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ASYMMETRIC INFORMATION AND LEARNING IN THE AUTOMOBILE INSURANCE MARKET

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Asymmetric Information and Learning in the Automobile Insurance Market

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Abstract

This paper tests the predictions of adverse selection models using data from the automobile insurance market. In contrast to what recent research has suggested, I find that the evidence is consistent with the presence of informational asymmetries in this market: higher insurance coverage is correlated with more accidents. Consistent with the presence of learning by policyholders about their risk type, such a coverage correlation exists only for policyholders who have had three or more years of driving experience prior to joining their insurer. Consistent with the presence of learning by insurers about repeat customers, I find that, as the experience of the insurer with a group of policyholders increases, the coverage-accidents correlation declines in magnitude and eventually disappears. Finally, consistent with insurers' having more information about their repeat customers than would be available to other insurers, I find that policyholders who leave the insurer are disproportionately ones with a poor claims history with the insurer, and that insurers make higher profits on repeat customers than on new customers.

JEL classification: D40, D80, D82, D83, L10, G22.
Keywords: Asymmetric information, adverse selection, screening, sorting, moral hazard, insurance, deductible, learning, information transmission, repeat customers.

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1 Introduction

Ever since the seminal works of Akerlof (1970) and Rothschild and Stiglitz (1976), economic theorists have devoted much effort to developing models of adverse selection. This paper seeks to test the predictions of these models using data from the market for automobile insurance.

The paper uses a unique and rich data set that I obtained from an insurer operating in the automobile insurance market in Israel. Because the data includes *all* the information known by the insurer about its policyholders, it is especially fitting for studying adverse selection. The data includes the insurer's information about more than 200,000 policies issued during a five-year period. In particular, the data contains (i) all the characteristics (including past claims history) of policyholders known to the insurer, (ii) the price-deductible menus offered to policyholders and the choices made by them, and (iii) the claims and payments resulting from each policy.

When policyholders have private information about their risk type, adverse selection models predict that high-risk types will purchase higher insurance coverage. Consistent with this prediction, I find that policyholders with low deductibles are associated with more accidents and higher total losses to the insurer.

I also find that subsets of the pool of all policies differ systematically in how strong the correlation is (or even in whether it exists). The identified differences are consistent with the presence of learning by policyholders and by insurers.

As to the learning by policyholders, I find that, for policyholders with little or no driving experience, low deductibles are not associated with more accidents. Such policyholders might have had relatively little opportunity to obtain private information about their risk type and thereby to gain an informational advantage over the insurer. However, such an association does exist for policyholders that have sufficient driving experience. Furthermore, driving experience prior to joining the insurer might be especially helpful in providing policyholders with an informational advantage over the insurer; consistent with this possibility, I find that the coverage-accidents correlation exists only for policyholders who had three or more years of driving experience prior to joining the insurer.

As to the learning by the insurer, I find evidence that the correlation between low deductibles and more accidents is especially strong for new customers or ones who have been with the insurer for a relatively short period. For repeat customers, this correlation diminishes in magnitude over time and eventually disappears.

Theory Society. I also wish to thank the IDI Company for the data and Shai Fogel, its CEO, for very helpful discussions about the company and its market.

When a policyholder has stayed with the insurer for a sufficiently long period, the insurer's experience with the policyholder might erode whatever informational advantage the policyholder might have had when joining the insurer.

The above findings concerning a coverage-accidents correlation address questions raised by recent research. Chiappori and Salanie (2000) suggest that the evidence is inconsistent with a coverage-accidents correlation in the market for automobile insurance. Also studying this market, Dionne, Gouriéroux and Vanasse (2001) suggest that the evidence is inconsistent with residual adverse selection in each of the risk classes formed on the basis of parameters known to the insurer. The findings of these studies have already had a significant impact. In the materials accompanying the award of the Nobel Prize for work on asymmetric information, the Swedish Royal Academy of Science (2001) cited the Chiappori - Salanie findings as a reason for viewing the evidence on the presence of asymmetric information in markets as "mixed." These findings also provided motivation for the recent work of De Meza and Webb (2001), who develop a model of insurance markets with asymmetric information that does not predict an association between insurance coverage and accidents.

In contrast to this recent empirical work, using a data set that is more complete than the data used in prior work, I obtain robust results that are overall consistent with the coverage-correlation prediction of classic adverse selection theory. My findings confirm that such correlation does not exist for the subset of policies on which the Chiappori-Salanie study focused – those sold to policyholders with less than three years of driving experience. My findings, however, also indicate that this result does not carry over to policyholders with three or more years of driving experience who account for a substantial majority of all policyholders.

In addition to investigating informational asymmetries between policyholders and their insurer, I also examine whether insurers obtain an informational advantage with respect to their repeat customers over rival insurers. In the insurance market that I study, as is the case in the US, when a policyholder switches to a new insurer, the new insurer would not receive from the current insurer information about the priori insurer's experience. The information that the new insurer would have – from the customer's own reporting, from inferences drawn from the customer's making a switch, or from public sources – can be expected to be less complete than the claim history information possessed by the current insurer. I find that the evidence is indeed consistent with such differences in information among insurers.

In particular, I find that the performance of switchers is worse than what would be predicted if their self-reports of past claims were assumed to be as reliable as the insurer's records about its own repeat customers. Also, I find that policyholders who leave the insurer are disproportionately ones who had a bad record with the insurer and who thus could benefit from switching to an insurer that would know less about them. Policyholders who remain with the insurer, in turn, are disproportionately ones with a good past claims record and ones that subsequently perform better than new customers. Furthermore, consistent with insurers' obtaining private information and thus market power with respect to repeat customers with good records, I find that the insurer makes higher profits on repeat customers than on new customers.

It should be noted that, while a coverage-accidents correlation is consistent with adverse selection models, it is also consistent with moral hazard models. Under a moral hazard story, a correlation between low deductibles and more accidents can be expected because policyholders with higher insurance coverage will have lower incentive to take precautions. Thus, my findings concerning the existence of coverage-accidents correlation indicate only that the presence of adverse selection cannot be rejected. Because adverse selection and moral hazard both produce a correlation between coverage and accidents, disentangling them empirically is widely viewed as difficult (Royal Academy of Science (2001)). Putting aside the coverage-accidents correlation, which can be easily explained under both adverse selection and moral hazard stories, some of my other findings concerning the dynamics of behavior over time do not appear readily explainable by a standard moral hazard story. Disentangling adverse selection and moral hazard, however, is beyond the scope of the present study.

The analysis of this paper is organized as follows. Section 2 describes the predictions of adverse selection models that I will test. Section 3 discusses prior empirical work. Section 4 describes the data used for the study. Section 5 conducts tests concerning the prediction of coverage-accidents correlation. Section 6 tests various predictions concerning learning and behavior over time. Finally, Section 7 concludes.

2 Tested Predictions

2.1 Coverage-Accidents Correlation

As is common, the insurer whose data I use offers a menu with different levels of deductible (and associated levels of premium). Policyholders that choose different deductibles must be different. They might differ in their risk-aversion,[1] and such

[1] One possible reason for having deductibles is to eliminate coverage for small claims that would produce administrative costs (which are ultimately borne by policyholders) but would

differences would not affect the costs of their policies to the insurer. They also might differ in the risks that they face; such differences in risk, of course, would affect the costs of their policies to the insurer.

The coverage choices made by individuals that have private information about their risk type have been studied by the seminal work of Rothschild-Stiglitz (1976) and subsequent work (e.g., Riley (1979), Spence (1978), Miyazaki (1977), Wilson (1977), and Grossman (1979)).[2] One basic prediction of these models is that, in the presence of such private information, a menu of different deductibles will result in sorting, with high-risk policyholders more likely to choose low deductibles.[3] I therefore will test the following hypothesis:

H1: *Policyholders that choose lower deductibles will be associated with more accidents.*

2.2 Learning and Policyholders' Informational Advantage over the Insurer

The prediction of a coverage-accidents correlation arises from models that assume that policyholders have an informational advantage over the insurer with respect to the policyholders' risk type. Whether and to what extent such informational asymmetries exist might well depend on the learning of information by the policyholder and by the insurer over time.

One type of possible learning is by policyholders. While nature accurately knows any individual's risk-type, the individual might well be imperfectly informed about this risk-type when getting a driving license. It is plausible to assume that there is a limit to how much an individual can learn about the individual's risk-type by mere introspection, i.e., without actual experience with driving. Thus, the more driving experience a policyholder has, the more information the policyholder is likely to obtain about the policyholder's risk type. Thus, other things equal (including how long policyholders have been with the insurer), the more driving experience a group of policyholders has, the more likely it is that the group will exhibit a coverage-accidents correlation.

