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Marco Cosconati

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via del Quirinale 21 – 00187 ROMA
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NO NEWS IS GOOD NEWS: MORAL HAZARD IN OLIGOPOLISTIC INSURANCE MARKETS*

MARCO COSCONATI†

Abstract. I conduct inference on moral hazard in the Italian automobile insurance market. I disentangle moral hazard from adverse selection and state dependence by exploiting nonlinearities in the penalties for accidents across driving records and companies, and a discontinuity in the penalty in the last 60 days of the contractual year. I employ a representative matched insurer-insuree panel dataset, containing rich information on 4,316,647 auto insurance contracts underwritten by *all* insurers. The results demonstrate that moral hazard is a pervasive feature of the market and that its magnitude varies across companies.

Keywords: Moral hazard, Adverse Selection, Risk, Risk Aversion, Asymmetric Information, Self-Selection
JEL classification: D82, G22, J24

Economic analysis of the role of asymmetric information in determining market failures has been extremely influential (see Arrow (1963), Akerlof (1970) and Rothschild and Stiglitz (1976)). There are two main sources of asymmetric information: moral hazard–when someone takes more risks because someone else bears the cost of those risks–and adverse selection–when high-risk individuals self-select into more generous coverage. Within the context of the auto insurance market, Chiappori and Salanie (2012) say that "moral hazard occurs when the probability of a claim is not exogenous but depends on some decision

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† Banca d'Italia and IVASS. e-mail: marco.cosconati@gmail.com.

made by the subscriber (e.g., effort of prevention)."

Recent literature has attempted to assess empirically whether asymmetric information exists. In a seminal paper, Chiappori and Salaniè (2000) tested the well-known positive correlation property: if there are informational asymmetries, high-risk individuals purchase higher coverage than low-risk individuals and file more claims. They find no evidence to corroborate the existence of asymmetric information in the French automobile insurance market. Unfortunately, the positive correlation property does not allow one to distinguish between moral hazard and adverse selection. Understanding which kind of asymmetric information is present is crucial because welfare implications and policy recommendations differ depending on whether moral hazard or adverse selection exist in a contractual relationship. In the auto insurance industry, in the absence of moral hazard, changing the structure of penalties will not lead to reductions in the accident rate because the insured drivers do not respond to financial incentives.

The auto insurance market has traditionally been considered an ideal laboratory to study private information because of the standardized contracts–summarized by a limited number of variables–in contrast to employment contracts. However, empirical estimates on the importance of moral hazard vary; see Abbring, Chiappori, and Zavadil (2008), Abbring, Chiappori, and Pinquet (2003), and Dionne, Michaud, and Dahchour (2013). This conflicting evidence is resolved by arguing that the "institutional" aspects of the market matter. Unfortunately, as researchers typically conduct inference using samples of contracts underwritten by only one or two companies, the available estimates are not necessarily robust to self-selection of drivers into companies. In fact, even in the highly regulated auto insurance market, insurers can choose discretionary penalty structures to incentivize safe driving and heterogenous premium-coverage menus, leading to possible sorting into companies.[1]

[1]A more careful examination of modern auto insurance markets reveals that contracts are increasingly differentiated–in Italy and in the United Kingdom, the so-called insurance telematics represents a remarkable manifestation of this phenomenon–but companies also provide a variety of services, such as assistance in the event of an accident, and differ in their intrinsic quality, e.g., efficiency in liquidating claims.

The primary goal of this article is to test for and measure moral hazard in the Italian automobile insurance market by applying two identification strategies that allow me to control for adverse selection and state dependence. This latter confounder–accidents might be correlated over time because they change preferences for risk–has often been neglected. Newly collected representative matched insurer-insuree panel data, which are far more comprehensive and complete than data used in previous research, give me the opportunity to go beyond the analysis of moral hazard within specific companies and examine its effect on the entire market.[2]

Disentangling moral hazard from adverse selection is often difficult. A prominent strategy for doing so is based on the idea that under adverse selection, the probability of accidents should be constant regardless of the incentives faced by the insured party. In contrast, in the presence of moral hazard, there are certain observable relationships between accident rates and incentives, relationships that are typically governed by experience rating systems. This approach, which originated in labor economics (see Heckman (1991)), characterizes several papers in the literature surveyed by Cohen and Siegelman (2010), under the label "dynamic properties" (DPA). Specifically, DPA exploits the nonlinearity of the premium-driving record schedule: under moral hazard, the higher the penalty for having an accident–the slope of the premium schedule at a given point–the higher the effort exerted by the policyholder. To the extent that driving records are subject to exogenous time-variation, repeated observations of the same policyholder allow DPA to control for adverse selection. For example, exploiting the evolution of the French bonus-malus system, Abbring, Chiappori, and Pinquet (2003) and Abbring, Chiappori, Heckman, and Pinquet (2003) show that because the next accident will be costlier in terms of insurance rate increases, people who have an accident face a financial incentive to drive more carefully, and, as a result, they should be less likely to have another accident. As noted by Ceccarini (2007) and Israel (2004), a driver might respond to an accident by driving more carefully or giving up the car for a while, leading to state dependence. As these papers find evidence of negative state dependence, the authors argue that neglecting this channel leads researchers to

[2]I have been leading a two-person team in charge of designing the structure of the data, the sampling procedure, the technical documentation, the legal/administrative aspects, the interaction with the companies, and the organization/maintenance/quality check of the data.

underestimate moral hazard.

I distinguish moral hazard from adverse selection and state dependence using two different methods. First, I apply DPA by implementing a two-step procedure. In the first step, I recover the slopes of the premium-driving record schedules in the market. I document the presence of a large number of non linearities in the penalties both within and across companies. In order to identify the effect of financial penalties on driving attentiveness, in a second step, I regress the event of one or more accidents on the driving record. As my panel follows policyholders across change of companies, I can also control for state dependence by exploiting the changes in the penalties faced by switchers. I infer moral hazard from the correlation between the estimated accident probabilities at each driving record and company with the corresponding penalties. I minimize the chances of an incorrect rejection of the hypothesis of moral hazard by combining the many identifying variations within and across driving records and companies.

The second research design is based on a unique feature of the Italian bonus-malus experience rating system: accidents during the last 60 days of contractual year t–the grace period–cannot be used to update the driving record of year $t+1$ but, instead, only that of year $t+2$. Thus, the monetary cost of accidents that occur during the grace period of year t will be reflected only on the premium covering year $t+2$. Moreover, accidents during the grace period of year t are likely to disappear from the driver's record if the insured party switches to another company (see section 2). My striking descriptive evidence of moral hazard–the hazard rate increases during the grace period, and the peak is more marked in the sample of switchers–motivates an event history analysis to check whether policyholders are less careful during a time period in which accidents would be less costly. I also argue that the grace period-variation disentangles moral hazard from state dependence.

The results obtained from DPA are in accord with moral hazard: a higher penalty translates into a lower accident probability. The negative correlation is stronger in some companies than others. I also find evidence of negative state dependence.
The event history analysis also indicates that moral hazard is at play. I find that

the baseline hazard rate of the last month with respect to the ninth month–my preferred measure of moral hazard–equals 21 percent. The estimated effect of moral hazard is larger when using the sample of switchers–about 116 percent–and heterogeneous across companies, ranging from 100 to 188 percent. A back of the envelope calculation suggests that heterogeneity in the preferences for risk plays an important role in determining the different effects across companies. Taken together, my findings suggest data limitations, coupled with sorting into companies, as a novel explanation to rationalize the conflicting evidence in the previous research.

The data I employ represent a remarkable advancement along several dimensions. Notably, my panel is a representative and large–4,316,667 contracts and related claims from 2013 to 2017:Q1–matched insurer-insuree dataset, following policyholders after changing companies. Moreover, the details on the contracts are richer than usual: along with the traditional variables, information on nine additional clauses shifting the premium and the expected indemnities are available.[3]

The relationships I examine empirically are interpreted within a duopoly model in which heterogenous drivers dynamically sort into companies, characterized by different premium-driving record schedules. I provide conditions under which, under moral hazard, a negative association between penalties and accident probabilities arises. The model allows me to cast the identification problem as one in which, given information on penalties and accidents, an average treatment effect–the average moral hazard in the market–has to be recovered. I also clarify the relationship between, and the external validity of, the parameters identifiable with representative and company-specific samples of contracts.

[3]To put these features into perspective, the seminal paper by Chiappori and Salanié (2000) employs a single cross-section of 20,716 contracts subscribed by a set of 21 companies accounting for 70 percent of the French auto insurance market. Abbring, Chiappori, and Zavadil (2008) and Jeziorskiy, Krasnokutskaya, and Ceccarini (2017) base their inference on 1,730,559/12,576 contracts subscribed by a *single* Dutch/Portuguese company, respectively; Dionne, Michaud, and Dahchour (2013) employ a rotating representative French panel of approximately 20,000 records with self-declared variables; Ceccarini (2007) employs data on 300,000 policyholders covered by a small Italian company.

This paper is structured as follows. In section 1 I describe the duopoly model and discuss the identification problem. In sections 2 and 3 I describe the institutional features of the Italian insurance market and the data I employ in my analysis; the estimates of the slopes of the premium-driving record schedule are in section 4, and the estimates of their effect on the accident probability are in section 5. In section 6 I then carry an event history analysis, present the estimates from the conditional analysis, and address possible reverse causality bias; section 6.4 documents the variability of moral hazard across companies. Concluding remarks are in section 7; section 8 contains tables.
The online appendix is structured as follows: section 10 presents the results on the effect of the grace period on the size of the damage and a discussion on the importance of fraudulent claims and ex-post moral hazard. I discuss three confounding factors–seasonality effects, learning, and misreporting–in section 10.1; in section 10.2 I document selective attrition effects in company-specific panel data. The online appendix also includes a description of the sampling procedure in section 11 and of the variables I use in my econometric analysis in section 11.1. Section 12 contains a number of omitted tables.

1. The Identification Problem

A risk-averse agent with intrinsic risk η–a shifter of the accident probability–initial wealth w, and observable individual and car characteristics X lives for T contractual years. At most one accident can occur within a year; i.e., $a_t = 1$ if an accident occurs and is zero otherwise. Let n_t signify the driving record at the beginning of period t: $n_t = \sum_{i=1}^{t-1} a_i$. Two companies, a and b, are active in the market; contracts are exclusive and cover one contractual year. The premium charged by company j for year t evolves according to a nonlinear pricing rule $h(\cdot)$ increasing in n_t

$$p_t^j = h^j(p_j, n_t, v_t^j) \;\text{ for }\; j \in \langle a, b\rangle. \tag{1}$$

The deterministic part of the base premium p_j depends implicitly on X, $v_t^j \in R^+$ is an iid shock distributed according to a smooth distribution G. Let $\Delta_j(n)$ denote the "penalty"–the increase in the premium after an accident–at n when covered by company j and $P_t = (p_t^a, p_t^b)$ the vector containing the deterministic part of the base premium. Without loss of generality, let $\Delta^a(n) < \Delta^b(n)$ and $p_a > p_b$. These inequalities imply a dynamic tradeoff the policyholder faces when choosing the company: a low base premium versus a high marginal increase of the premium if an accident occurs.

The state space at the beginning of each period is represented by $s_t = (P_t, n_t, a_{t-1}, i_{t-1})$, where $i_t \in \langle a, b\rangle$ provides information on the company chosen in the previous period. The timing of the events is as follows. At the beginning of period t, conditional on s_t, the driver decides to stay with the current company ($c_t = 0$) or switch ($c_t = 1$), and subsequently an effort level $e_t \in [0, \bar{e}]$ is selected. a_t realizes and n_t is updated. At the beginning of year $t+1$ the two random shocks v^j_{t+1} are drawn and P_{t+1} is updated according to (1); the driver chooses c_{t+1} and e_{t+1} conditional on s_{t+1}, and so forth.
The flow utility for an insuree covered by j reads

$$u(e_t, c_t; n_t) = u(w - h^j(p_j, n_t, v^j_t)) - \theta c_t - \lambda(e_t) \tag{2}$$

where $\theta > 0$ captures a switching cost, and $u(\cdot)$ and $\lambda(\cdot)$ are utility and effort disutility functions, respectively. Moreover, $u(\cdot)$ and $\lambda(\cdot)$ are increasing and concave and convex, respectively. Let the accident production function be

$$a_t = f(e_t, a_{t-1}, \epsilon_t; X, \eta) \in \{0, 1\} \tag{3}$$

where $f(\cdot)$ is decreasing in e_t and increasing in the risk parameter η; a_{t-1} captures state dependence (SD) and ϵ_t is a "structural" iid random variable distributed according to a cdf F. Let $\Pi(e_t, a_{t-1}) = \Pr(a_t = 1|e_t, a_{t-1})$ denote the accident probability. Henceforth, to ease notation I will omit the dependence on (X, w, η).

