costs per car insured.[15] The results in this study suggest that screening complements costly consumer search as an explanation for price dispersion.

Finally, Barron, Black, and Loewenstein (1987) raised the possibility that the larger employers' policy of screening workers more intensively might become known to job applicants, thus increasing the proportion of high-ability workers in their applicant pool. Similarly, screening insurers could advertise the stringency of their screens in an effort to increase their pool of low-risk drivers that apply for insurance. Future empirical work could investigate the relationship between loss cost per car insured and insurer advertising to see if there is some empirical support for this hypothesis.

[14] Classes 08, 10, and 11 are three of the five smallest classes.

[15] The firm size-premiums regression results are available from the authors upon request. Dahlby and West (1986) also found that, for a number of driver classes, the firm's relative market share varied inversely with the deviation of the firm's premium from the average premium for that class.

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