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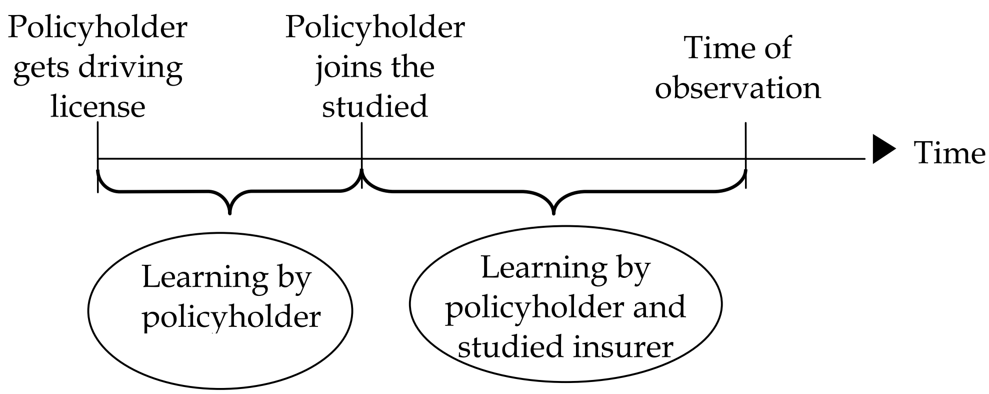
provide only minimal benefit in terms of saving risk-bearing costs to the policyholder. Focusing solely on considerations of risk-bearing costs and administrative costs, the greater an individual's degree of risk-aversion, the lower the optimal deductible for this individual.

[2] For excellent recent surveys of adverse selection models, see Riley (2001), who surveys such models in general, and Dionne, Doherty, and Fombaron (2000), who focus on adverse selection models of insurance markets.

[3] These models also analyze the optimal choices of menus that insurers will make in equilibrium. The prediction that a menu will result in high-risk types choosing more coverage will arise, however, even if the menus offered are not optimally set.

I just discussed the potential effect of the policyholder's driving experience holding constant other variables including the experience of the insurer with the policyholder. This suggests that it is useful to distinguish, as is done in the diagram below, between two periods: (i) the period (if any) during which a policyholder was driving prior to joining the insurer – i.e., during which the policyholder gained experience with driving but without the insurer gaining experience with the policyholder, and (ii) the period (if any) during which the policyholder has been with the insurer – i.e., during which both the policyholder has been gaining driving experience and the insurer has been obtaining experience with the policyholder.



During the first period (i) in which the policyholder drove prior to joining the insurer, the realization of risks produced by the policyholder's driving was observed by the policyholder – and often also by the policyholder's insurer at the time (as will be presently discussed) – but not by the studied insurer. As will be discussed below, in the market I study (and often in other insurance markets as well), insurers generally do not get – either from prior insurers of new customers or from self-reporting by such customers – a complete and accurate picture of the past claims history of these customers. Thus, driving experience during the period prior to joining the insurer might provide the policyholder with an informational advantage over the insurer. The more driving experience a new policyholder had before joining the insurer, the greater the likely asymmetry of information between the policyholder and the insurer. Accordingly, the hypothesis that I will test is:

H2: *The more experience a group of policyholders had prior to joining the insurer, the stronger (or more likely to exist) the correlation in this group between low deductibles and more accidents.*

During the second period – the period if any between the time in which the policyholder joined the insurer and the time of observation -- information about the realization of risks has flown to both the policyholder and the insurer. Although there might be some private information received by the policyholder even during this period, existing models have assumed that new information arriving during this period has been by and large observed by both the policyholder and the existing insurer (see, e.g., Kunreuther and Pauly (1985), Watt and Vazquez (1997)). Under this assumption, the Bayesian updating that each side will do will work to reduce whatever informational asymmetry the policyholder had when joining the insurer. The reason for this is that, when a policyholder has an informational advantage when joining the insurer, the informational benefit from observing the subsequent realization of risks will be greater for the insurer than for the policyholder. Indeed, assuming that after a policyholder joins an insurer they both observe all realization of risks, Watt and Vazquez (1997) prove that, for any given informational asymmetry that the policyholder has when joining, the asymmetry will go to zero after a sufficiently long period with the insurer.

Thus, under the considered story, the longer the period that a group of policyholders has been with the insurer, the less likely it is that policyholders will have an informational advantage over the insurer even if they had such an advantage when joining the insurer. Accordingly, the hypothesis that I will test is:

H3: *The more experience the insurer has had with a group of policyholders, the weaker (or less likely to exist) the correlation in this group between low deductibles and more accidents.*

2.3 Learning and Differences in Information among Insurers

The information that an insurer learns about its repeat customers might create a difference in information between the insurer and other insurers to which these customers might subsequently turn. Of course, if the repeat customer does turn to another insurer, this other insurer will ask the customer to report past claim history. However, there is evidence that such self-reporting is often substantially incomplete or inaccurate (Insurance Research Council (1991)). Furthermore, there is evidence that most of the accidents for which claims are submitted do not appear in public records and new insurers thus cannot learn about them from inspecting public records (Insurance Research Council (1991)). Finally, in the Israeli market I study, as in the US market, insurers do not provide information about their experience with policyholders to other insurers.[4] Therefore, a new insurer would likely have an

[4] Fombaron (1997b) and de Garidel (1997) study the difference between the cases in which insurers are and are not required to provide a new insurer with all the information that they have with respect to departing customers, and they also examine the desirability of requiring

informational disadvantage compared with a repeated customer's incumbent insurer.

To be sure, a new insurer could draw inferences from the fact that a new customer has decided to switch from the customer's prior insurer. If all switchers were ones with a bad record, the insurer could have inferred that such a switcher must have such a record. But in a world in which some policyholders change insurers for other reasons (say, relocation or dissatisfaction with some services of the insurer or the intermediating insurance agent), an insurer generally would not be able to infer fully a new customer's past claims record from the customer's decision to switch. In particular, when a customer who in fact has a bad past record switches to another insurer, this other insurer would not be able to tell for sure that whether the switch has been motivated by the customer's bad past record or by other reason.

This adverse selection story with informational differences among insurers yields several testable hypotheses. To start, this story implies that reports of past claims provided by policyholders switching to the insurer from other insurers will be less complete than the records that the insurer has about the past claims of its repeat customers. Accordingly, I will test the following hypothesis:

H4: *New customers who report a given past claims history will perform in the future less well than repeat customers for whom the insurer has observed such a past claims history.*

Furthermore, although some policyholders will leave the insurer each year for reasons that have nothing to do with their record with the insurer, some will leave because of the poor record they have with the insurer. Because new insurers will be unable to tell that a switch was motivated by such a poor record, customers with a bad record with an insurer might have something to gain from switching to a new insurer. Accordingly, I will test the following hypothesis:

H5: *Policyholders that leave the insurer will be disproportionately ones with a poor past claims record.*

2.4. Learning and the Pricing of New and Repeat Customers

Turning to the subject of the pricing of customers over time, note that substantial work has been done on developing multi-period models of adverse selection. Some of these models have focused on the optimal design of policies that

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insurers to do so. In the market under consideration, such a requirement is not established by law or by agreement among insurers, and insurers do not share information about customers.

commit customers to a multi-period contract (e.g., Dionne (1983), Dionne and Lasserre (1985), Cooper and Hayes (1987)) or that involve a one-sided commitment of the insurer to offer the policyholder certain terms in subsequent periods (Dionne and Doherty (1994), De Garidel (1997)). Although such policies are observed in certain countries (see, e.g., Dionne and Vanasse (1992)), many insurance markets use only one-period policies that involve no commitments on the part of either the customer or the insurer (Kunreuther and Pauly (1985)). In particular, this is the case for all the insurers operating in the Israeli automobile insurance market, including the insurer whose data I study.

For our purposes, then, the relevant models are the "no-commitment" models that were developed by Kunreuther and Pauly (1985), Fombaron (1997), and Nilssen (2000). The informational advantage that insurers obtain over competing insurers with respect to their repeat customers, which was discussed earlier, plays an important role in these models. When an insurer has an informational advantage over rival insurers with respect to the insurer's repeat customers, the insurer will have market power with respect to repeat customers that the insurer has identified to be low-risk types. As a result, the insurer will be able to charge these customers more than the break-even price reflecting their low risk, as these customers will be unable to obtain this break-even price from other insurers to which the customers' low-risk type would not be known for sure.

Relatedly, the above dynamic models also predict *lowballing* with respect to new customers. When a new customer joins an insurer, the insurer will anticipate the possibility of charging more than the break-even price down the road in the event that the customer turns out to be a low-risk type. Therefore, the insurer might be willing to charge new customers in their first period less than the break-even price reflecting their risk.