To characterize the equilibrium it is useful to define two sequences of company-specific value functions $\langle V^j_t(v^j_t, n_t, a_{t-1}, j)\rangle^T_{t=1}$ for the insuree, where by company-specific value function I mean the value function in case the contractual relationship is renewed at each periods ($c_t = 0$ for all t). Each sequence can be obtained by proceeding backward. At $t = T$ the value function reads

$$V^j_T(v^j_T, n_T, a_{T-1}, j) = -\lambda(0) + u(w - h^j(p_j, n_T, v^j_T)) \tag{4}$$

where the optimality condition $e_T = 0$ is incorporated in the problem. The generic t-period problem is

$$\begin{aligned} V_t(v^j_t, n_t, a_{t-1}, j) = \max_{e^j_t} \Big\langle & u(w - h^j(p_j, n_t, v^j_t)) - \lambda(e^j_t) + \\ & \beta\Pi(e^j_t, a_{t-1})E[V_{t+1}(v^j_{t+1}, n_t + 1, 1, j) - V_{t+1}(v^j_{t+1}, n_t, 0, j)] + \\ & \beta E[V_{t+1}(v^j_{t+1}, n_t, 0, j)]\Big\rangle \end{aligned} \tag{5}$$

where $\beta \in (0, 1)$ denotes the discount factor. Letting $e^j_t(n_t, a_{t-1})$ denote the optimal effort strategy of a policyholder covered by company j, the following proposition provides sufficient condition on h^j such that the optimal effort is increasing in the penalty $\Delta^j(n)$.

Lemma 1. *Let the pricing rule be specified as follows:*

$$h^j(n_t, v_t^j) = p_j + \delta_j^{n_t} + v_t^j \quad \textit{for } j \in \langle a, b \rangle. \tag{6}$$

If penalties are increasing in n_t ($\delta_j > 1$), policyholders will drive more carefully as their driving record worsens.

Proof. Given that Π is decreasing in e and using the standard monotonicity arguments, it is enough to show that

$$V_{t+1}(v_{t+1}^j, n_t + 1, 1, j) - V_{t+1}(v_{t+1}^j, n_t, 0, j)$$

is decreasing in δ_j. Applying the envelope theorem and plugging (6) into the value functions,

$$\frac{\partial V(v^j, n+1, 1, j)}{\partial \delta_j} < \frac{\partial V(v^j, n, 0, j)}{\partial \delta_j} \Leftrightarrow$$
$$u'(w - p_j - \delta_j^n - v_j) n \delta_j^{n-1} < (n+1)\delta_j^n u'(w - p_j - \delta_j^{n+1} - v_j)$$

Given the concavity of u, the inequality holds if $\delta_j^{n-1} < \delta_j^n$. This condition holds if $\delta_j > 1$. □

The particular functional form in (6) is only assumed for convenience; nevertheless, it provides an acceptable approximation of the most common pricing strategies adopted by the market.[4] Notice that what drives moral hazard is the degree of convexity in n, indexed by δ_j. There is little hope of deriving a testable implication under general conditions if the slope of the premium-driving record schedule is left unrestricted; see Ceccarini (2007).

Given the company-specific value functions, the optimal sequence of switching decisions can be characterized by proceeding backward. At T

$$c_T^j(s) = 1 \Leftrightarrow u(w - h^j(p_j, n_T, v_T^j)) - \theta > u(w - h^k(p_j, n_T, v_T^k)) \quad \text{with} \quad j \neq k,$$

where $c_T(s_T)$ denotes the optimal switching choice; the value function at T for an insuree covered by company j at $T-1$ can be written as

$$\mathbf{V}_T(s_t) = \max_{c_T} \langle (1 - c_T) u(w - h^j(p_j, n_T, v_T^j)) + c_T[u(w - h^j(p_j, n_T, v_T^j)) - \theta] - \lambda(0) \rangle$$

[4]It can be verified that the lemma holds if the law of motion of the premium were to be specified as $p_t^j = h^j(n_t, v_t^j) = p_j + n_t^{\delta_j} + v_t^j$, or if the shock is multiplicative.

with $j \neq k$. The value function at t for an insuree covered by company j at $t-1$ reads

$$\mathbf{V}_t(s_t) = \max_{c_t} \langle (1-c_t)V_t^j(v_t^j, n_t, a_{t-1}, j) + c_t[V_t^k(v_t^k, n_t, a_{t-1}, k) - \theta] \rangle$$

Abusing notation, let $c_t^j(s_t)$ denote the switching strategy of an insuree covered by j at period $t-1$. Given the monotonicity of u, it follows immediately that

$$c_t^j(s_t) = 1 \Leftrightarrow v_k < \tilde{v}_j(p_j, v_j, n_t, a_{t-1}) \tag{7}$$

where $\tilde{v}$ is a company-specific critical cut-off. Intuitively, if the premium offered by k is small enough with respect to j, switching from j to k will be profitable despite θ. This implication will motivate a placebo test I employ to address reverse causality when using the grace period research design.

Letting $Z = (X, \eta, w)$ and omitting the time indexes, the equilibrium induces a company-specific conditional distribution $g^j(Z|n, a)$ and a conditional effort strategy $e^j(n, a|Z)$. Abusing notation, let $\pi^j(n|a, Z) = \Pi(e_t^j(n, a|Z))$ denote the realized, in equilibrium, accident probability for a type Z, in driving category n and history of accidents a.[5]

The structure now allows me to interpret the behavioral responses observed in the data in terms of meaningful treatment effects resulting from the optimizing behavior of agents.[6] A driver assigned to driving category n and covered by company j is "treated" if the driving category is exogenously increased by one unit while still being covered by company j; the no-treatment status is defined as staying in category n while being covered by company j. Moral hazard at driving category n for a type Z covered by company j reads

$$MH^j(n|a, Z) = \pi^j(n+1|a, Z) - \pi^j(n|a, Z) \quad \text{with} \quad n \in \{1, \dots, N\} \tag{8}$$

where $N = T$ because only one accident can occur in a year. Conceptually, this marginal effect can be thought as the response of a type-Z when the penalty goes from $\Delta^j(n)$ to $\Delta^j(n+1)$. In the absence of moral hazard $\pi^j(n|a, Z)$ is constant at all n. Thus, moral hazard depends on the individual "responsiveness" to incentives, a parameter determined in equilibrium by the optimal effort, which

[5]This notation reflects the fact that the driving category n and the company j pin down the penalty $\Delta^j(n)$, the variable on which drivers condition their effort.

[6]Heckman and Vytlacil (2005) provide a bridge between the various treatment effect parameters analyzed in the program evaluation literature.

depends on the primitives–such as $u(\cdot)$ and $\lambda(\cdot)$–and on Z. A company-specific average effect, obtained by integrating over $g^j(Z|a,n)$, can be defined as

$$AMH^j(n) = \int \pi^j(n+1|a,Z)g^j(Z|n+1,a) - \int \pi^j(n|a,Z)g^j(Z|n,a) \quad (9)$$

It is now useful to define two assumptions

(RS): Z is randomly distributed across companies *at each point in time*

(HP): pricing is homogeneous in the market, e.g., $\delta_j = \delta$ for all j

If drivers randomly sort into companies and switching is also random–(RS) holds–$AMH^j(n)$ represents an average treatment effect (ATE). Namely, the effect on the accident probability of increasing penalties according to company j's rule for an average driver. On the contrary, if (RS) is violated AMH represents an average treatment-on-the-treated (ATT). Notice that even if (RS) holds, the magnitude of the effect one measures with a company-specific sample will not change across companies only if (HP) also holds.

In sum, the economic interpretation and the policy implications of the parameter identifiable by applying DPA to a company-specific sample of contracts depends crucially on the assumptions one is willing to make on the mechanisms governing the market.

Given the availability of a matched insurer-insuree panel–the kind of data I use in my analysis–it is useful to define the parameter I can identify when (RS) and (HP) do not hold and to relate this parameter to the one previously identified. As DPA exploits changes in the incentives from year t to year $t+1$, one can distinguish between an ATT for stayers and for switchers. Specifically, the nature of the data allows me to recover the behavioral responses of those who move from company k to j, between t and $t+1$

$$AMH^{jk}(n) = \int \pi^j(n+1|a,Z)g^j(Z|n+1,a) - \int \pi^k(n|a,Z)g^k(Z|n,a) \quad (10)$$

One can define a meaningful ATT–the average moral hazard in the market–identifiable through a matched insurer-insuree panel by weighting $AMH^{jj}(n)$–the effect among stayers identified by company-specific panel data–and $AMH^{jk}(n)$:

$$AMH(n) = \sum_{j\in(a,b)} w_{jj}AMH^{jj}(n) + \sum_{j\neq k\in(a,b)} w_{jk}(n)AMH^{jk}(n) \quad (11)$$

where w_{jj} and w_{jk} represent the proportion of stayers and switchers in driving category n covered by company j.

In the presence of sorting, $AMH(n)$ measures more accurately than $AMH^{jj}(n)$ the effect of financial incentives in the market, as it comprises the behavioral responses of all types. The formula shows that i) the average moral hazard in the market depends on a weighted average of the parameters that previous research identified using company-specific samples (the AMH^{jj}'s) and ii) in the presence of endogenous switching, previous research could not identify the true company-specific moral hazard because the behavioral responses of policyholders changing companies were not accounted for. In fact, the distinction between average treatment effects among stayers and switchers is not immaterial; in section 10.2 I demonstrate that better types are overrepresented in company-specific panel data because policyholders with a poor driving record are more likely to switch companies.

I now argue that if (HP) does not hold and one is willing to assume that switching companies is partially random, applying DPA to a matched insurer-insuree database also allows me to distinguish moral hazard from state dependence.

State Dependence To distinguish moral hazard from state dependence, a variable shifting a_{t-1} and not $\Delta(n_t)$, or vice versa, is needed. Unfortunately, as ϵ_t affects both, another source of identifying variation is needed.[7] Now, if (HP) does not hold–penalties are heterogeneous across companies at any given driving record–and drivers are followed over change of companies, the difference in the accident probabilities from t to $t+1$ among switchers with no change in accident histories can be attributed to moral hazard. Again, the heterogeneity in the slopes of the premium-accident schedules aids the identification problem. This argument rests on the existence of some randomness in the switching decisions. In the simple duopoly model, this is achieved by allowing the base premium to be stochastic. Obviously, it is crucial to assume that v_t^j is i.i.d., namely uncorrelated with Z.

[7]As an alternative, one could exploit unexpected changes over time of the pricing rule. Israel (2004) exploits an "insurance event" implied by the pricing rule of an American company.

2. Institutional Background

Italian law establishes that vehicles must be covered by basic rc auto insurance ("*Responsabilità Civile Auto*"), a mandatory motor third-party liability insurance contract. The rc auto contract covers damage to third parties' health and property in accidents where one is not at fault. It is possible to purchase comprehensive insurance contracts to cover one's own property damage; however, in practice, because of the high cost of insurance, the vast majority of contracts only feature the compulsory coverage.

Henceforth, by accident I mean an accident at fault. Both for historical reasons and because of a peculiar law–if a deductible exists, the insurer must initially refund the entire amount of damage and, subsequently, the policyholder must return it to the company–deductibles are almost always absent.[8] On the other hand, contracts are often characterized by a number of clauses–see section 3–that alter the size of the indemnity and the premium. The law establishes a mandatory minimum of liability coverage ("*massimali*"): 1 million and 6 million euros for property and health damage to third parties, respectively. The policyholder is responsible for any amount exceeding the liability limit. Section 3 shows that many policyholders choose higher coverage than the compulsory liability limits. The owner of the car and the subscriber of the contract typically are the same person, and the default length of the policy is one year; contracts that cover more or less than 12 months are quite rare. Contracts are exclusive and are not automatically renewed at the end of the contractual year.

Each accident is characterized by a percentage of liability (*"percentuale di responsabilità"*), denoted by $r \in [0, 100]$. For accidents involving two vehicles there exists "major" liability (*"responsabilità principale"*) if $r > 50$ and "equal" liability (*"responsabilità paritaria"*) if $r < 50$. A driver is at fault if $r > 50$, in which case no indemnity is received; if $0 \leq r < 50$, the indemnity equals $1 - r$ times the own damage. For accidents involving more than two vehicles, a driver holds major responsibility if the percentage of fault is greater than that attributed to the other drivers combined. The indemnities in multiple vehicle accidents are also determined according to the proportional criterion.

[8]Companies discourage deductibles because the legal disputes after drivers refuse to refund the company are costly.

In Italy, as in many other countries, a uniform experience rating system relates the history of accidents to class of risk, the so-called bonus-malus (bm) class. The bm class is specific to the pair subscriber-vehicle, so if the same individual underwrites multiple contracts to cover multiple vehicles, she may hold different bm classes.

The driving history at the beginning of a new contractual year is summarized by a public certificate, "*attestato di rischio*" (AR), a *paper* document that reports the bm class and the number of accidents over the previous five years with major and equal liability (with associated r). The AR also records the expiration date of the contract, vehicle information, and the level of deductible (if any); companies are free to establish their own system of penalties based on the driving history on the AR. The law prescribes that companies send the AR at least 30 days before the expiration date of the contract; if someone wants to insure a vehicle for the first time or change companies, the AR must be provided to get a quote. The AR is usually received during the last 60 days, when consumers can "shop around" for other contracts and companies.

There are 18 bm classes; class 1 is the best, and class 18 is the worst. New drivers are assigned to class 14. The bm class is updated using the information in the AR according to the rule in table 10: if the malus (bonus) is applied, the bm class increases (decreases) two (one) categories. The malus is applied if an additional accident with major liability or if multiple accidents with equal liability with cumulative $r > 50$ appear on the AR.