Insurers thus can be expected to over-charge repeat customers (relative to the price that would reflect their risk according to the insurer's information) and, furthermore, might under-charge new customers (compared with the price that would reflect their risk). Therefore, insurers can be expected to make higher profits – and therefore have a lower loss ratio (i.e., ratio of insurance payments to premia)[5] – on repeat customers than on new customers. This yields the last hypothesis that I will test:

H6: *The insurer's loss ratio will be lower for repeat customers than for new customers.*

[5] Loss ratio is the standard measure of profitability of policies used by insurers. The loss ratio on a given policy is equal to the insurer's total payments for claims arising from the policy divided by the total premium received from the policyholder. (See Appendix II for a formal specification.)

3 Prior Empirical Work

3.1 Existence of Asymmetric Information

Evidence consistent with adverse selection and coverage-risk correlation has been found in some studies of insurance markets. Surveying the evidence on the health insurance market, Cutler and Zeckhauser (2000) conclude that, in this market, adverse selection is present and quantitatively large.[6] Furthermore, Friedman and Warshawsky (1990), Bruggiavini (1993) and, most recently, Finkelstein and Poterba (2000) have found evidence consistent with adverse selection in the annuity market. However, with respect to the market for automobile insurance, recent work has argued that the evidence is inconsistent with the presence of adverse selection.[7]

A main focus of prior work about the automobile insurance market has been on testing the prediction that higher insurance coverage is correlated with more accidents. Three initial studies suggested the presence of adverse selection, but their findings were criticized by subsequent research as unreliable. Dahlby (1983) and Dahlby (1992), the first two studies on the subject, did not have individual data on coverage. Puelz and Snow (1994) did use individual data obtained from a Georgia insurer, but subsequent work questioned their results. Although Puelz and Snow had individual data, they did not have some of the variables affecting risk type – such as the policyholder's years of driving experience and the policyholder's past claim history – that the insurer had. In contrast, my data includes all the information about individual policyholders known to the insurer.

Dionne, Gouriéroux, and Vanasse (2001) recently raised another objection to the Puelz-Snow study. They suggest that the insurer's risk classification is sufficient (in the sense that there is no residual adverse selection in each risk class in the insurer's portfolio) once nonlinear effects, not considered by Puelz and Snow, are taken into account. To address the problem suggested by these authors, I checked the robustness of my results by controlling for the suggested non-linearity bias in unreported regressions, and I obtained the same robust results throughout.

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[6] One notable exception in this area is Cardon and Hendel (2001), who find no evidence of adverse selection in their study of the health insurance market.

[7] Recent work (Cawley and Philipson (1999)) has also questioned whether adverse selection exists in the market for life insurance.

Chiappori and Salanie (1997, 2000) suggest that the correlation between deductible choice and risk type should be tested using bivariate probit. Chiappori and Salanie (2000) apply this test to French data. Two kinds of insurance coverage are offered in France, and the authors tested whether individuals who bought higher coverage turned out to be riskier. Finding no such correlation, they inferred that the existence of adverse selection in this market can be rejected.

The testing done by this study, however, was limited to policyholders with no more than two years of driving experience. Thus, the study tested the existence of coverage-correlation correlation only among beginning drivers who constitute a small subset of all policyholders. The absence of such correlation in the case of such drivers, who have had little opportunity to develop through driving experience an informational advantage over the insurer, does not necessarily imply that such correlation does not exist among other drivers.

In my analysis I conduct tests with respect to the whole pool of policies as well as separately for beginning and more experienced drivers. As will be discussed in detail later, my analysis confirms the Chiappori-Salanie finding that correlation between coverage and accidents does not exist for beginning drivers. The analysis indicates, however, that such correlation does exist with respect to policyholders drivers with more than two years of driving experience and, because such policyholders constitute a very large majority, also for the pool of all policies.

3.2 Learning

There has been relatively less empirical work on learning over time about policyholders' risk type.[8] The studies that conducted testing for the presence of coverage-accidents correlation in a large pool of policies have commonly not broken the pool into subsets based on the experience of the insurer with the customer or on the driving experience of the insurer. For example, Puelz and Snow (1994) and Dionne, Gouriéroux, and Vanasse (2001), which have reached opposite results concerning the existence of correlation in a general pool of policies, have not examined how their results hold for subsets of the pool defined by insurer or policyholder experience. As will be seen, in the data that I examine, such subsets differ in whether and to what extent a coverage-accidents correlation exists.

There has been some work on the temporal pattern of profits on new and repeat customers in this market. The two studies that considered it (D'Arcy and Doherty

[8] Because my focus is on asymmetric information about policyholders' risk type, the learning on which I focus concerns information about customers' risk type. Another type of learning that might go on when policyholders stay with the same insurer concerns learning by policyholders about the quality of the insurer's services (Israel (2001)).

(1990) and Dionne and Doherty (1994)) reached opposite conclusions (one suggesting lowballing with respect to new customers and one suggesting highballing with respect to such customers). In contrast to this paper, these two studies relied on aggregate data.

As discussed, one of the elements that I will study is the possibility that during the period in which a policyholder stays with an insurer, the insurer and the policyholder will by and large receive the same information about accidents occurring in that period. It is worth noting in this connection the recent work by Hendel and Lizzeri (2001) about the market for life insurance. They find evidence that is consistent with symmetric learning taking place after a policyholder joins an insurer. [9]

4 The Data

4.1 The Insurer and its Records

The paper is based on data that I received from an insurer that operates in the market for automobile insurance in Israel. The insurer started selling insurance policies in November 1994, and the data I received covers the subsequent five years of operation. The insurer's share of the total market of automobile insurance in Israel during this period was on the order of 5%.

The data contains information about 216,524 policies and about 111,138 different policyholders (some policyholders bought policies in two or more years). The data includes all the information that the insurer had about each of these policies. Each observation has the following variables with respect to the policyholder: (the list of all variables appears in Appendix I):

(1) *Policyholder's demographic characteristics*: age, education, gender, family status, place of birth, immigration year, and place of residence;

(2) *Policyholder's car characteristics*: size of engine, model year, value of the car, value of the radio, commercial vehicle or not, main vehicle or not, type of protection against theft;

(3) *Policyholder's driving characteristics*: years since getting driving license, number of claims in the past three years, young driver or not, age of young driver,

[9] In contrast to the automobile insurance market that I study, the life insurance market commonly involves one-sided commitment by insurers, which commit to the level of premia in the event that the policyholder will elect to stay in future periods. Hendel and Lizzeri find evidence that actual contract have front loading, which is what is predicted for contracts with one-sided commitment and learning over time. Because the market I study involves one-period contracts with no commitment, learning in this market has different implications.

gender of young driver, license years of young driver, whether the policyholder had insurance in the past, additional drivers (if any);

(4) *Menu of contract terms offered:* the company offered four deductible-premium alternatives – low-deductible, regular-deductible, high-deductible, and very-high-deductible contracts -- which will be described in detail in subsection 4.2 below;

(5) *Deductible choice*: what deductible (and accompanying premium) was chosen by the policyholder;

(6) *Period covered:* the length of the period covered by the purchased policy (which was usually one year); and

(7) *Realization of risks covered by the policy*: the number of claims submitted by the policyholder and a description of each submitted claim, including the amount of damages reported and the amount that the insurer paid or was expected to pay. Table 1 displays descriptive statistics of the variables.

I also received from the insurer the estimate that, when calculating its costs, the insurer used for the average administrative costs involved in processing a claim. In testing for differences in profits on new and repeat customers, I included these estimated costs of processing claims in calculating the insurer's total costs. Because these processing costs were estimates and not "hard" number like the other variables, I checked in all cases whether the reported results hold ignoring these estimated costs and I found that the results did hold.

4.2. The Deductible-Premium Menu

Israeli insurers are allowed to develop their own formula for determining insurance premia, provided that they submit them for approval by the insurance regulator. The factors that the regulator does not allow insurers to use in setting the premium are place of birth, place of residence, occupation, and education. The insurer under study attempted to take into account in its pricing decisions all the information that it was permitted to use.

The insurer offered its potential customers a menu of contract choices after first obtaining from them all the information described in subsection 4.1. The potential customer was then given a menu of four premium-deductible contracts. One option, which was labeled "regular" by the company, offered a "regular" deductible and a "regular" premium. The term "regular" was used for this deductible level both because it was relatively similar to the deductible levels offered by other insurers and because it was chosen by most policyholders. The regular premium was a function of all the characteristics of the policyholder used in the insurer's formula. The regular deductible was set at the level of 50% of the (regular) premium that was associated with the regular deductible, except that the regular deductible was capped at 1400 New Israeli Shekels (NIS) (about $350 during the considered period).

The three other price-deductible contracts included in the menu offered to potential customers were: 1) a "low" deductible, set at 60% of the level of the regular deductible, coming with a premium equal to 1.3 times the level of the regular premium; 2) a "high" deductible, set at a level equal to 1.8 times the level of the regular deductible, coming with a premium equal to 0.7 times the regular premium; and 3) a "very high" deductible, set a level equal to 2.6 times the level of the regular deductible, and coming with a premium equal to 0.685 times the regular premium.

Because I did not have an access to the company's formula for determining premia, I regressed the regular premium quoted to each customer on all the customer's characteristics that the company was allowed to use in its formula to test how well a linear regression can explain the premium. The regression, which appears in Table 2, has an R^2 of 0.71, which indicates that a linear model can be used instead of the actual formula.[10]

4.3 Summary Statistics

Table 3 provides summary statistics for the whole period covered by the data. The table indicates that, compared with regular-deductible policyholders, low-deductible policyholders have higher claim frequency and loss ratio, and policyholders with high or very high deductibles have lower claim frequency and loss ratio.

Since only a very small fraction of the customers chose high or very high deductibles (apparently the company did not price them low enough to make them attractive), my focus below will be on differences between low-deductible and regular-deductible policyholders. Policyholders who chose low deductibles had a larger incidence of one or more claims during the life of the policy. For example, 28% of low-deductible policyholders had at least one claim, whereas only 21% percentage of regular-deductible policyholders had at least one claim.

Note that low-deductible policyholders were able to file claims also for accidents whose damages were too small to claim under policies with a regular, high, or very high level of deductible. Thus, it is useful to compare low-deductible and regular-deductible policyholders in terms of the number of claims of a type that can be submitted by both groups of policyholders. The data indicates that, counting

[10] Most of the regressions below use all the characteristics of the policy as covariants. For robustness check, in unreported regressions I used the regular premium instead of the characteristics of the policy, and I obtained results that were similar in terms of both significance and magnitude throughout.

only claims for damages exceeding the level of the regular deductible (claims that could be submitted by both low-deductible and regular-deductible policyholders), the percentage of policyholders filing such claims is significantly higher for low-deductible policyholders than for regular-deductible policyholders. Similarly, counting only claims for damages exceeding 1.5 and 2 times the level of the regular deductible, the percentage of policyholders filing such claims is also significantly higher for low-deductible policyholders than for regular-deductible policyholders.

5 Are Lower Deductibles Correlated with Higher Risks?

The summary statistics presented in section 4 are consistent with the prediction that low-deductible policyholders are associated with higher claim frequencies and higher losses for the insurer (hypothesis H1). This section tests this prediction. I continue to focus on differences between low-deductible and regular-deductible policyholders because, as noted, the overwhelming majority of policyholders in the data belong to these two groups, with less than 2% choosing high or very high deductibles.

5.1 Testing for Coverage-Accidents Correlation

I start by comparing low-deductible and regular-deductible policyholders in terms of the number of claims submitted. As noted earlier, this comparison should focus on claims that can be submitted by both types of policyholders. If we were to count all claims reported by low-deductible policyholders, then we would expect to find more claims submitted by low-deductible policyholders even if the two groups did not at all differ in their risk type; this would happen because low-deductible policyholders can submit claims with respect to a larger range of accidents. Below I therefore compare these two groups in terms of claims that exceed the level of regular deductibles and thus can be submitted by policyholders in both groups. As will be noted below, the results hold also when making the comparisons in terms of claims exceeding certain higher thresholds.

I first tested for a correlation between low deductibles and more accidents using OLS specification. For the set of all the policyholders choosing either low or regular deductible, I regressed the number of claims exceeding the regular deductible on all the characteristics of the policyholder and the vehicle and on a dummy variable representing whether a regular or a low deductible was chosen. I ran this regression for the whole pool of policies and also separately for the policies in each of the insurer's five years of operation.

The results, which are displayed in Table 4, indicate that the number of claims exceeding the regular deductible is higher (at the 1% confidence level) for low-deductible policyholders than for regular-deductible policyholders. This is the case both for the whole pool and for each of the five years of operations. For the whole pool, low-deductible policyholders had on average 0.03 claims more than regular-deductible policyholders (at the 1% confidence level). This difference is significant relative to the average number of claims that exceeded the regular deductible for either low- or regular-deductible policies. The average number of claims exceeding the regular deductible was 0.23 for low-deductible policyholders and 0.18 for regular-deductible policyholders (see Table 1). Low-deductible policyholders have about 20% more such claims than regular-deductible policyholders in each of the five years included in the data.

The second test that I used is the bivariate probit recommended and used by Chiappori and Salanie (2000). The bivariate probit estimates the correlation ρ between the error terms of two binary equations. These two equations are the choice of the deductible on the policyholder's characteristics and the occurrence of at least one claim on the policyholder's characteristics. If the error terms of the two equations are independent, then ρ will be equal to 0. The results, which are shown in Table 5, provide an estimate for ρ that is negative, statistically significant (at the 1% confidence level) and equal to –0.057. Thus, the hypothesis that the two equations are independent can be rejected.

In addition to the above two tests, I also used other specifications. In particular, I used Poisson distribution for the number of accidents, a logit distribution for a variable that was equal to 1 if the policyholder had an accident and 0 otherwise, and a similar probit test. In all cases, the results were similar both in direction and in magnitude.

Finally, it might be argued that regular-deductible policyholders might sometimes be reluctant to submit claims for accidents whose damage exceeds the regular deductible but just barely. They might elect not to submit such claims, so the argument goes, in order to avoid the transaction costs involved in submitting a claim and/or to avoid having a claim in their record that might lead to an increase in the premium in subsequent years (see Hosios and Peters (1989)). To ensure that the above results are not vulnerable to this problem, I did the tests discussed above also for claims exceeding 1.5 times the level of the regular deductible as well as for claims exceeding 2 times the level of the regular deductible. In both cases I obtained similar results, namely that the number of claims exceeding the used threshold is higher (at the 1% confidence level) for low-deductible policyholders than for high-deductible policyholders. It is worth noting that I followed a similar procedure of using alternative, higher thresholds also for all the other tests in this paper that involve the number of claims, and I obtained similar results throughout; all of the results reported below are thus robust to this problem.

5.2 Losses from Accidents

I now turn to comparing low-deductible and regular-deductible policyholders in terms of the costs to the insurer produced by claims exceeding the regular deductible. I regressed the total insurance payments made by the insurer in connection with such claims on all the characteristics of the policyholder and on a dummy variable reflecting whether a regular or low deductible was chosen.

The regressions, which are displayed in Table 4, indicate that such total insurance payments are higher (at the 1% confidence level) for low-deductible policyholders. This result holds for the whole pool and for each of the five years in the data. The regression indicates that the insurer's total insurance payments in connection with claims exceeding the regular deductible was higher (at the 1% confidence level) for low-deductible policyholders than for regular-deductible policyholders by 230-315 NIS (~\$58-\$78). This increase is roughly equal to 20% of the average level of total insurance payments among regular-deductible policyholders.

5.3 Beginning vs. Experienced Drivers

As discussed earlier, Chiappori and Salanie (2000), studying the performance of policyholders with less than three years of driving experience, found no coverage-accidents correlation for such policyholders. Below I explore source for the difference between this result and the results obtained above for the pool of all policyholders. In particular, I examine whether in my data the results are different for the relatively small subset of policyholders with little driving experience.

To examine this possibility, I first regressed (in unreported regressions) the number of claims on the deductible level controlling for all the other variables *separately* for policyholders with less than three years of driving experience and for policyholders with three or more years of such experience. I found that the coefficient of the deductible was not significant for the first group of beginning drivers but was negative and significant (at the 1% confidence level) for the second group of more experienced drivers.

I also ran the bivariate probit test used by Chiappori and Salanie (2000) separately for policyholders with less than three years of driving experience and for policyholders with three or more years of such experience. For policyholders with less than three years of driving experience, I found (see Table 6, columns 1 and 2) that the correlation between the error terms of the two binary equations, ρ, has a positive value of 0.023 that is not statistically significant (with a standard error of 0.059). The non-existence of statistically significant correlation for this subset of my data is consistent, of course, with the findings of Chiappori and Salanie who studied policyholders with less than three years of driving experience.[11]

However, for the group of policyholders with three or more years of driving experience, a correlation between low deductibles and more accidents does exist. For this group, the results indicate (see Table 6 columns 3 and 4) that ρ has a negative value of -0.06 that is statistically significant (at the 1% confidence level). This enables rejecting the independence of the two equations.

Thus, although the Chiappori-Salanie findings of statistical insignificance of ρ are confirmed for policyholders with less than three years of driving experience in my data, they do not carry over to policies purchased by policyholders with more driving experience. The latter policies purchased by drivers with such experience account for a very substantial majority of the policies sold by the considered insurer and in the Israeli automobile insurance market in general (as well as in the French market considered by Chiappori and Salanie). Because of the numerical dominance of policies purchased by experienced drivers, the pool of all policies is also characterized (as identified earlier) by a correlation between low deductibles and more accidents.