Accidents in the so-called period of observation (*"periodo di osservazione"*) are used to update the bm class and number of accidents on the AR holding at the beginning of year t. For vehicles with a sufficiently long insurance history, such a period includes the contractual year $t-1$ except the last 60 days and the last 60 days of year $t-2$, about 12 months. For recently insured vehicles, the period of observation is from the first day of year $t-1$ until 60 days before the expiration date, about 10 months. Therefore, accidents in the last 60 days of year $t-1$–henceforth *the grace period*–are not reflected immediately on the AR and only increase the premium in year $t+1$. As a result, the cost of accidents in the grace period is delayed.

No news is good news The delay-rule is enforced after a change of company if the new insurer checks that the AR provided at the beginning of year $t+1$ reports the whole history of accidents, including those in the grace period of year $t-1$, covered by a different company. Such scrutiny can be accomplished by consulting a database on claims held by the Italian association of insurers (ANIA). In practice, however, companies rarely do so. This glitch in the system–the "unpleasant" information can be endogenously eliminated by switching companies–generates a shift in the incentives during the contractual year I exploit to identify moral hazard.[9]

3. Data

The central source of information for this study is a new administrative database–a matched "insurer-insuree" panel–denominated IPER ("*Indagine sui prezzi effettivi per la garanzia rc auto*")–and collected by IVASS (*"Istituto di Vigilanza per le Assicurazioni"*), the Italian supervisory authority. The data contain information on basic rc auto contracts subscribed by a representative sample–the core sample–of 989,581 individuals, identified by their social security number (SSN), who had one or more auto insurance contracts in 2013. Contracts covering motorcycles and other types of vehicles are excluded. The stratification scheme is non-proportional in that younger age groups are oversampled. However, the degree of oversampling is very mild: the weighted and unweighted average premiums over the period of observation are 457.7 and 470.2 euros, respectively. More details are in the online appendix.

The main innovation by IPER is in the representation of the "insurance histories" of the core sample. That is, information on the evolution of initial contracts underwritten in 2013 and of new ones subscribed afterward is available; IPER represents the Italian auto insurance market equivalent of the well-known matched employer-employee databases used in the labor literature. Because the unit of observation is the SSN, not the plate-number in the databases used insofar, a variety of dynamics typically absent are represented: switching from one company to another, multiple contracts subscribed by the same individual for the same contractual year, contracts covering new vehicles purchased after 2013,

[9]IVASS recently implemented the "*dematerialization of the AR*", establishing that all information on the AR will become paperless and stored in a centralized database on claims that companies have to update. The new company will base the premium on the true history of accidents in the observation period.

Table 1. Number of Contracts and Policyholders

Contractual Years	2013-2014	2014-2015	2015-2016	2016-2017	2017:Q1
No. of Policyholders	989,581	886,280	848,590	838,409	227,086
No. of Contracts	1,111,285	1,012,726	979,395	975,937	237,304

and suspensions in the coverage period of a given vehicle. The representativeness of the sample constitutes a notable advantage over all previous empirical papers on auto insurance; information on contracts underwritten by virtually all of the companies operating in the Italian market is available. The number of companies subscribing contracts varies over time because of mergers, ranging from 49 in 2014-2015 to 37 in 2017-2018. The estimating sample is large: there are 4,316,667 contracts identified by a pair SSN-plate number covering at most five years, from 2013 to 2017:Q1.

Patterns Table 1 shows the number of contracts and policyholders at each contractual year. For 2017 only contracts underwritten in the first quarter are available. As can be inferred by comparing the total number of contracts with the number of subscribers, about 11 to 15 percent of the core sample covers more than one car across the first four contractual years. Interestingly, about 30 percent of multiple subscribers purchase insurance from multiple companies. There is some attrition, both as a consequence of the aging process of the individuals in the core sample and because of the economic cycle: during recessions car usage is reduced in favor of public transportation, and insurance contracts are less likely to be renewed.

Table 2 describes the most common histories in the data; 136,069 contracts are available for all five contractual years, and 527,468 contracts are available for the first four contractual years. 29,688 contracts are subscribed for the first time in 2016 and renewed in 2017, reflecting the coverage of new vehicles.

Driving record and other characteristics The data contain the typical variables used by insurers for pricing: age, gender, province of residence, and characteristics of the car, including the car's age, power in KW, cubic cylinder, and type of power source (16 mutually exclusive categories). The information on the driving record–bonus-malus class and number of accidents at fault during the past five years–is also available. IPER also contains the altimeter zone

Table 2. Availability of Contracts

	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018
527,468	✓	✓	✓	✓	✗
136,069	✓	✓	✓	✓	✓
127,199	✓	✗	✗	✗	✗
16,533	✓	✓	✗	✗	✗
118,036	✓	✓	✓	✗	✗
87,083	✗	✗	✗	✓	✗
75,466	✗	✗	✓	✓	✗
38,573	✗	✓	✓	✓	✗
29,688	✗	✗	✗	✓	✓
16,3753			other patterns		

Note. This table describes the dynamics of contracts in IPER.

group of the city of residence and variables related to its geomorphological classification.

Contracts IPER provides information on the yearly premium paid and, if the contract was not subscribed online or by phone, on the discount applied by the agent.[10] The number of installments in which the premium is divided–anecdotal evidence suggests that such a variable is correlated with wealth–is also reported. Although, as explained in section 2, very few contracts feature a deductible, the data contain information on its presence and amount as well as detailed information on several common clauses, generating nine additional variables. Clauses play a major role in screening consumers–a second-degree price discrimination–in highly regulated insurance markets in which insurance is mandatory, such as the Italian market.

Among the additional types of information on the contractual relationship, it is worth mentioning the upper limit on the amount the company will pay for accidents at fault (labeled coverage) and whether the coverage equals the minimum mandatory liability limit of 6 million (1 million for property damage and 5 million for health damage); in addition, there is information on whether the clause "*risarcimento in forma specifica*" exists (if an accident not at fault

[10]About 88 percent of contracts are underwritten through an agent/broker. If this is not the case, the discount is, by definition, zero.

occurs, the vehicle has to be repaired by a specified list of body shops). Furthermore, information on the so-called driving clause is reported; in essence, this clause makes the indemnity a function of the identity of the driver. For example, the "free driving clause" does not condition the size of the indemnity on the person driving. Importantly, it is reported whether there are other clauses on the contract that increase the base premium beyond those explicitly asked about. This dummy variable helps to control for unobserved features of the contract. The interested reader can find a detailed description of the available clauses in the online appendix.[11] These variables are new in the literature; typically, the data include only the premium and the deductible.

Claims The "*Banca Data Sinistri*" (BDS), containing information on the universe of claims filed in the market, has been used to complement the data on claims. Specifically, each pair SSN-plate number of the core sample has been matched with the BDS to gather information on the first three accidents (in chronological order) filed within a contractual year. Information on the date of the accident, when the claim has been filed, and the size of the damage has been obtained. It is also known whether the refunding procedure has been terminated, e.g., the claim is not on-hold. Table 3 describes the distribution of claims per contractual year; the probability of being responsible for one or more claim in the first and second contractual year is 5.13 percent, and 5.27 and 4.65 in the third and fourth contractual years. Being responsible for more than one accident within the same year is a very low probability event.

TABLE 3. Distribution of the Number of Claims in IPER

	Contractual Year				
Number of Claims	2013-2014	2014-2015	2015-2016	2016-2017	Q1:2017
0 claims	94.87	94.87	94.73	95.35	97.85
1 claim	4.80	4.81	4.97	4.41	2.09
2 claims	0.28	0.28	0.27	0.22	0.05
3 or more claims	0.04	0.03	0.03	0.02	0.00
Number of contracts	1,111,285	1,012,726	979,395	975,937	237,304

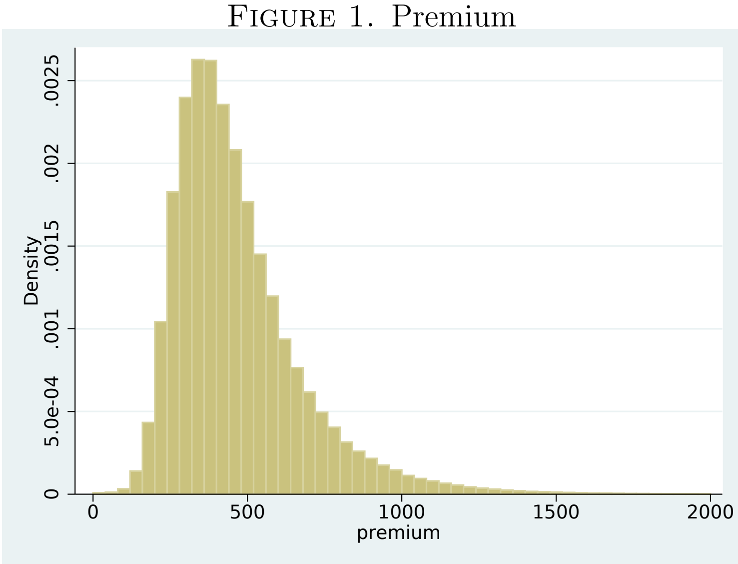
Note. In this table the percentage of contracts involving a given number of claims is reported. Sampling weights have not been used.

[11]In an ongoing work with Gaurab Aryal, the role of the clauses in shaping the choice of the contract of the company is examined.

Given the time span covered by the BDS and the fact that accidents can be filed after the end of the contractual year, only the claiming history of the contracts covering the first three contractual years and the first quarter of the fourth year can be considered complete.

3.1. **Descriptive Statistics.** Figure 1 depicts the histogram of the premium in the Italian market from 2013 to 2017:Q1. The mean premium–457 euros–is among the highest in Europe and is such that the compulsory insurance coverage is in the top 10 most expensive items purchased by Italian households. The statistics of the premium, in table 4, show that the mean and the median differ by about 48 euros, 5/50 percent of the policyholders pay less than 227/422 euros, and 5 percent are charged more than 876 euros. The standard deviation is about 216 euros. A simple OLS regression of the premium on the variables related to the expected cost of the insuree–section 4 describes the specification of a hedonic premium regression–yields an R^2 of about 0.5. Therefore, half of the variability is left unexplained.

FIGURE 1. Premium



Note. This graph depicts a histogram of the premium (in euros) reported on the contracts over the period 2103-2017:Q1. Contracts featuring a premium higher than 2000 euros–3,802 records–have been excluded from the sample used to graph the density. Sampling weights have not been used.

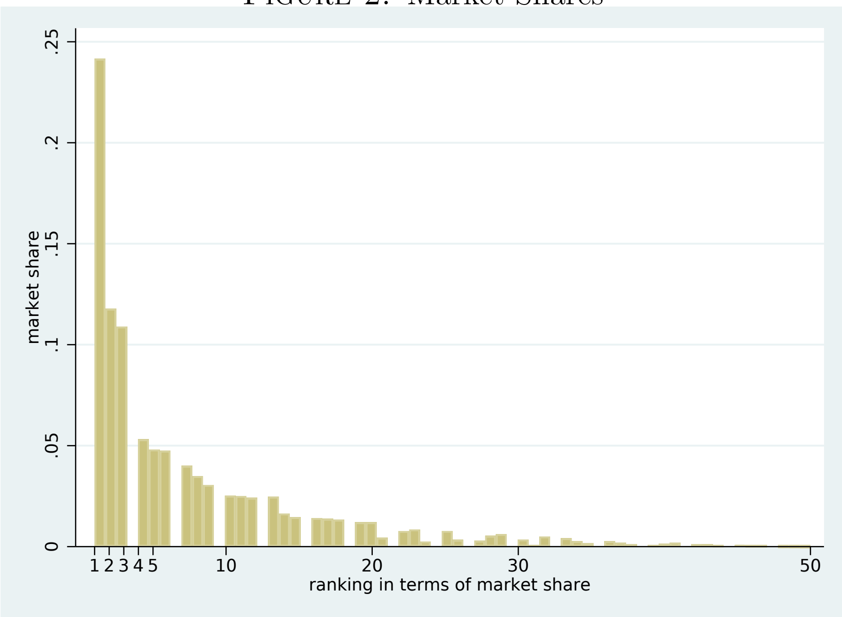
As can be seen from figure 2, the Italian market is quite concentrated. The first five companies cover 24.59, 12.14, 10.9, 5.13, and 4.81 percent of the market, accounting for 57.5 percent of the market. The first 10 and 20 companies hold

Table 4. Statistics of the Premium

5^{th} perc.	25^{th} perc.	Median	75^{th} perc.	95^{th} perc.	Mean	St. dev	Skewness	Kurtosis	N
227.27	325.76	422.26	559.18	876	470.2	216.37	2.10	11.52.	4,315,503

Note. This table reports statistics on the premium reported on the contracts over the period 2103-2017:Q1.