The identified difference between young and experienced drivers highlights the possible importance of learning of information in this market. The next section will study the subject of learning more systematically.

6 Learning

6.1 Learning by Policyholders

I start by testing the prediction concerning learning by policyholders and, in particular, concerning the effects of driving experience that policyholders had before

[11] Note that the results reported above are ones that do not exclude the information I have in my data on past claims history, whereas the Chiappori-Salanie findings were reached using data that did not include information on past claims history which they did not have. To duplicate with my data exactly what these authors did, I excluded the information that I have on the past claims history of policyholders and then did the bivariate probit test on policyholders with less than three years of experience. Again, I found that ρ, the correlation between of the error terms of the two equation, is very close to zero (0.0023) and the 95 percent interval is equal to [-0.111, 0.116]. This is similar to the Chiappori-Salanie finding that zero falls within the 95 percent confidence interval for ρ.

joining the insurer (hypothesis H2). According to this hypothesis, a coverage - accidents correlation is more likely to exist for groups of policyholders with more driving experience prior to joining the insurer.

To test this hypothesis, I divided all the policies in the data into 5 sub-groups – made of the policyholders that have respectively 0, 1, 2, 3, or 4 or more years of driving experience *not* with the insurer. I then tested the presence of coverage-accidents correlation for each sub-group separately.

The results, which are reported in Table 7, indicate that a coverage-accidents correlation does not exist for the groups of policyholders with only 0,1, or 2 years of driving experience prior to joining the insurer. Such correlation does exist, however, for the two groups of policyholders who have 3 years or 4 or more years of driving experience not with the insurer. Thus, the results are consistent with the story that, the longer the driving experience prior to joining the insurer of a group of policyholders, the more likely its members to have an informational advantage over the insurer, and thus the more likely to exist a coverage-accidents correlation.

Interestingly, finding that a coverage-accidents correlation does not exist for policyholders with no or little driving experience, I am able to reject the possibility that policyholders can obtain significant private information about their risk type in connection with automobile accidents from mere introspection or from observing their performance in other dimensions of life. The data is consistent with significant private information about this risk type coming only from actual experience with one's own driving.

6.2 Learning by Insurers

I now turn to testing the prediction that, as the experience of the insurer with a policyholder increases, the policyholder's initial informational advantage over the insurer (if any) can be expected to diminish and ultimately disappear (hypothesis H3). To examine this issue, I test whether the coverage-accidents correlation declines or disappears for groups of policyholders with whom the insurer has had long experience.

To this end, I divided all the policies in the data into 5 sub-groups – those in which the insurer has had respectively 0, 1, 2, 3, or 4 years of prior experience with the policyholder. For each group, I regressed the number of claims exceeding the regular deductible on the choice of the deductible and all of the policyholder's characteristics. As Table 8 shows, the coefficient on the deductible choice decreases with the length of the insurer's experience with the policyholder.

For example, for the group of policyholders with zero years of company experience, the coefficient on the deductible choice is equal to –0.037 and is statistically significant (at the 1% confidence level). In contrast, for the group of policyholders with four years of company experience, the coefficient on the deductible choice decreases to –0.008 and (with a standard error of 0.008) is no longer statistically significant. Thus, the coverage-accidents correlation no longer exists for the group of policyholders with more than three years of experience with the insurer.

Because my data covers the first five years in which the insurer sold automobile insurance, it is worth distinguishing between learning by the insurer about particular policyholders and learning by the insurer about the general pool of policyholders it faces. Looking back at the results that Table 4 displays for each of the five years of the insurer's operations in the data, these results indicate that the coefficients on the deductible choice are all essentially the same both in magnitude and in significance. Thus, the evidence is consistent only with the possibility that the coverage-accidents correlation can be eliminated through policyholder-specific learning by the insurer about its repeat customers – and not with the possibility that such correlation can be eliminated by some general learning of the insurer about the general pool of policyholders in the market.

Finally, if insurers can over time learn enough about repeat customers to eliminate whatever informational advantage the customers had when joining the insurer, does that imply that informational asymmetries between policyholders and their insurer can be at most a short-run phenomenon in this market?[12] The answer is no, because insurers in this market keep getting new customers. New drivers constantly join the pool of policyholders and, furthermore, policyholders change insurers (as will be presently documented). Therefore, since the market cannot be expected to reach a situation in which all the purchasers of insurance are repeat customers with long experience with the insurer, a coverage-accidents correlation cannot be expected to vanish completely in the long run.

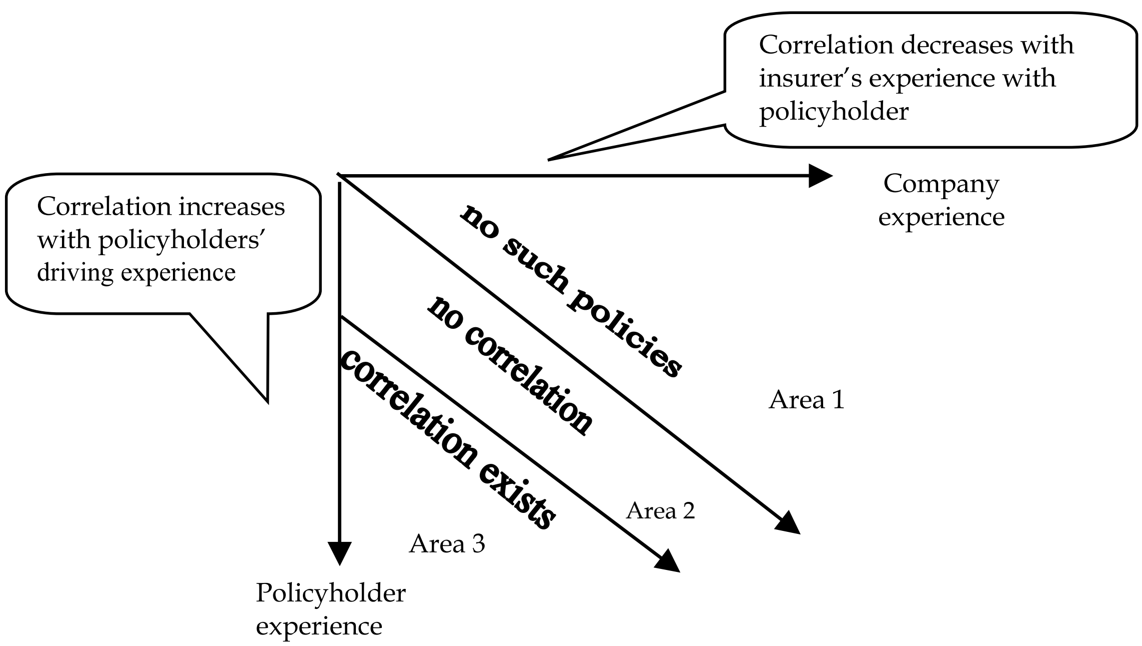
6.3 The Combined Effects of Policyholder and Insurer Learning

Of course, the extent to which an informational asymmetry is present in any given case depends *both* on (i) the driving experience (if any) of the policyholder had prior to joining the insurer *and* on (ii) the experience (if any) that the insurer has had with the policyholder since then. As we have found, other things equal (including the insurer's experience with the policyholder), the more driving experience the policyholder had before joining the insurer, the more likely a coverage-accidents

[12] For a work stressing differences between short-run and long run effects in another insurance market, see Cutler and Reber (1998).

correlation to exist; and, other things equal, the longer the experience that the insurer has had with the policyholder since the policyholder joined, the less likely such a correlation to exist. Combining these two predicted relationships, if we draw two axis representing the driving experience of policyholders prior to joining the insurer and the insurer's experience with policyholders, we can expect the presence of coverage-accidents correlation to depend on these two parameters as depicted in the following diagram.

Correlation Between Low Deductibles and High Risks



By definition, there are no cases in which the policyholder has been driving for fewer years than the policyholder has been with the insurer (Area 1). When the policyholder has spent all or close to all of the policyholder's driving years with the insurer (Area 2), a coverage-accidents correlation is not expected. However, when the policyholder’s driving experience prior to joining the insurer is relatively substantial (Area 3), a coverage-accidents correlation is expected.

To test this prediction, which essentially combines hypotheses H2 and H3, I divided all policies in the data into 25 sub-groups, with each sub-group including all the policies with a given number of years of driving experience by the policyholder and a given number of years of experience with the policyholder by the insurer. I then tested the presence of coverage-accidents correlation for each group separately.

The results of these regressions, which are reported in Table 9, are largely consistent with the tested prediction. To illustrate, the column with sub-groups of customers that just joined the insurer (and thus have zero years of experience with the insurer) indicates that a correlation appears only for the sub-groups of such customers that have three or more years of driving experience; in contrast, the column with sub-groups of customers that have four years of experience with the insurer indicates that a correlation appears only for customers that have six or more years of driving experience (and thus two or more years of driving experience prior to joining the insurer).

Similarly, the row with sub-groups of policyholders that have three years of driving experience indicates that the correlation disappears for customers who have spent these three years with the insurer. In contrast, the row with sub-groups of policyholders with five or more years of driving experience indicates that the correlation disappears only for those customers who have spent at least four years with the insurer.

6.4 Learning and Differences in Information among Insurers

I now turn to investigating whether the information obtained by insurers about their repeat customers produces a difference in information among insurers with respect to these customers. To begin, note that some of the results obtained in the preceding sections 6.1-6.3 are already ones that are predicted by this story. These results indicate that the effect of driving experience on the presence of a coverage-risks correlation depends on whether this driving experience was acquired during (i) the period prior to the policyholder's joining the insurer (if any) in which the policyholder was insured by other insurers, or (ii) the period (if any) in which the policyholder has been insured by the current insurer. Driving experience during the latter period spent with the insurer reduces or even eliminates the correlation between low deductibles and more accidents but driving experience in the first period prior to joining the insurer does not (on the contrary). Such difference between driving experience with the current insurer and with prior insurers would not be expected if an insurer accepting new customers could obtain from prior insurers the complete and full information that they have about these customers. With this in mind, let us proceed to investigate the possibility of informational differences among insurers by testing the two hypotheses H4 and H5.

6.4.1. Inside vs. Outside Records as Predictors of Performance

The studied insurer requested that customers report to it the number of claims they submitted in the preceding three years. I now wish to test whether such reports by new customers systematically under-report past claims. On this story, the actual past claim history of new customers is systematically worse than what is reported by such customers. According to hypothesis 4, the number of accidents by new customers is expected to be higher than what would be predicted if the customers' self-reporting of past claims history were assumed to be accurate.

To test this hypothesis, I looked at a subset of all policies that were sold to either (i) new customers, or (ii) customers who have been with the insurer for three years. The number of claims in the past three years that appears in the insurer's data is based on self-reporting for the first group and on the insurer's own records for the second group.

I regressed the number of claims exceeding the regular deductible, as well as the total insurance payments and the total costs to the insurer from such claims on all the characteristics of the policyholder, including the number of past claims in the insurer's data, and on whether the policyholder is a new customer or a repeat customer. The results, which are displayed in Table 10A, indicate that the number of claims, the total insurance payment, and the total cost to the insurer are all higher (at the 1% confidence level) for new customers. In unreported regressions, I find that this result holds when I run separate regressions for customers with one, two, or three or more claims in their past. [13]

6.4.2. Departing Customers

A related hypothesis is that departing customers will be disproportionately ones with a poor past claims record with the insurer (hypothesis H5). Customers with such a record could gain from switching to a new insurer that would have less information about their past history.

To test this prediction, I created a dummy variable that was equal to 1 when a policyholder decided at the end of the policy period to stay with the insurer for another period and 0 otherwise. The decision whether to stay was regressed on whether the policyholder had claims during the period preceding the decision and

[13] It is worth noting that, although the insurer puts the self-reported claim history of new customers in its data, the data is consistent with the insurer's being aware that the new customers under-report their past claims. Regressing the premium charged on characteristics, I found that, controlling for other characteristics, new customers who report a clean record of no claims in the past three years are charged a higher premium than a repeat customer who have been with the company for three years and have had such a clean record in those three years.

on all the characteristics of the policyholder (including the deductible choice in the preceding period).

The results of this regression are displayed in Table 10B. They indicate that the probability of staying with the insurer for another year is smaller by 0.1 (at the 1% confidence level) for policyholders who had claims in the period preceding the decision than for policyholders who had no such claims. Overall, whereas policyholders in general have an average probability of 0.7 of staying with the insurer for another year, policyholders who have had claims in the year preceding the decision have a probability of only 0.6 of staying with the insurer for another year.

These results suggest that departing customers tend to be disproportionately ones whose record with the company included claims. One might still wonder whether such departing customers are indeed more likely to be high-risk types or simply policyholders who simply had claims due to bad luck. To examine this question, I looked at the realization of risks for policyholders who stayed and tested whether such policyholders tended to have subsequently good performance relative to the general pool of customers.

In particular, I ran two regressions with respect to policies sold in the fifth year of the company's operations. For each of the deductible groups (low-deductible and regular-deductible policyholders), I regressed the number of claims on all the observable characteristics including the number of years of prior experience that the insurer has had with the customer (company experience). The results, which are reported in Table 10C, show that the coefficient on the company experience is negative and statistically significant. The longer the insurer's experience with the policyholder, the lower the likelihood that the policyholder will have claims. For example, for low-deductible policyholders, each year of experience reduces the number of claims by 0.013 (at the 1% confidence level). This amounts to 6% of the number of claims that low-deductible policyholders have. Repeat customers, then, are correlated with less accidents.[14]

6.5 Profits on New and Repeat Customers

[14] This effect seems to be larger for low-deductible policyholders than for regular-deductible policyholders. For example, each year of experience decreases the number of claims by 0.013 (0.003) for low-deductible policyholders and by 0.003 (0.0008) for regular deductible policyholders. And each year of experience decreased the total insurance payments by the insurer by 152 NIS for low-deductible policyholders and by 35 NIS for regular-deductible policyholders.

Recall the prediction of "no-commitment" multi-period models that an insurer will obtain some market power with respect to repeat customers that the insurer will identify as low-risk types. Because other insurers to which such customers might turn will not know their low-risk type for sure, the insurer will be able to over-charge these customers relative to the price reflecting their low risk. Furthermore, anticipating that such a possibility might arise down the road with respect to any new customer, insurers might be willing to under-charge new customers. This yielded the last hypothesis to be tested, namely that the insurer will have for repeat customers a loss ratio (the standard measure of higher profitability used by insurers) that is lower than the loss ratio for new customers (hypothesis H6).

To test this hypothesis, I estimated an expected loss ratio for each policyholder. I first generated a measure of expected loss ratio, LRETAC, which is equal to the expected total annual costs divided by the yearly premium.[15] I regressed each of the expected loss ratios on all the policyholder's characteristics (including the choice of the deductible) and on the insurer's experience with the customer.

The results, which are reported in Table 11, are consistent with the tested hypothesis. They indicate that the expected loss ratio decreases (at the 1% confidence level) with the insurer's experience with the customer. For example, an increase of one year in the insurer's experience with the customer reduces the expected loss ratio by one percentage point (at the 1% confidence level).[16]

6.6 Note on Moral Hazard

As noted in the introduction, a correlation between coverage and accidents is consistent not only with the existence of adverse selection but also with the existence of moral hazard. Indeed, it might be suggested that the identified coverage-accidents correlation, although consistent with adverse selection, could be produced wholly by moral hazard and that the considered market thus could involve no adverse selection.

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[15] The total annual costs used in calculating the LRETAC variable include in addition to the total insurance payments (if any) made to the policyholder also incurred administrative costs in the event of an accident and reimbursements of premia paid in the event of departure prior to year-end. (See Appendix I for a precise definition.) I checked and found that the results hold for alternative standard measures of loss ratio.

[16] It is worth noting that higher profits on repeat customers are also consistent with a model in which there are switching "transaction costs" that discourage customers from switching and thus provide insurers with market power over customers that they already have. Note that a model with switching costs and no adverse selection, however, cannot readily explain another finding of this section – that policyholders switching to other insurers are disproportionately ones with a bad past claims record.

Although disentangling moral hazard and adverse selection in this market is beyond the scope of this paper, it might be worth noting that some of the findings in this section concerning dynamics over time do not seem readily explainable by a standard moral hazard story. For example, if the coverage-accident correlation were produced by low deductibles leading to low precautions, why would such a correlation not arise with respect to young drivers? Are incentives not important with respect to such drivers? It might be argued in response to this question that some driving experience might be needed for policyholders to know what precautions to take. But if this were the case, why would the coverage-accidents correlation eventually disappear for policyholders that have been with the insurer for a long period of time? Do incentives to take precautions lose their significance when one stays with the same insurer for some time?

Furthermore, if the coverage-accidents correlation were produced by pure moral hazard and no adverse selection existed, why would policyholders who leave their insurer tend to be ones with a poor past claims record? If insurers generally have the same information as policyholders about the policyholders' risk type, why will policyholders with poor past claims record have more to gain from switching insurers? All these are issues that should be considered by future research seeking to disentangle moral hazard and adverse selection in this market.

7 Conclusion

Using a unique and rich database, which includes all the data that an insurer had about its policyholders, this paper has tested the predictions of adverse selection models. Consistent with the presence of asymmetric information, I found that an insurance menu with different deductibles results in sorting that produces a coverage-accident correlation. Low-deductible choices are correlated with more accidents and higher losses from accidents.