Figure 2. Market Shares



Note. This graph depicts the market share held by companies over the period 2013-2017:Q1. The market shares are computed without using the sampling weights. Companies are indexed in terms of their market shares from the largest (1) to the smallest.

about 75 percent and 92 percent of the market, respectively. The Herfindahl-Hirschman index (HHI) over the period considered equals 994.73. The other companies hold negligible market shares ranging from 0.85 to 0.01 percent.[12]

Tables 10 and 11 present weighted means of several characteristics of the contract, policyholder, and vehicle. Each statistic is available for the market, for the first five largest companies, for the set of medium companies–a company belongs to this group if its ranking in terms of market share is greater than 5

[12]These statistics are computed using the sampling weights. The unweighted market shares are very similar.

and smaller than 20–and for the remaining companies, the small companies.[13]

The average policyholder is 52 years old, and 60 percent of insured drivers are male. The average bm class and number of accidents on record are 1.92 and 0.16, respectively. About 12 percent of policyholders switch companies at the end of the contractual year; the retention rate is higher than those in other auto insurance markets.[14] The accident rate across the period–the probability of provoking one or more accidents in a year–is about 5 percent, and the average size of the damage–the indemnity perceived by the third parties–is about 2,145 euros.

Driving Record To summarize the information on the driving record, I group bm classes in the following categories: class 1, classes 2-3, classes 4-10, and classes 11-18. The majority of drivers–77.84 percent–are assigned to bm class 1, 9.11/11.43 percent to classes 2-3/4-10, and very few–1.62 percent–are in classes 11-18; only 12.24/1.42 percent of policyholders have provoked one/two accidents in the past five years, while driving records with more than two accidents in the past five years are extremely rare. Table 5 contains the transitions matrix of the bm class and of the number of accidents on record. The persistence of the bm class–the diagonal–is non-monotonic in the class: those in class 1 at t are very unlikely to move at $t + 1$, while those in class 2 have a 50-50 chance of staying or moving to class 1. For the accidents on record, the higher their number, the lower the persistence. Overall, these patterns indicate that except for the clean record policyholders–bm class 1 and no accidents on record–driving records fluctuate considerably over time.

Variations across companies The premium varies considerably across companies; it ranges from 378 to 498, and there is no clear correlation with market shares. Age and other observable variables, such as the area of residence, display moderate dispersion in the market. The average number of accidents on record and bm class vary substantially, ranging from 0.18 to 0.12 and from 1.82 to 2.04, respectively. The switching rate varies too and is higher

[13]For antitrust reasons, it is not possible to exactly rank companies according to their market shares; companies A-D belong to the set of the five largest companies without any ordering.

[14]Honka (2014) estimates a retention rate of 74 percent in the US market.

Table 5. Transitions in the BM Class and in the Number of Accidents on the AR

	bm class $t+1$					acc. on AR $t+1$			
bm class t	1	2-3	4-10	11-18	acc. on AR $t+1$	0	1	2	>2
1	97.16	2.76	0.07	0.01	0	91.74	2.78	0.07	0
2-3	48.31	47.99	3.69	0.01	1	18.17	78.15	3.54	0.14
4-10	0.21	20.41	78.71	0.67	2	4.89	27.89	62.91	4.31
11-18	0.6	0.09	31.91	67.4	>2	2.17	9.17	28.91	59.75

at small and medium companies. Interestingly, despite these differences, the accident rate is quite stable at around 5 percent (panel A of table 11); in contrast, the average size of the damage ranges from 2,014 to 2,308 euros, indicating that the average cost of a contract differs across companies. This aspect is reflected, at least partially, in the differences in vehicle characteristics (panel C of table 10).

The data reveal considerable variability in the observable features of the contracts across companies (table 10). For example, 35 (15) percent of policyholders covered by $A(C)$ choose a "black box" clause, while among companies D, the medium companies, and small companies, the proportion is 0, 3, and 8 percent, respectively; analogously, the fraction of contracts in which the "free driving" clause is present ranges from 17 to 70 percent. The heterogeneity in the maximum liability ranges from 6.75 million to 29 million; the fraction of subscribers choosing the minimum mandatory coverage of 6 million varies from 39 to 75 percent. The other clauses also display a conspicuous volatility.

Product differentiation–some companies do not offer some clauses such as the black box– cannot fully rationalize these descriptive statistics. That is, one may argue that drivers sort randomly into companies and that the observed variability in the clauses reflects the different choice set faced by consumers. A counterexample to this narrative is provided by documented variability of the minimum liability coverage–"coverage" and "min coverage" in table 10–a mandatory feature of all contracts. Therefore, the differences in the features of the contracts also reflect the variation of the unobservable preferences for risk across companies, an indication that company-specific samples of contracts are non random.

4. The Effect of the Driving Record on Insurance Rates

Letting p_{ijt} denote the premium paid by consumer i for coverage of contractual year t if covered by company j, consider the following specification of the hedonic premium function

$$p_{ijt} = c_{jt} + \beta_j^{AR} X_{it}^{AR} + \beta_j^{BM} X_{it}^{BM} + \beta^a a_{i,t-1} + \beta^Z Z_{it} + \gamma_t + \eta_i + \epsilon_{it} \qquad (12)$$

where:

- X_{it}^{AR} contains *oneaccAR* and *twoaccAR*, indicators taking value one if one and two accidents are on record, respectively, and zero otherwise. The omitted category is an indicator taking value one if the AR is clean.[15] Let $\beta^{AR} = (\beta_{1,j}^{AR}, \beta_{2,j}^{AR})$ be the vector containing the associated company-specific coefficients.
- X_{it}^{BM} is a vector containing the dummy variables $\langle bm_1, \ldots, bm_{14} \rangle$ taking value one if the policyholder is assigned to each of the bm classes 1-14, and zero otherwise. The omitted category is represented by the bm classes 15-18. Let $\beta_j^{BM} = (\beta_{1,j}^{BM}, \ldots, \beta_{14,j}^{BM})$ be the vector containing the company-specific coefficients associated with the bm class indicators.
- $a_{i,t-1}$ is an indicator taking value one if the policyholder is responsible for one or more accidents in year $t-1$.
- Z_{it} contains the individual and car characteristics, the contractual clauses, province and company dummies, characteristics of the city the subscriber lives in, and the number of "installments."[16]
- c_{jt} is a dummy taking value one if contractual year t is covered by company j and zero otherwise; γ_t contractual year fixed-effect effects.

I am interested in identifying $(\beta_j^{AR}, \beta_j^{BM})$, the effect of the driving record on the premium. If the accident does not alter the driving record, the entire effect is captured by β^a; if it does–section 2 describes when this happens–β^a captures the residual effect. If companies adopt a *nonlinear pricing scheme*–penalties depend on the driving history–the company-specific bm coefficients and number of accidents on record will turn out to be statistically different.

[15] Recall that the AR reports accidents at fault over the previous five years. A negligible proportion of policyholders have three or more accidents on record.

[16] The greater the number of installments, the higher the premium. This variable is a proxy for wealth.

Penalties Let Δp_bmk^j be the penalty in class k when covered by company j, defined as the increase in the premium after the occurrence of an accident (the malus) minus the decrease in the of case of no accident (the bonus). The evolution of the bm class described in table 9 is such that the malus is represented by the premium in class $k+2$ and the bonus by the premium in class $k-1$ implying that $\Delta p\_bmk^j = \beta^{BM}_{k+2,j} - \beta^{BM}_{k-1,j}$; the penalty in class 1 is represented by $\Delta p\_bm1^j = \beta^{BM}_{3,j} - \beta^{BM}_{1,j}$. Because the effect of classes 15-18–the omitted category–is not identified, only the penalties for classes 1-12 combined with zero and one accidents on the AR can be identified.
Letting Δp_ARn^j signify the penalty enforced by company j if n accidents are on record, the penalty for policyholders with a clean record is $\Delta p\_AR0^j = \beta^{AR}_{1,j}$. Identifying the penalty if one accident is on record is complicated by the fact that no information on the year in which the accident on record happened is available. Therefore, it is not possible to establish whether, in the case of no accident, the following year the AR will still report one accident, in which case $\Delta p\_AR1^j = \beta^{AR}_{2,j} - \beta^{AR}_{1,j}$ or if there will be no accident, in which case $\Delta p\_AR1^j = \beta^{AR}_{2,j}$. In an effort to provide a more conservative estimate of the penalty I will adopt the first measure, underestimating the average penalty to which policyholders with one accidents on record are subject. The overall penalty associated to the combination bm class k-n number of accidents on the AR–a generic driving record (k, n)–is represented by $\Delta p_{j,k-n} = \Delta p\_bmk^j + \Delta p\_ARn^j$.

Omitted Variables One could think of η_i–the unobservable component of the premium–in terms of unobservable vehicle characteristics such as car value and the presence of an airbag as well as individual characteristics such as marital status, occupation, zip code, and number of children under 18 living in the household that are used for pricing and absent in the data. While it is unlikely that any dataset could include all variables used for pricing, IPER contains a richer set of variables related to the contract, such as the contractual clauses, than analogous datasets used insofar. η_i could also be interpreted as the policyholder's ability to negotiate good prices. This source of unobserved heterogeneity is relevant because agents enjoy a relative amount of discretion in applying discounts to reach sales targets.

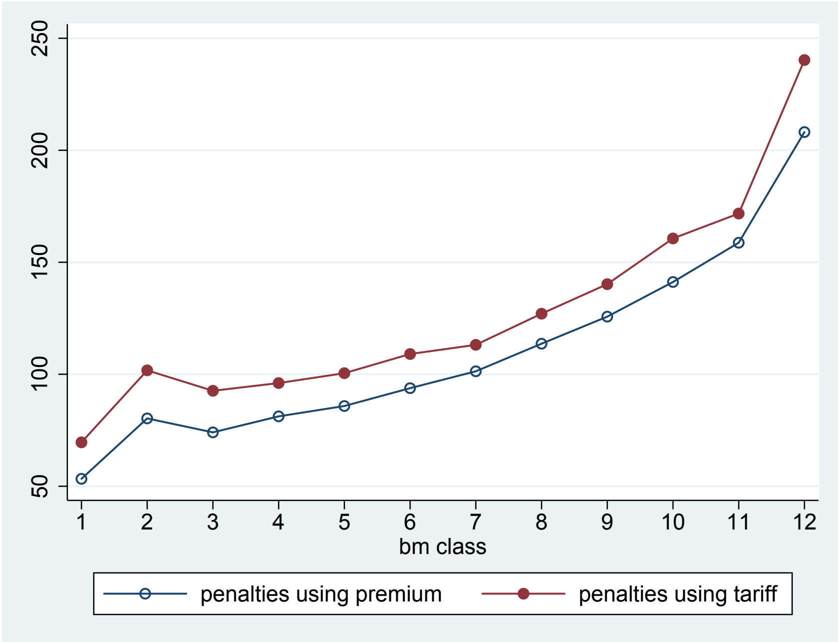
Identifying variations The longitudinal aspect of the data allows me to eliminate η_i by means of the traditional fixed-effect transformations. Under the assumption that η_i is uncorrelated with the number of contracts subscribed, the cross-sectional variation across contracts underwritten by the multiple subscribers further allows me to net out η_i. Along the same lines, the company-specific parameters are identified by the information from the switchers and from the fraction (about 30 percent) of multiple subscribers purchasing insurance with different companies.

4.1. **Results.** The effect of accidents not captured by the driving record (β^a) is statistically significant but the small in magnitude; tables 12 and 13 contain the estimates of $(\beta_j^{AR}, \beta_j^{BM})$, using as a dependent variable the premium in logs and in levels, respectively. Column (1)–labeled "Market"–presents the estimates of a restricted specification in which $\beta_j^{BM} = \beta^{BM}$ and $\beta_j^{AR} = \beta^{AR}$ for all j–the slope of the premium-driving record schedules are restricted to be uniform across companies–while columns (2)-(7) contain the estimates of the company-specific parameters of the baseline specification.

From column (1) of table 12 it can be seen that having one and two accidents on record generates average insurance rate increases of about 10 percentage points and 18 percentage points, respectively; these penalties translate into increases of 47 and 103 euros. Relative to the omitted category–classes 15-18–the discount on the premium decreases monotonically as the bm class increases in the range 1-12, and goes from 48 percent (class 1) to 2 percent (class 12). The coefficients become negative and close to zero for classes 13 and 14. In euros, these numbers translate into discounts as large as 505 euros (class 1) and 67 euros (class 13) (see table 13). Considering that the average premium in the estimating sample is about 457 euros, the estimates suggest that the cost of careless driving is large.