Whether any informational asymmetry is present (and, if so, what its magnitude is) might change over time, as parties obtain more information. Consistent with the presence of learning by policyholders, I found that the coverage-accidents correlation exists only for groups of policyholders that have had sufficient driving experience prior to joining the insurer. Consistent with the presence of learning by insurers about the risk type of their customers, the coverage-accidents correlation diminishes in magnitude over time and eventually disappears for policyholders who stay with the same insurer for a sufficiently long period of time.

Finally, the evidence is consistent with insurers' obtaining information about their repeat customers that other insurers to which such customers might turn would not fully have. Consistent with switchers' under-reporting past claims history, I found that switchers perform less well than repeat customers with the same past claims record as self-reported by the switchers. Furthermore, consistent with new insurers having less information about the past record of switchers than the switchers' prior insurers, I found that customers that leave their insurer are disproportionately ones with a poor past claims record. Finally, consistent with insurers gaining market power with respect to repeat customers that they have identified as low-risk types, I found that insurers make higher profits on their repeat customers than on new customers.

One aspect of adverse selection models that I have not investigated concerns the consistency of the evidence with cross-subsidization of high-risk (high-coverage) policyholders by low-risk (low coverage) policyholders. Such cross-subsidization is predicted by the Spence-Miyazaki line of adverse selection models but not by the Rothschild-Stiglitz-Wilson-Riley line of such models. Also, as already noted, it would be worthwhile to disentangle moral hazard and adverse selection by examining predictions that, unlike the prediction of coverage-accidents correlation, are associated with only one of the two phenomena. Investigation of these issues will provide a fuller picture of the role and influence of asymmetric information in the market for automobile insurance.

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Appendix I

List of Variables (in Alphabetical Order)

Academic education	Equal to 1 if the policyholder has a university degree and equal to 0 otherwise
Actual profit	Earned premium minus payments paid by the insurer plus expenses on processing claims
Age	Age of policyholder
Age-gender	Interaction between age and sex
Car model year	Car model year
CC	Size of engine
Claim Index	Equal to 1 if the number of claims in the current year is greater than 1 and equal to 0 otherwise
Claim1 - Claim4	Number of claims occurs in the first (second/third and forth) year that the policyholder was enrolled in the insurance company
Company experience	Equal to the number of years that the policyholder has been with the insurer
Calendar year	Equal to the calendar year
Damage	The amount of the damages reported in a claim
Deductible level	Equal to 1 if the level of the deductible is regular and equal to 0 otherwise
Driving experience	Length (in years) that the policyholder has had a driving license
Earned premium	[Premium] * [Period]
Immigrant index	Equal to 1 if the policyholder is an immigrant
Immigration year	The year in which an immigrant policyholder immigrated to Israel
Expected profit	Equal to yearly premium minus the expected Total Actual Payment
Gender	The policyholder's gender
LRETIP	Expected [Total insurance payments] divided by [Earned premium]
LRETAC	Expected [Total Annual Cost] divided by [Premium]
Main car	Equal to 1 if the car is used as main car and equal to 2 otherwise
No experience last year	Equal to 1 if the policyholder did not have a driver license in the year prior to joining the insurer
No experience three years ago	Equal to 1 if the policyholder did not have a driver license during the year that was three years prior to joining the insurer
No experience two years ago	Equal to 1 if the insured did not have a driver license in the year taking place two years prior to joining the insurer
Number of claims	Number of claims submitted during the life of the policy
Number of claims last year	Number of claims occurring in the year prior to joining the insurer
Number of claims three years ago	Number of claims occurring three years prior to joining the insurer
Number of claims two years ago	Number of claims two year before the policyholder joined the insurer
Number of drivers	Equal to 1 if only the policyholder and the policyholder's spouse use the car and 0 otherwise
Period	Length of the period covered by the policy (in years)
Premium	Yearly premium

Regular deductible	Equal to 1 if the policyholder chose a regular deductible and 0 otherwise
Regular Premium	The premium the policyholder were quoted for a regular deductible (and was charged if the policyholder chose such a deductible)
Single	Equal to 1 if the policyholder is single and to 0 otherwise
Social and private use	Equal to 1 if the car is used for social and private needs and equal to 0 otherwise
Stayed	Equal to 1 if the policyholder was insured by the company in the preceding year
Total annual costs	All payments resulting from the issuance of the policy = payments made to the policyholder in connection with claims + administrative expenses in handling a claim + reimbursements of premia payments made in the event of early departure
Total insurance payments	Payments made to the policyholder in connection with claims
Value of the car	The value of the car
Young driver age	The age of the youngest driver who is allowed to use the car
Young driver experience	The driving experience of the youngest driver using the car
Young driver gender	The youngest driver's gender
Young driver index	Equal to 1 if the a young driver used the car and equal to 0 otherwise.
Young last year	Equal to 1 if the policyholder was considered a young driver in the year prior to joining the insurance company
Young three years ago	Equal to 1 if the policyholder was considered a young driver three years prior to joining the insurance company
Young two years ago	Equal to 1 if the policyholder was considered a young driver two years prior to joining the insurance company

Appendix II

1) Claim frequency – The total number of claims made by customers divided by the number of policies weighted by the exposed time of the policy, which is the time (in year unit) that the policy was in effect.

$$\frac{\sum_i number\ \ of\ \ claims_i}{\sum_i \exp osetime_i}$$

2) Loss ratio (damage) – The sum of all damages incurred to policyholders divided by the sum of the insurer's earned premium, which is the sum of all annual premium weighted by the exposed time of the policy.

$$\frac{\sum_i damage_i}{\sum_i premium_i * \exp osetime_i}$$

3) Loss ratio (cost) – The sum of all the payments made to customers by the insurer divided by the insurer's total earned premium.

$$\frac{\sum_i payment_i}{\sum_i premium_i * \exp osetime_i}$$

4) Average premium – The sum of all earned premium divided by the exposed time

$$\frac{\sum_i premium_i * \exp osetime_i}{\sum_i \exp osetime_i}$$

5) Average damage per policy – The sum of the damages incurred to the policyholders divided by the exposed time.

$$\frac{\sum_i damage_i}{\sum_i premium_i * \exp osetime_i}$$

6) Average cost per policy – The sum of the payments made by the insurer divided by the total exposed time of policies.

$$\frac{\sum_i payment_i}{\sum_i premium_i * \exp osetime_i}$$

7) Average damage per claim – The sum of the damages incurred to policyholders divided by the number of claims.

$$\frac{\sum_i damage_i}{\sum_i number\ \ of\ \ claims_i}$$

8) Average cost per claim – The sum of all the payments made by the insurer divided by the number of claims.

$$\frac{\sum_i payment_i}{\sum_i number\ \ of\ \ claims_i}$$

Table 1: Descriptive Statistics

Type of policies	All the policies		Regular deductible policies		Low deductible policies	
Variable	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Buyer Demographics characteristics:						
Age	42.5	12.54	42.6	12.47	42.4	12.78
Gender	1.32	0.47	1.31	0.47	1.32	0.46
Single	0.13	0.33	0.13	0.33	0.13	0.33
Academic education	0.26	0.04	0.25	0.43	0.32	0.46
Buyer's car characteristics:						
CC	1,565	3750	1,566	380	1,559	358
Car model year	1992.9	3.20	1993.02	3.20	1992.6	3.20
Value of the car	61,932	34,998	60,997	34,780	65,202	35,559
Social and private use	1.08	0.27	1.08	0.27	1.07	0.26
Main car	1.15	0.36	1.15	0.36	1.14	0.35
Buyer 's driving characteristics:						
Driving experience	19.03	10.13	18.97	10.12	19.2	10.13
Number of claims last year	0.07	0.27	0.07	0.26	0.08	0.28
Number of claims two years ago	0.05	0.22	0.04	0.22	0.05	0.23
Number of claims three years ago	0.04	0.20	0.04	0.19	0.04	0.19
Claim1	0.052	0.023	0.05	0.22	0.07	0.28
Claim2	0.026	0.17	0.02	0.15	0.04	0.21
Claim3	0.01	0.11	0.008	0.10	0.02	0.15
Claim4	0.003	0.06	0.002	0.05	0.006	0.08
Number of claims	0.19	0.45	0.18	0.44	0.23	0.50
Damage	2,136	8,718	2,032	8,561	2,501	9,239
Total insurance payments	1,538	7,301	1,455	7,163	1,824	7,755
Average cost	1,383	6,725	1,618	7,082	1,316	6,618
Total actual payment	2,028	7,526	1,966	7,382	2,246	8,004
Number of drivers	0.25	0.43	0.25	0.44	0.22	0.41
Young driver index	0.17	0.04	0.17	0.38	0.18	0.38
Stayed	0.7	0.46	0.7	0.46	0.69	0.46
N	213,660		166,118		47,542	