Table 14 shows the penalties for each driving category and company. Panel A and B contain the penalties for those with zero and one accident on record, respectively. For policyholders with a clean driving record $(0, 1)$ an accident implies, on average, a rate increase of $100.7(= 53.31 + 47.461)$ euros, the result of the transition from bm class 1 to 3 and of the penalty for having one accident on record. Figure 3 shows the penalties associated with each bm class, computed using the restricted specification. Penalties are increasing in the bm class, except for a non-monotonicity between classes 2 and 3. Therefore, insurance rates are non-linear and mostly convex in the bm class. Figure 4 shows the

FIGURE 3. Penalties in the Market

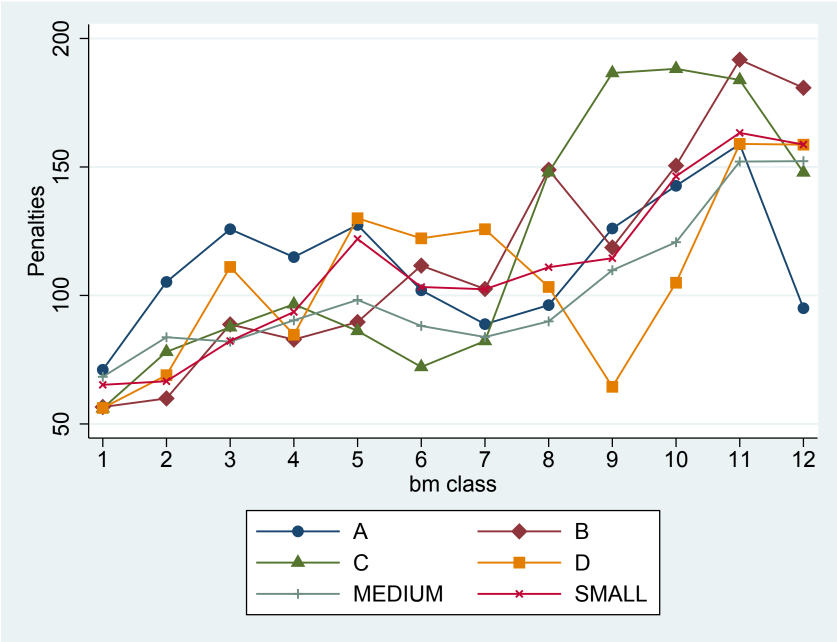


Note. This graph depicts the estimates of the average penalties in the market across bm classes estimates using the realized price for insurance and the theoretical tariff.

penalties as a function of the bm class across companies. There are remarkable differences both in the levels–for example, the penalty associated with bm class 1 is 71 euros for company A, while it is 56 euros for company B–and in the shapes of the curves; the pattern at company D is rather non-monotonic as opposed to company B. It also emerges that small companies adopt a relatively flat schedule. The differences in the pricing strategies appear to be more marked at higher bm classes, indicating that the heterogeneity on the supply side–the structure of loading costs–plays a more important role when ex-ante risk is high.

Companies also adopt heterogenous pricing strategies with respect to the number of accidents on record. Having one accident generates an insurance rate increase of 47 and 203 euros for policyholders covered by company A and B, respectively. Having two accidents on the AR implies a penalty with respect to the no accident on record situation of 103 and 300 euros if covered by company A and by a small company, respectively. Interestingly, some companies penalize one accident on record more than two accidents–A, B and the small companies–while the other insurers choose the opposite approach.

Figure 4. Penalties Across Companies



Note. This graph depicts the estimates of the company-specific penalties across bm classes using the realized price for insurance.

To summarize, the data suggest that 1) financial penalties are substantial, and 2) the slopes of the premium-driving record schedules–the numbers in each row of table 14–are quite heterogeneous in the market, representing a rich source of identifying variations. As a consequence, even if drivers sort randomly into companies, having access to company-specific samples of contracts does not necessarily allow the researchers to conduct "valid" inference.

I now examine the relationship between driving records and accident probabilities.

5. The Effect of the Driving Record on the Accident Probability: Testing for Moral Hazard

Let $a_{ij,k-n,t}$ be a dummy taking value one if driver i with a driving record (k, n) is responsible for one or more accidents during year t while being covered by company j, and zero otherwise. Consider the following specification of the accident probability

$$\Pr(a_{ij,k-n,t} = 1) = \Phi(c_j + \alpha^{dr}_{j,k-n} dr^{k-n}_{it} + \alpha^a a_{i,t-1} + \alpha^Z Z_{it} + \text{contr. year FE} + \theta_i)$$

(13)

where dr_{it}^{k-n} is a dummy taking value one if driver i is assigned to driving category (k, n) at time t. The coefficients of interest are the $\alpha_{j,k-n}^{dr}$'s, capturing the effect of monetary incentives on the likelihood of an accident.

Identifying variations The longitudinal aspect of the data allows one to eliminate θ_i and distinguish moral hazard from adverse selection. In order to illustrate how DPA allows me to separate moral hazard from state dependence–distinguishing α^a from the $\alpha_{j,k-n}^{dr}$–by exploiting the variation of penalties across companies conditional on a driving record, it is useful to apply the estimates of the penalties in table 14. Consider a driver with a clean record–bm class 1 and zero accidents on record–covered by company B at t and by company D at $t+1$. If an accident occurs, the insurance rate increases 260 euros at t and 134 euros at $t+1$. Under moral hazard, the accident probabilities are lower in period t than in period $t+1$. Any variation of this kind observed in the data cannot be rationalized by state dependence–the history of accidents is left unchanged–allowing one to identify $\alpha_{j,k-n}^{dr}$.

Testing The null hypothesis of no moral hazard translates into

$$H_0 : \alpha_{j,k-n}^{dr} = 0 \text{ against } H_A : \alpha_{j,k-n}^{dr} \neq 0$$

for all driving records (k, n). To put it differently, once unobservable risk is taken into account, the driving record should be inconsequential for the accident probability. Lemma 1–accident probabilities and penalties are negatively correlated–can be used as a basis to test the hypothesis of moral hazard. There are two main identifying variations in the data:

(1) $\Delta p_{j,k-n} > \Delta p_{j,h-n} \Rightarrow \alpha_{j,k-n}^{dr} < \alpha_{j,h-n}^{dr}$ for all $k \neq h$
(2) $\Delta p_{j,k-n} > \Delta p_{h,k-n} \Rightarrow \alpha_{j,k-n}^{dr} < \alpha_{h,k-n}^{dr}$ for all $j \neq h$

that can be combined to construct the following test of moral hazard

$$H_0 : corr(\Delta p_{j,k-n}, \alpha_{j,k-n}^{dr}) < 0 \text{ against } H_A : corr(\Delta p_{j,k-n}, \alpha_{j,k-n}^{dr}) \geq 0$$

where $corr(\cdot,\cdot)$ denotes the correlation between two variables. In other words, I accept the hypothesis of moral hazard if, "on average", increasing the cost of an accident translates into a lower accident probability. Measuring moral hazard in terms of the correlation between a relatively large number of penalties and accident probabilities obtained by combining the variation across driving records within companies–implication (1)–and across companies conditional on driving records–implication (2)–increases the power of the test. In other words, the existence of some "local" positive or zero correlation–(1) or (2) do not hold for some driving record–does not necessarily lead me to reject the null of moral hazard.[17] This approach is in contrast with some previous works, which typically focus on a single nonlinearity–see Abbring, Chiappori, and Pinquet (2003)–to test for moral hazard.

Accident Probabilities My benchmark specification of Φ is a linear function because the linear probability model permits a direct computation of the marginal effect of the driving record. As the presence of the lagged outcome variable in the conditioning set is such that the standard within-group (WG) transformations do not eliminate the fixed effect when the covariates are only predetermined and not strictly exogenous, my preferred estimator is the one proposed by Arellano and Bond (1991) (AB). Tables 15 and 16 contain the estimates of the parameters by the AB estimator associated with bm classes 1-14 conditional on having zero and one accident on record, respectively. Tables 20 and 21 in the online appendix present the estimates obtained by the WG estimator, while tables 22 and 23 present the estimates by the fixed-effect logit estimator. Column (1) presents the estimates of a restricted specification–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ for all driving records (k, n)–capturing their average effect in the market, while the estimates of the company-specific coefficients $(\alpha^{dr}_{j,k-n})$ in the baseline estimating equation specified in (13) are in columns (2)-(7).

The province and company dummies turn out not to be statistically significant across the various estimators, indicating that any systematic difference in risk across local markets and companies is fully captured by my controls. Importantly, the lagged outcome variable I control for–a dummy (L.ACC) taking value one if one or more accidents occurred in the previous year–is statistically significant at the 1 percent level. The estimates of α^a obtained by the AB, WG, and FE logit estimator are -0.03, -0.39, and -4.20, respectively. This evidence of negative state dependence–consistent with Ceccarini (2007)–indicates that neglecting this channel leads to misspecification bias.

[17] Controlling for the type I error rate in the presence of multiple hypothesis testing is the object of recent investigations in econometrics and statistics. See Romano, Shaikh, and Wolf (2010) and List, Shaikh, and Xu (2016).

Focusing on the average effects in the market–column (1) of tables 15 and 16–all the coefficients of interest are statistically significant at the 1 percent level, regardless of the estimator employed. These results also hold when the WG and FE logit estimator is used. The coefficients estimated by the WG estimator are smaller in magnitude than the ones I estimated by the AB estimator, indicating that the assumption of strict exogeneity is too restrictive. The company-specific coefficients of the effect of the driving record–$\alpha^{dr}_{j,k-n}$'s in the baseline estimating equation specified in (13)–are all significant at the 1 percent level.[18] Therefore, the null hypothesis of no moral hazard cannot be accepted.

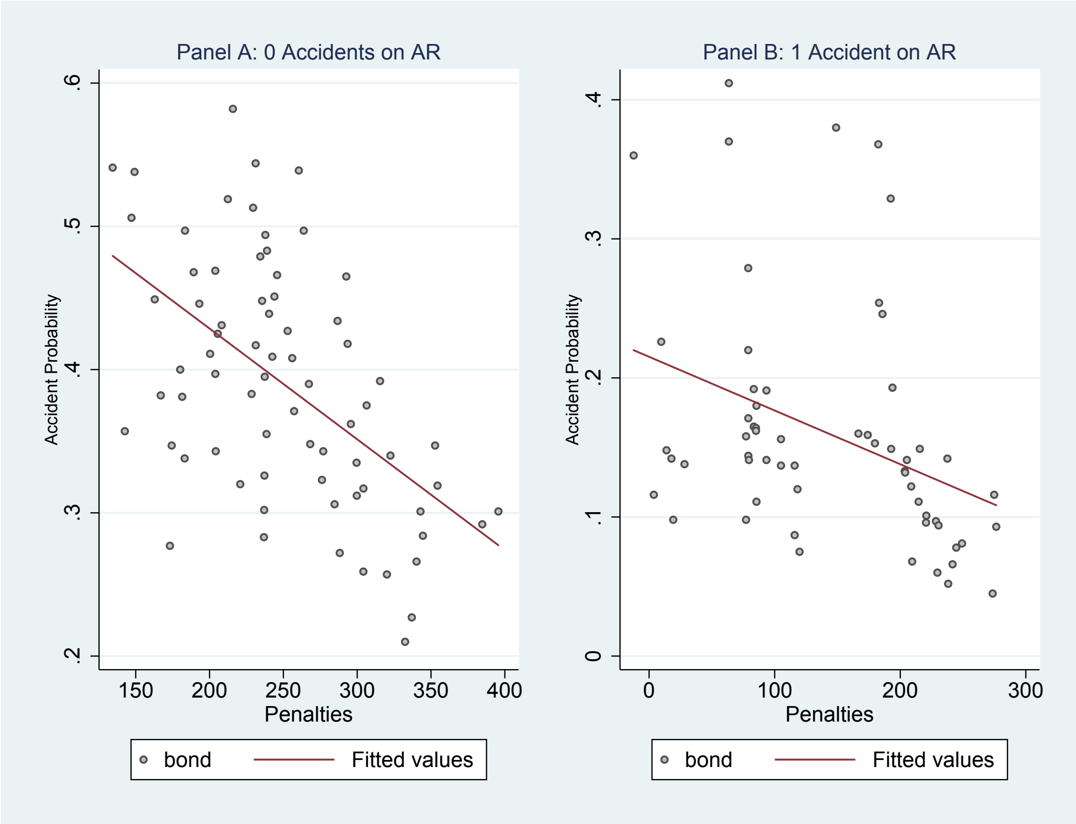
Panels A and B of figure 5 show the scatter plots of the accident probability-penalty pairs $(\alpha^{dr}_{j,k-n}, \Delta p_{j,k-n})$ across bm classes k, conditional on $n = 0$ and $n = 1$, respectively. There exists a negative association in both cases, although the response to monetary incentives is higher when no accident is on record. This result is robust across estimators and companies. Panel A of table 17 presents the coefficient of correlation (ρ) between the penalties and the accident probabilities at bm classes 1-12, conditional on $n = 0$; panel B presents the correlation at bm classes 1-10, conditional on $n = 1$. Columns (2), (4), and (5) present the correlation conditional on $n = 0$ when the accident probabilities are estimated by the AB, WG, and FE logit estimator, respectively. Columns (7), (9), and (10) present the correlation at bm classes 1-10, conditional on $n = 1$.[19] The first row–labeled "all companies"–contains the correlation computed using all the available pairs from the all set of companies (72 pairs if $n = 0$ and 60 pairs if $n = 1$); rows 2-7 contain ρ when using the company-specific set of pairs (12 and 10 pairs if $n = 0$ and $n = 1$, respectively). The last row presents the correlation when the driving records are assumed to have a uniform effect across companies on prices and accident probabilities. I compute ρ conditional on n because I am worried about the bias introduced by my approximation–an accident on record at year t will remain on record at year $t+1$–in the estimates of the penalties conditional on $n = 1$.

Focusing on the correlation between penalties and accident probabilities estimated by the AB estimator using the "all companies" sample, ρ equals -0.509

[18]Because of the small sample size, the effect of bm classes 12-14 conditional on $n = 1$ are not precisely estimated.

[19]I do not consider the pairs associated with the driving records $(k, 1)$ with $k = 11, 12$ because for some companies the corresponding accident probabilities are not significant.

FIGURE 5. Penalties and Accidents



Note. This graph depicts the correlation between accident probabilities estimated by the AB estimator and penalties at each bm class across companies. In panel A and B the penalties are computed conditional on zero and one accident on the AR, respectively.

when $n = 0$, ranging from -0.421 (company A) to -0.936 (small companies) when the correlation is computed using company-specific sets of pairs' penalty-accident probability. When $n = 1$ the correlation is weaker; $\rho = -0.378$, ranging from -0.546 to -0.774.

Because the association in the market is negative irrespective of the estimator, the null hypothesis of moral hazard cannot be rejected. While unambiguously moral hazard is at play, the strength of the phenomenon, as measured by the value of ρ, varies across companies.

The validity of these results rests on the assumption that policyholders fully optimize on the premium-driving record schedules enforced by companies, e.g., the pricing schemes are "salient". Given the complexity of pricing schemes in some cases, it is arguable whether the salience assumption holds in all segments of the market.[20] However, if anything, its violation decreases the chances of a false positive and increases the power of the test. In other words, having found evidence of moral hazard under a strong assumption on the information set drivers is comforting. On the other hand, a closer inspection of the estimates in tables 15 and 16 reveals mild differences in the estimates of the accident probabilities across companies, despite substantive differences in the penalties. For example, the penalties for the clean driving record $(1, 0)$ at companies A and B are estimated at 149 and 260 euros (table 14). However, the corresponding accident probabilities nearly coincide at 0.53. Analogously, the corresponding penalty for the group of small companies is 238 euros, and yet the accident probability is estimated at 0.483. To the extent that the AB estimator fully controls for unobservable heterogeneity, the pattern of the accident probabilities across bm classes suggests that drivers are generally aware of the shape of the premium-driving record schedule–whether the marginal cost of an accident is increasing or not–but are not well-informed about the differences in the magnitude of the penalties among companies. In other words, the data seem to support implication (1) and not implication (2). I consider these reduced-form results as useful information if one wants to model the mechanism leading to sorting across companies.[21]

Price vs. Tariff Recovering the structure of penalties by estimating the elasticity of "true" prices with respect to the driving records represents a departure from the traditional approach, focusing on the theoretical tariff(=premium+agent's discount) decided by companies at a central level. The underlying assumption justifying my procedure is that policyholders can correctly anticipate the response of the price for insurance–the variable they care about–to the evolution of the driving records.[22] To the extent that agents apply discretionary discounts (see Jeziorskiy, Krasnokutskaya, and Ceccarini (2017)), the tariff might differ substantially from the true price for coverage. To investigate the importance

[20]The importance of salience has been extensively investigated in public finance. In particular, Chetty (2009) shows that taxes explicitly indicated in the posted prices–more salient taxes–have a larger effect on demand. Finkelstein (2009) examines the role of salience by exploiting the introduction of electronic toll collection.

[21]Einav and Finkelstein (2017) argue for the importance of reduced-form evidence to guide the assumptions underlying structural models.

[22]This information can be easily acquired by communicating and/or bargaining with the agents.

of the measurement error introduced if one estimates the structure of penalties using the tariff, I extrapolated the tariff–the data contain information on the discount applied by the agent on each contract–and used it as the dependent variable in the restricted specification–the driving record is not interacted with the company dummies–of the estimation equation in (12). The coefficients related to the driving record are larger in absolute value with respect to the estimates using the actual premium paid for coverage. To get a sense of the bias introduced by the traditional approach, figure 3 shows that penalties would be systematically overstated by about 20 euros, although the shape of the schedule is unchanged. Thus, if penalties were to be inferred from the tariff, it would seem that large penalties translate into relatively small accident probabilities, leading researchers to reject moral hazard more often than they should (type II error).

5.1. **Testing with company-specific samples.** The availability of contracts underwritten by all companies allows me to ascertain whether my tests would deliver different results had I used a company-specific sample. To address this issue, I estimated the hedonic premium regression specified in 12 and the accident probability in (12) on each company-specific sample. The results on the premium regression are presented in table 24 in the online appendix. When comparing the coefficients with those in table 13, obtained using the entire sample, it appears that company-specific samples lead one to underestimate the effect of the bm class on the premium. For example, the coefficient of bm class 1 for company B is estimated at -491 and -626 euros using the all sample and the company-B-specific sample, respectively. The difference is even more dramatic for company D: -579 versus -352 euros. The bias in estimating the effect of the number of accidents on record is also quite large. The relevance of sample selection bias–also driven by the unavailability of information on the contracts underwritten by those who change companies–can be appreciated by comparing table 25, containing the estimates of the penalties I would have obtained through company-specific samples, with those obtained using the all sample (table 14).

Perhaps surprisingly, the accident probabilities estimated by the AB estimator using company-specific samples turned out to be very similar to the estimates I obtained using the all sample.[23] For all of the 25 largest companies,

[23]The results are available upon request.

the bm class dummies and the indicators for the number of accidents on record turned out to be statistically significant at the 1 percent level. The coefficients associated with the bm class displayed a reasonable decaying pattern: the lower the bm class, the larger the accident probability. Therefore, even if penalties would be poorly estimated, a company-specific sample of contracts would still lead me to reject the null hypothesis of no moral hazard. Columns (2) and (8) of table 14–labeled (AB-CS)–contain the ρ's one would obtain by estimating the penalties and the accident probabilities by the AB estimator using company specific samples. They are always negative, although there are some differences in their magnitude with respect to what I obtain using the entire sample. Again, data limitations would not prevent one from accepting the hypothesis of moral hazard.[24]

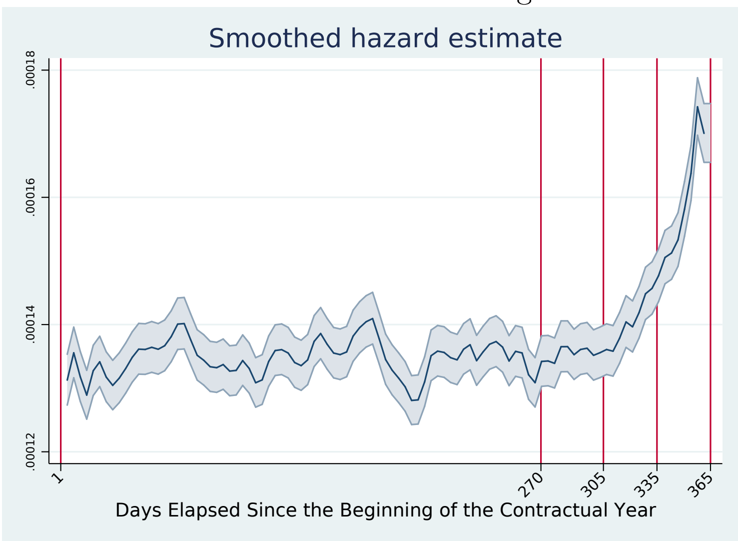
A direct consequence of these findings is that, most likely, some previous studies applying DPA did not accept the hypothesis of moral hazard for reasons other than sample selection bias, such as ignoring state dependence and/or inaccurate information on the penalties. This not to deny that data limitation can have an effect on inference. In the next section, I exploit a quasi-natural experiment–the grace period–to provide evidence of moral hazard also from a quantitative point of view. I will make the case that once we go beyond testing, accounting for the differential incidence of moral hazard across companies is actually important to quantify moral hazard in the entire market.

[24]It is possible that for some companies belonging to the medium and small categories, there is no correlation or a positive correlation between accidents and penalties.

6. Grace Period

Descriptive Analysis Figure 6–showing the pattern of the hazard rate during the contractual year–provides clear descriptive evidence of moral hazard. The hazard rate at the beginning of the year experiences a 1.5-fold increase at the end of the year. At first blush this phenomenon is surprising, as one would suspect that many policyholders are not aware of the change in the penalties in the last 60 days. If this is the case, the grace period effect understates moral hazard.

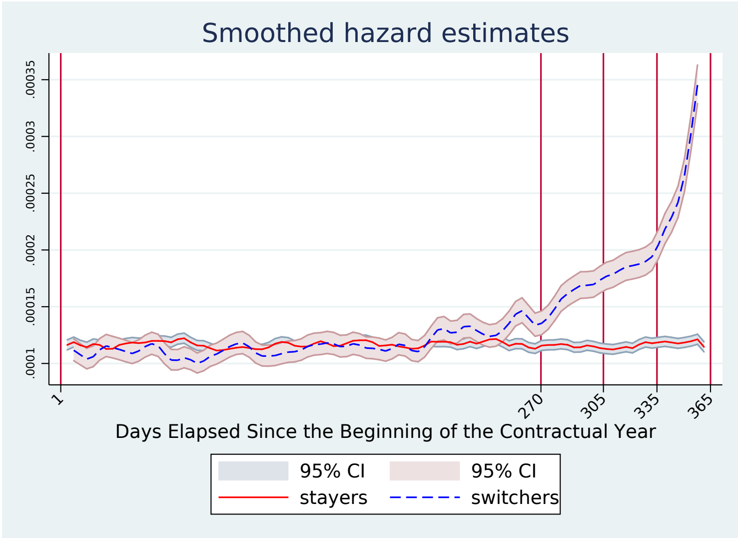
Figure 6. Hazard Rate of Accidents During the Contractual Year



Note. The hazard rate is bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rate.
Source: IPER (contractual years 2013-2014, 2014-2015 and 2015-2016)

Because drivers can escape the penalty for accidents during the grace period by switching companies, it is natural to examine how such a decision is related to the pattern of the hazard rate. Figures 7 describes the pattern of the hazard rate for stayers and for switchers. Interestingly, the two curves nearly overlap before the grace period, indicating that switchers' and stayers' risk are roughly similar. However, the grace period effect is far more pronounced among switchers–a 3.5-fold increase–a clear sign of an association between the glitch in the system and the switching decisions.

Figure 7. Hazard Rate and the Switching Decision



Note. The hazard rates are bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rates.
Source: IPER (contractual years 2013-2014, 2014-2015 and 2015-2016)

Unfortunately, because the date on which the driver decided to change companies is not known, one may worry that this pattern is driven by self-insurance (see Elrich and Becker (1972)). In other words, it could be that having an accident during the grace period induces people to switch. This is a confounder because according to the moral hazard story, the casual relationship between the switching decision and accidents in the grace period goes into the opposite direction: anticipating that they can change companies, drivers are more careless. Although these two mechanisms are indistinguishable, notice that the hazard rate increases monotonically during the grace period. If only self-insurance were at play, the hazard rate would exhibit a jump after the grace period and stay flat, as the accident probability only reflects adverse selection. On the contrary, moral hazard can reasonably rationalize the monotonic increase observed in the data. Under the assumption that a roughly constant fraction of drivers decides to change companies at each date, the proportion of "actual" switchers *gradually* increases over time during the grace period. In the presence of moral hazard, this dynamic selection is such that the average driving effort monotonically decreases over time, consistent with the shape of the hazard rate in figure

7.[25] In addition to this informal argument, I will address the reverse causality problem by implementing a placebo test in section 6.3. I now describe my quasi-experimental research design and carry over an event history analysis.

6.1. **The research design.** Let $G \in \{0, 1\}$ take value one if an accident occurs during the grace period and zero if no accident occurs or if it occurs before the last 60 days; let $c \in \{0, 1\}$ take value one if the policyholder changes companies and zero if she stays. The grace period generates, for a policyholder assigned to driving record (k, n) and covered by company j, the following research design:

$$\Delta p_{j,k-n} = \begin{cases} \Delta p_{j,k-n} & \text{if } \; G = 0 \\ \beta \Delta p_{j,k-n} & \text{if } \; G = 1 \;\text{ and }\; c = 0 \\ 0 & \text{if } \; G = 1 \;\text{ and }\; c = 1 \end{cases} \tag{14}$$

where $\beta \in (0, 1)$ denotes the discount factor. Accidents during the grace period either cost less because of a discounting effect–if the policyholder stays with the current company–or imply no cost if she decides to change. Either way, in the absence of moral hazard and other time effects, the hazard rate should be constant along the contractual year. In contrast, if policyholders change their driving effort in response to the change in penalties, the hazard rate should increase in correspondence of the grace period. Observe that:

(1) G is uncorrelated with the history of accidents of the previous years and only changes the penalty for accidents within the same contractual year
(2) if $G = 1$ and $c = 1$, penalties for accidents are uniformly zero across insurers

Observation (1) is such that, as in Israel (2004), the grace period generates an "insurance event" that allows me to distinguish state dependence from moral hazard. The idea is that the variation in the penalties within the contractual year is exogenous to the history of accidents. As argued in section 1, variation in the penalties arising from a change in the experience rating class are instead, by definition, correlated with past accidents. According to observation (2), the research design can be thought as an experiment eliminating all penalties across insurers for a subset of drivers, the switchers. While the argument will be clearer later, for now notice that because in the grace period the heterogeneity

[25]The peak observed during the last 10 days is consistent with anecdotal evidence suggesting that much of the shopping around happens at the very end of the year.

of penalties is exogenously removed, differences in the accident rates across companies in the last 60 days must reflect underlying heterogeneity.