Table 2: Premium and Total Annual Costs as a Function of Characteristics

Dependent Variable:	Premium		Total annual cost	
OLS	Coef.	std.	coef.	std.
Buyer demographic characteristics:				
Age	1.38***	0.34	-1.19	5.30
Gender	92.74***	9.40	-37.58	144.62
Agesex	-3.72***	0.22	-2.35	3.37
Single	98.03***	3.84	76.64	59.02
Academic education	-55.17***	2.78	-218.60***	42.66
Buyer's car characteristics:				
CC	0.21***	0.004	-0.36***	0.06
Car model year	-13.11***	0.58	-78.39***	8.85
Value of the car	0.02***	0.00006	-0.021***	0.001
Main car	-54.60***	3.36	-86.02*	51.68
Buyer's driving experience:				
Driving experience	-4.75***	0.23	-19.79***	3.47
Number of claims last year	447.91***	4.45	757.46***	68.42
Number of claims two years ago	303.95***	5.40	633.76***	82.93
Number of claims three years ago	254.77***	5.96	500.47***	91.48
No experience last year	196.35***	14.41	186.13	221.41
No experience two years age	189.57***	16.22	419.24*	249.15
No experience three years age	328.74***	10.26	120.49	157.57
Number of drivers	-88.20***	2.80	-152.21***	43.00
Young driver age	-283.60***	3.50	-222.14***	53.80
Young driver experience	-263.28***	4.22	142.44***	64.90
Young driver gender	-172.83***	5.75	-339.12***	88.37
Young driver index	2194.64***	12.75	2040.01***	195.86
Young driver last year	235.87***	27.65	785.71	424.82
Young driver two years age	223.34***	30.81	529.52	474.15
Young driver three years ago	274.34***	23.40	-382.95	359.45
Claim1	443.19***	5.41	564.48***	83.15
Claim2	346.30***	7.850	432.25***	120.66
Claim3	245.29***	12.50	183.00***	191.98
Claim4	250.79***	25.42	666.74*	390.47
Other:				
Company experience	-74.26***	1.00	-62.67	15.43
Time Fixed Effect	YES		YES	
N	166,116		166,116	
Adj-R^2	0.71		0.79	

***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 3: Summary Statistics

Level of Deductible	"Low"	"Regular"	"High"	"Very high"
Percentage of choosing	21.96%	76.72%	0.74%	0.6%
Claim frequency	27.76%	21.33%	14.05%	11.37%
Loss Ratio (damage)	99.59%	93.04%	91.7%	63.62%
Loss Ratio (cost)	72.62%	66.65%	65.29%	42.34%
Average premium	2,853	2,623	2,085	1,920
Average Damage per policy	2,841	2,440	1,911	1,222
Average cost per policy	2,071	1,748	1,361	813
Average damage per claim	10,233	11,443	13,600	10,750
Average cost per claim	7,462	8,198	9,683	7,154

- See Appendix II for the exact definition of each of the above terms.

Table 4: The Association between Deductible Choice and Accidents

Column	1	2	3	4	5	6
Company year	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999	All years
Number of claims	-0.04*** (0.007)	-0.03*** (0.007)	-0.03*** (0.005)	-0.03*** (0.005)	-0.03*** (0.005)	-0.03*** (0.002)
Adjusted-R^2	0.0073	0.0076	0.0091	0.0073	0.0153	0.0224
Total insurance payments	-241.44*** (126.6)	-286.14*** (92.1)	-236.89*** (83.3)	-315.19*** (80.5)	-229.28*** (63.8)	-221.61*** (38.4)
Adjusted-R^2	0.032	0.035	0.034	0.038	0.008	0.0127
Number of observations	21,715	38,201	45,760	50,571	57,410	213,660

- I only report the coefficient of interest
- standard errors adjusted for clustering on policy base
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 5: Bivariate Probit for the Choice of Deductible and the Occurrence of a Claim

Dependent variable:	**Regular Deductible**	**Claim Index**
ρ	-0.057*** (0.005)	[95% conf. interval] [-0.067,-0.048]
Time Fixed Effect	YES	
N	213,657	

- I only report the coefficient of interest
- standard errors adjusted for clustering on policy base
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 6: Bivariate Probit for Young and Experienced Drivers

Column:	1	2	3	4
Dependent variable: Driving experience:	Regular Deductible 0-2 years	Claim Index	Regular Deductible 3 or more years	Claim Index
ρ	0.023 (0.059)	[95% conf. interval] [-0.09,0.14]	-0.058*** (0.004)	[95% conf. interval] [-0.07,-0.05]
Time Fixed Effect	YES		YES	
N	1,774		211,866	

- I only report the coefficient of interest
- standard errors adjusted for clustering on policy base
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 7: The Effect of Driving Experience before Joining the Insurer

Dependent variable: Number of claims

Number years of experience not in the insurance company	0	1	2	3	4+
Deductible level	0.04	-0.026	-0.045	-0.071***	-0.05***
	(0.07)	(0.053)	(0.04)	(0.025)	(0.002)
Time fixed effect	YES	YES	YES	YES	YES
N	393	778	1421	2318	208363
Adjusted R^2	0.1073	0.0833	0.0446	0.0450	0.0236

- I only report the coefficient of interest
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 8: The Effect of Company Experience

Dependent variable: Number of Claims

Company years of experience	0	1	2	3	4
Deductible level	-0.037***	-0.036***	-0.034***	-0.021***	-0.008
	(0.004)	(0.005)	(0.006)	(0.006)	(0.008)
Time Fixed Effect	YES	YES	YES	YES	YES
N	97,976	56,628	31,423	15,634	8,558
Adj-R^2	0.0218	0.0217	0.0218	0.0230	0.026

- I only report the coefficients of interest
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 9: The Two Dimensions of Experience

Years of company experience / Years of driving experience	0	1	2	3	4
0	NO Number of Observation: 200				
1	NO Number of Observation: 344	NO Number of Observation: 147			
2	NO Number of Observation: 570	NO Number of Observation: 158	NO Number of Observation: 117		
3	-0.126 (0.04) Number of Observation: 947	-0.103 (0.07) Number of Observation: 286	NO Number of Observation: 95	NO Number of Observation: 93	
4	-0.104 (0.04) Number of Observation: 1398	-0.06 (0.04) Number of Observation: 505	NO Number of Observation: 40	-0.28 (0.08) Number of Observation: 72	NO Number of Observation: 77
5	-0.104 (0.03) Number of Observation: 2052	-0.20 (0.042) Number of Observation: 768	-0.072 (0.06) Number of Observation: 336	-0.095 (0.08) Number of Observation: 135	NO Number of Observation: 109
6+	-0.06 (0.004) Number of Observation: 92523	-0.054 (0.005) Number of Observation: 54796	-0.057 (0.005) Number of Observation: 30695	-0.036 (0.006) Number of Observation: 15369	-0.015 (0.007) Number of Observation: 8218

All the reported figures are statistically significant in the 1% confidence level

Table 10A: Inside vs. Outsize Records as Predictor of Subsequent Performance

In the regression below I include (i) all new customers that reported no claims in the preceding three years, and (ii) all repeat customers that have been with the insurer during the preceding three years and had no claims.

Dependent variable:	**Number of claims**	**Total insurance payment**	**Total annual cost**
New	0.033*** (0.005)	194.50*** (85.5)	316.0*** (88.05)
Time fixed effect		YES	
N		93,812	
Adj-R^2	0.015	0.010	0.010

- I only report the coefficient of interest
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 10B: Past Record of Departing vs. Staying Customers

Dependent variable: stayed

	OLS	**LOGIT**
Number of claims	-0.102***	-0.522***
	(0.002)	(0.0124)
Deductible level	0.0157***	0.1182***
	(0.002)	(0.016)
Time Fixed Effect	YES	
N	156,245	
Adj-R^2	0.3100	0.3021

- I only report the coefficients of interest
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 10C: The Performance of Repeat Customers

Testing whether, within each group (low/regular deductible), the number of claims is lower for individuals with more years of experience with the insurer:

Dependent variable: number of claims

Deductible level:	**Low**		**Regular**	
	OLS	**std.**	**OLS**	**std.**
Company years of experience	-0.013***	0.003	-0.003***	0.001
N	7,712		49,698	
Adj-R^2	0.0167		0.0172	

- I only report the coefficient of interest
- This regression includes only data for the company fifth year of operation. Doing the same for the whole sample (for the whole five years of the company operation) yields similar results.
- ***,**,* - Significant at 1%, 5%, and 10% confidence level, respectively

Table 11: Profits on New and Repeated Customers

Dependent variable:	**LRETAC**
	OLS
Company years of experience	-0.0094***
	(0.0003)
N	213,642
Adj-R^2	0.031

- I only report the coefficient of interest
- All the coefficients are significant with 1% confidence level