6.2. **Event history analysis.** Let time, a given day of a contractual year, be indexed by τ, with $\tau = 1, \ldots, 365$. Let the "structural" hazard rate of an accident for policyholder i, covered by company k at day τ of a given contractual year be expressed in terms of a proportional Cox hazard model (Cox (1972))

$$\lambda(\tau|X_{ik}) = \lambda_0(\tau)\exp(\beta X_{ik}) \tag{15}$$

where X_{ik} includes a rich set of controls related to intrinsic risk: the driver and vehicle characteristics, the driving record, company and province dummies, a dummy for whether the driver had an accident the previous year, the features of the contract, and the number of installments. In the absence of confounding external time-effects, the pattern of $\lambda_0(\tau)$–the baseline hazard rate (bhr)– describes how driving effort changes along the contractual year.[26]

A natural way to conduct inference is to partition the duration along the contractual year into J intervals with cut-points $0 = \tau_0 < \tau_1 < \cdots < \tau_J = 365$, where the j^{th} interval is defined as $[\tau_{j-1}, \tau_j)$ and to approximate $\lambda_0(\tau)$ by a step function. Operationally, I divide the year into 30-day intervals until day 270, and the remaining fraction of the contractual year as follows: [270,305), [305,335), and [355,365], a total of 12 intervals.[27] I denote by λ_j, with $j = 1, \ldots, 12$, the baseline hazard rate in the j^{th} interval and by $\Delta_j = (\lambda_j - \lambda_{j-1})/\lambda_{j-1}$ the percentage change of the j^{th} interval-specific baseline hazard rate with respect to the $j-1^{th}$ interval. The hazard rate in interval j for a generic contractual year for policyholder i covered by k is as follows:

$$\lambda_{ijk}(\tau|\tau_{j-1} \leq \tau \leq \tau_j) = \lambda_j \exp(\beta X_{ik}) \tag{16}$$

with $j = 1, \ldots, 12$. This model is known as the piecewise exponential model (PEM)–see Friedman (1982)–because the distribution of the survival time within any interval is exponential, implying an interval-specific constant hazard rate

[26]This specification is consistent with a model in which policyholders choose their driving effort on a daily basis, as opposed to the model in section 1 in which the effort decisions are made on a annual basis.

[27]Using a finer grid would make the estimation computationally harder. In fact, to estimate PEM in STATA the original dataset needs to be transformed into a "derived" dataset through the command **stsplit**. The finer the grid, the larger such a dataset. Intuitively, each "subject" is associated with a number of rows proportional to the number of intervals. The derived dataset using the three contractual years and the 30-days grid is approximately 90 GB.

λ_j. The large number of contracts available is instrumental to precisely estimate the λ_j's in 30-days intervals, allowing a flexible approximation of the baseline hazard rate. The jumps in the hazard rate are interpreted as the effect of the shift in incentives caused by the grace period.[28] Later on, I will more formally define my test of moral hazard and how measure it.

Multiple events Although having more than one accident in a year is an extremely rare event (see table 3), the econometric model has to accommodate possible *repeated events*–multiple accidents in a year–and the possible state dependence between them. I do so by relying on variance correction methods.[29] The idea underlying these models is to use the non-independence of the events to correct for the standard error of the estimates. The sequential nature of the events naturally falls into one of those models, the conditional risk set model, proposed by Prentice, Williams, and Peterson (1981) (PWP). The assumption is that an observation is not at risk for a later event until all prior events have occurred. Thus, the conditional risk set at day τ for accident k, with $k = 1, 2, 3$, is made up of all drivers under observation at day τ that have had accident $k-1$ or no accident. There are two variations to this approach: time from entry and time from previous event (the so-called gap time model). In the first variation, time to each event is measured from entry time, and in the second variation, the gap time model, the duration of the k^{th} accidents is measured from the date of the $k-1^{th}$ accident (see section 3.2.3 of Cleves (2000)). I adopt the gap time approach; nevertheless, the shape of unconditional hazard arising from the two models turns out to be nearly identical.

My estimating sample is represented by all contracts covering the first three contractual years; I excluded contracts covering the fourth and fifth years to minimize the bias arising from the incompleteness of the history of accidents. As contracts covering different time periods are pooled together, the estimated λ_j's are an average of the year-specific λ_j's. By doing so, to the extent that they differ across contractual years, I minimize the bias from confounding external

[28]My approach is analogous to Meyer (1990), who studies the effect of unemployment benefits on the duration of unemployment, and to Finkelstein and Poterba (2004), who adopt a PEM to examine the annuitant survival rate after purchasing an annuity.

[29] Cleves (2000) describes the various methods to model repeated events and how to implement them in Stata. Box-Steffensmeier and Zorn (1982) provides a survey on variance-correction models.

time effects, such as the trend of the aggregate accident rate.

To correctly interpret the results, it has to be taken into account that accidents that occur right before day 305–in the ninth month of the contractual year–are also less likely to appear after switching. This is because companies have little time to update the information and print and mail the driving record.[30] To incorporate this aspect into the analysis, I define the average moral hazard as $AMH = [\lambda_{12} - \lambda_9]/\lambda_9$. The definition captures the "fixed-effect" idea underlying DPA: comparing the hazard rate at different points in time allows one to net out the time-invariant component of risk. The estimate of λ_{12}–the baseline hazard rate of the last month–captures the average effect of moral hazard at a time in which incentives to drive safely are the weakest. λ_9–my reference point–reflects the average driving effort when the benchmark penalties are enforced. The relatively short time period–three months–allows me to further minimize the bias arising from other confounding factors related to time, such as learning.

Testing and Measuring If one is interested only in checking for the presence of moral hazard, the null hypothesis $H_0 : AMH > 0$ against $H_A : AMH = 0$ can be tested using the all sample, containing contracts underwritten by both stayers and switchers. However, if one wants to interpret AMH as true measure of moral hazard, pursuing this strategy can be misleading because stayers and switchers face a different set of incentives. Arguably, switchers respond to a more sizable change in the monetary incentives. Furthermore, the interpretation of AMH is more transparent: the percentage change in the hazard rate when the penalty drops from its baseline to zero. To the extent that stayers and switchers systematically differ in their characteristics, one may worry that focusing on switchers to measure AMH might generate sample selection bias.

[30]The grace period is not, stricto sensu, a regression discontinuity design, as there is no random assignment around the critical date. However, this aspect makes my identification strategy similar to a fuzzy regression discontinuity design in which the number of elapsed days represents the running variable and the outcome variable is the event that an accident appears on record.

To investigate the presence of selection on observables, I estimate the following specification of the switching probability

$$\Pr(s_{ijt} = 1) = \Phi(\beta Z_{ijt}), \tag{17}$$

where the dependent variable s_{ijt} takes value one if driver i covered by company j during year t changes company at the end of the year, and zero otherwise. Φ is the CDF of the normal distribution function, Z_{ijt} is a large set of controls–all the covariates in the specification of the premium equation (12)–including the variables related to the driving record, individual and car characteristics, features of the contract, province and company dummies and time fixed effects. I then predict, using an estimating sample of 2,736,518 contracts covering the first two years, the switching probabilities, i.e., the individual propensity score $\hat{p}_i$. Table 6 contains some statistics of the distribution of $\hat{p}_i$ for stayers and switchers. The difference in the average propensity score is of 3 percent and is higher for switchers; overall, the percentiles of the distribution are not far from each other and are higher for switchers. Therefore, the differences in the statistics between the two distributions are modest.

Another valid concern is that relevant unobservable factors, such as risk and risk aversion, also differ in the two groups. If so, these factors affect both the decision to change companies and the event of an accident. To analyze this issue, as in Chiappori and Salaniè (2000), I estimate a pair of probits

$$\begin{aligned} a_{ijt} &= \mathbf{I}[Z_{ijt}\beta + u \geq 0] \\ s_{ijt} &= \mathbf{I}[Z_{ijt}\gamma + v_i \geq 0] \end{aligned}$$

where $\mathbf{I}[\cdot]$ is the indicator function and $a_{ijt} \in \{0, 1\}$ is a dummy taking value one if one or more accidents occur during year t, and zero otherwise. $s_{ijt} \in \{0, 1\}$ takes value one if the policyholders switches companies and zero otherwise. Z_{ijt} is a vector containing the same set controls I employ to estimate the Cox model specified in (16), and u and v are normally distributed random error terms with mean zero and variance of one. The coefficient of correlation ρ conveys information on the extent to which these two events are driven by a common component of the unobservables related to the accident probability.

Table 6. Statistics of the Distribution of the Propensity Scores

5^{th} perc.	25^{th} perc.	Median	75^{th} perc.	95^{th} perc.	Mean	St. dev	Skewness	Kurtosis	N
Stayers									
0.06	0.09	0.12	0.16	0.23	0.13	0.05	1.34	8.72	2,379,070
Switchers									
0.07	0.11	0.14	0.19	0.28	0.16	0.08	3.36	27.15	357,448

Note. This table reports descriptive statistics of the distributions of the propensity score for stayers and switchers.

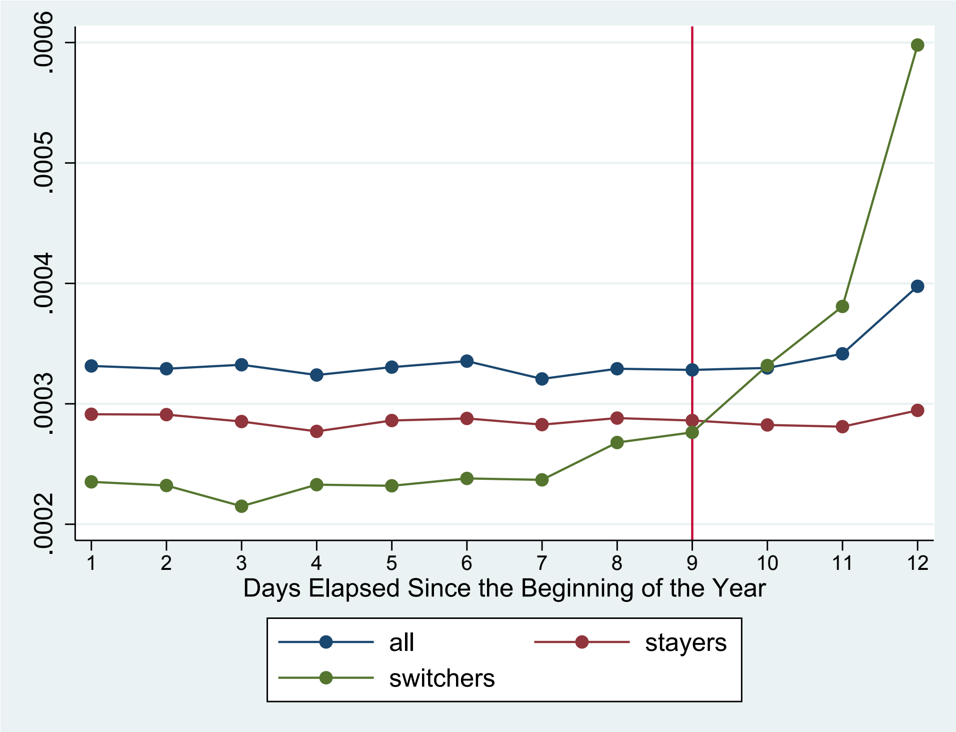
Using a sample of 2,538,093 contracts covering the first three contractual years, I obtain $\hat{\rho} = 0.02$, the standard error is 0.008 and the 95 percent confidence interval is $[0.001; 0.012]$. The statistically significant but nearly zero correlation between u and v suggests that stayers and switchers are roughly similar in terms of unobservables.

All in all, given this evidence and considering that the hazard rates before the grace period are nearly identical (see figure 7). I will regard the estimate of AMH using the sample of switchers–a "valid" sample–as my preferred measure of moral hazard.

Baseline Results The estimates of the logarithm of interval-specific baseline hazard rates obtained by estimating a piecewise exponential model are in table 19. The parameters are precisely estimated, and all are statistically significant at the 1 percent level. Figure 8 shows the pattern of the estimated baseline hazard rates for stayers and switchers. Table 18 provides more details on the pattern of the bhr and presents the estimates of the $\hat{\Delta}_j$'s. Columns (4)-(6) report the p-values of the test of the null hypothesis that each jump is equal to zero. Focusing on the all sample, the baseline hazard rate is quite flat until the last month–$\hat{\Delta}_{12}$ is statistically significant at the 1 percent level and is estimated at 16 percent. Therefore, driving effort mostly decreases during the last 30 days.
AMH using the all sample is estimated to be 21 percent and is statistically significant at the 1 percent level. Therefore the hypothesis of moral hazard cannot be rejected.

Interestingly, the baseline hazard rate among stayers is higher than switchers in the first eight months: the percentage difference ranges from 7 percent

FIGURE 8. The Pattern of the Baseline Hazard Rate



Note. This graph shows the estimates of the hazard rates–λ_j–appearing in the Cox model specified in equation (16); the estimates of $\log(\lambda_j)$ are in table 19. Each value on the x-axis represents the number indexing each interval. Intervals to the right of the vertical line belong to the "actual" grace period.

(eighth month) to 33 percent (third month), and the two curves overlap at the ninth month–the bhr among stayers is only 4 percent higher–when the expected penalties change. From the 10th month on, risk among switchers increases dramatically and the percentage differences becomes negative: -15, -26, and -51 percent in months 10, 11, and 12, respectively. As a result, $\hat{\Delta}_{10}$, $\hat{\Delta}_{11}$, and $\hat{\Delta}_{12}$ are statistically significant at the 1 percent level and are estimated to be 20, 14, and 57 percent. In contrast, the baseline hazard rate of stayers is roughly flat with an increase of 4.81 percent during the last month.

The AMH for stayers and switchers are estimated at 2.84 and 116 percent, respectively. Thus, when policyholders face no financial penalty, they dramatically lower their driving attentiveness.

6.3. **Reverse Causality.** To overcome the reverse causality problem–the increase in the hazard rate might be due to policyholders changing companies

after an accident in the grace period (self-insurance) and not moral hazard–I hinge on the intuition of the switching rule in (7) of the model described in section 1 to construct a placebo test. The idea is that, from an ex-post prospective, policyholders who received the more attractive outside offers–the sample of "lucky" switchers–would have changed companies regardless of whether an accident occurred during the grace period. Evidence of a grace period effect even among this subset of people–for whom there is no causal effect of accidents in the grace period on the decision to switch–can be attributed to moral hazard.
The main identifying assumption is that the arrival rate of outside options is random. Clearly, if drivers who provoke an accident during the grace period search more intensely for outside options, it is also more likely that they obtain an attractive offer and switch companies. In this case, the change in the premium upon switching–my instrument to identify the lucky switchers–is correlated with the number of accidents in the grace period no matter what.

In order to identify the set of "self-insurance free" policyholders, I adopt the following procedure. First, I estimate by OLS, using the sample of switchers, the following specification:

$$\Delta \log(p_{ijt}) = \beta \Delta X_{ijt} + \epsilon_{i,t} \tag{18}$$

where Δ denotes the first difference operator and X_{ijt} is the set of variables I control for in my hedonic premium regressions specified in section 4. I then use the estimates to predict $\hat{\epsilon}_{i,t}$, the part of the percentage change in the price unexplained by changes in the risk factors, e.g. clauses and time varying variables, such as age or province of residence. Finally, I use the percentiles p10, p20, p30, p50, p70, and p80 of the distribution of $\hat{\epsilon}_{i,t}$ to identify the groups $(G10, G20, \ldots, G80, G100)$: a switcher belongs to G10 if $\hat{\epsilon}_{i,t} \leq p10$, to G20 if $p10 \leq \hat{\epsilon}_{i,t} < p20$ and so forth, up to G100, in which case $\hat{\epsilon}_{i,t} > p80$.

Policyholders in the group G10, characterized by the greatest percentage reduction in the premium, are unlikely to have switched because of accidents in the grace period of year $t-1$, according to my argument, and can be used to run my placebo test.

I fit the Cox model specified in (16) on each G-sample and recover the baseline hazard ratio for the different groups of switchers. The estimates are presented

Table 7. Average Moral Hazard Across Groups of Switchers

	All	G10	G20	G30	G50	G70	G80	G100
AMH	116.41	182.92	149.93	146.70	151.68	101.98	94.25	77.89
av. % ch. in cond. premium	0	-0.46	-0.24	-0.14	-0.04	0.06	0.15	0.33

Note: The values of AMH are computed using the estimates of the interval-specific baseline hazard rates (λ_j) obtained by fitting the Cox model specified in equation (16) on each G-group. The estimates are presented in table 26. The last row is the mean of $\hat{\epsilon}_{it}$ in the group, the fitted residuals obtained after estimating the model specified in (18).

in table 26 in the online appendix. The estimates of AMH across the different groups are in table 7; the last rows presents the average percentage change in the conditional premium, the average of $\hat{\epsilon}_{i,t}$ for each group.

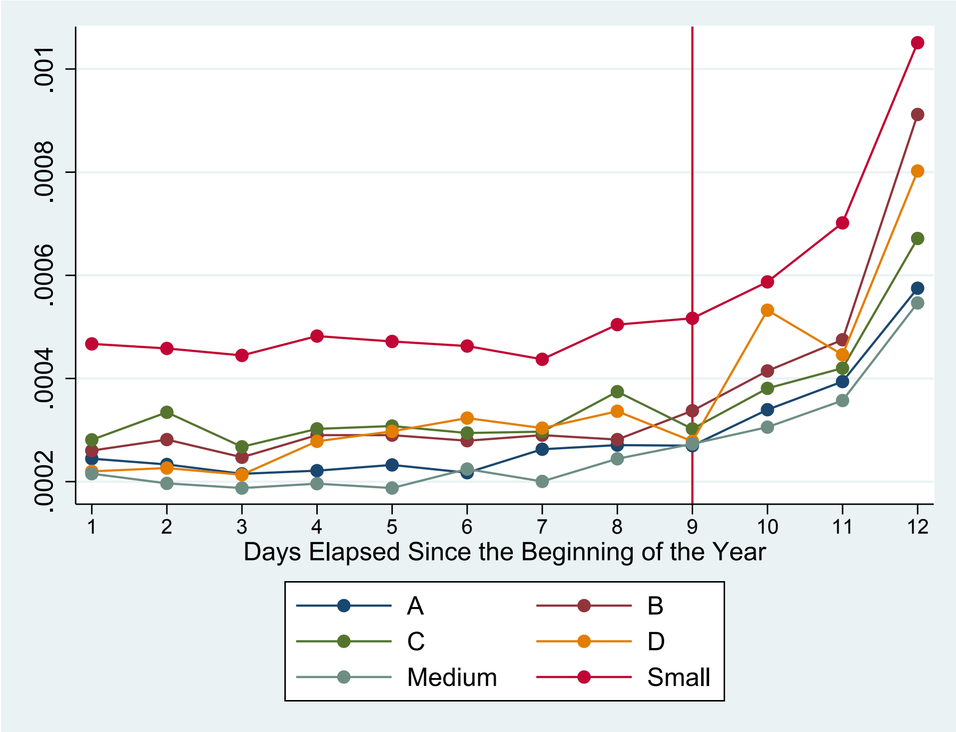
As one would expect, a positive relationship between AMH and the percentage reduction in the premium emerges: the grace period effect appears to be stronger when it is less likely to be due to self-insurance. For policyholders in group G10, the elimination of the penalties generates an increase in the hazard rate of 183 percent, a 2.8-fold increase of λ_{12} with respect to λ_9. This rather large effect suggests that the estimate of AMH using all of the switchers–116.41 percent–is a lower bound of the actual effect. In other words, self-insurance attenuates my estimate of moral hazard.

6.4. **Moral hazard across companies.** Consider the following specification for the hazard rate in the interval j for a policyholder i covered by company k:

$$\lambda_{ijk}(\tau|\tau_{j-1} \leq \tau \leq \tau_j) = \lambda_{jk} \exp(\beta X_{ik}) \tag{19}$$

where the company-specific baseline hazard rate captures the heterogeneity of moral hazard. The point estimates of the λ_{jk}'s using the all sample and the switchers are in tables 27 and 28, respectively, of section 12 of the online appendix. Figure 9 depicts the estimates of λ_{jk}'s obtained using the sample of switchers. Interestingly, the baseline hazard rate of the small companies is roughly threefold that of the first four companies and the set of medium companies. The patterns appear quite similar in that the baseline hazard rate increases monotonically, with the notable exception of company D, for which the baseline hazard rate decreases between intervals 10 and 11. Table 8 presents

FIGURE 9. Estimates of the Baseline Hazard Rate Across Companies



Note. This graph shows the estimates of the baseline hazard rates–λ_{jk}–appearing in the Cox model specified in equation (19); the estimates of $\log(\lambda_{jk})$ are in table 28. Each value on the x-axis represents the number indexing each interval. Intervals to the right of the vertical line belong to the "actual" grace period.

the results on the magnitude of AMH across companies for the switchers (panel A) and the full sample (panel B). While the differences using the all sample are

TABLE 8. AMH Across Companies

	Panel A: Switchers					
	A	B	C	D	Medium	Small
AMH	113.19	170.20	122.11	188.35	99.97	103.40
$\lambda_{12}/\lambda_{12}^{\text{medium}}$	1.052.	1.669	1.229.	1.468	1	1.923
	Panel B: Full Sample					
	A	B	C	D	Medium	Small
$100 \times [\lambda_{12} - \lambda_9]/\lambda_9$	21.29	28.92.	21.17	19.24	20.68	18.06

Note: Panel A and B report the values of AMH among switchers and in the full sample. AMH is computed by fitting the Cox model specified in (16) using the two samples. The estimates of the baseline hazard rates for the all sample and for the sample of switchers are presented in tables 27 and 28, respectively.

mild–AMH ranges from 18.06 to 28.92–there exists ample heterogeneity when the sample of switchers is employed. AMH ranges from 99.97 (medium companies) to 188.35 percent (company D).[31]

This empirical result–the magnitude of the moral hazard varies across companies–implies that having access to a representative sample is key to measure the average effect of moral hazard.

Heterogeneity vs. Incentives The differences in the estimated AMH across companies can result from two effects. The first effect is driven by heterogeneity; drivers sort into companies based on unobservable preferences for risk, generating different behavioral responses to the grace period. The second one has to do with the different structure of penalties faced by otherwise similar drivers across companies. A rigorous assessment of the relative importance of these two factors requires the estimation of a structural model. While this exercise is beyond the scope of the paper, it is still possible to provide a back of the envelope calculation of the importance of the first effect. Under the assumption that most policyholders have decided on the company before the last 30 days of the coverage period, observation 2) implies that $\hat{\lambda}_{12,j}$ is a sufficient statistics of the company-specific average risk.[32] This is because, conditional on switching, effort level is at its minimum in response to the no-penalty regime.[33] The second row of panel A of table 8 presents the company-specific $\hat{\lambda}_{12}$, normalized by the estimated value at the medium companies, the smallest one in the set. Differences are important–for example, average risk at the small companies is nearly twice that at medium companies. The estimates suggest the following ranking of companies in terms of risk: Small Companies > B > D > C > A > Medium. When compared to the ranking of companies in terms if AMH–the first row of table A of table 8–one can see that the correlation between moral hazard and unobservable risk preferences is non-monotonic. Interestingly, the realized risk of policyholders covered by small companies is the highest, but AMH is the lowest. These patterns suggest that the company-specific average

[31] I also estimated the model specified in equation 16 on each company-specific sample. The results coincided with those in table 8.

[32] In an ongoing work with Gaurab Aryal, the self-selection mechanism into companies is examined from the theoretical and empirical point of view.

[33] An additional mild assumption for this argument to be valid is that the effort level exerted for self-protection purposes is homogenous across agents.

moral hazard is determined by a non-trivial interaction between selection and the structure of penalties.

7. Conclusions

The literature on the auto insurance market has suffered from severe data limitations, impeding comprehensive empirical assessments of its efficiency. Recognizing this gap, considerable time and effort has been dedicated to collect the data used in this article, a matched insurer-insuree panel. The data are novel along many dimensions, including the size and representativeness of the samples, the richness of the information on the contracts, and the opportunity to follow policyholders after change of companies.

I used the data in this first project, to examine moral hazard in the Italian auto insurance market. I implemented two identification strategies that allow me to distinguish moral hazard from adverse selection and state dependence. This latter confounding factor has typically been neglected by previous work.

The first strategy is inspired by some papers on moral hazard, and relies on the non linearities–the slopes–of the premium-driving record schedules. The availability of data on premium and driving records reported on contracts subscribed by all the companies in the market allows to recover the financial penalties enforced in the market, a rich set of "treatments". As a result, the identification power of the traditional strategy is greatly enhanced. I also argue that the information on the insurance histories of those who change companies allows me to control for dependence. Overall, consistent with moral hazard, a negative and heterogeneous–across companies–correlation between penalties and accident probabilities emerges.

The second strategy relies on a quasi-natural experimental research design, generated by a glitch in the Italian experience rating system. I document at the descriptive level a monotonic increase of the hazard rate at the end of the year, the grace period. Consistently with the incentives at stake, the peak is more marked among switchers. The results from the event history analysis confirm that moral hazard is quantitatively important and heterogeneous across companies. My placebo test to take self-insurance into account–a confounding factor leading to reverse causality–implies that my estimates are likely to represent a lower bound of the overall effect.

The results obtained from my two different identification strategies suggest unambiguously that moral hazard is at play. Although sample selection does not seem an obstacle itself to obtain unbiased inference on the presence of moral hazard, my analysis suggests that in order to conduct unbiased inference it is important to rely on a rich source of identifying variations and to account for state dependence. The empirical analysis also sheds light on the relevance of the salience of the penalty structure and of the representativeness of the sample to quantify moral hazard in the entire market.

I conclude by arguing that this work sets the stage for a promising and policy-relevant research agenda. Structurally estimating the model I use to specify my econometric relationships is a natural extension of this paper. Enriching the model would allow one to ascertain the importance of the various channels–product differentiation, heterogeneity in the slopes of the premium schedule–in generating the sorting patterns. The data used in this article are also well suited to addressing other important issues. Among these are the quantitative importance of the switching costs, the effectiveness of contractual clauses in screening consumers and combating moral hazard, and the relationship between the intensity of competition and the efficiency of the market.

8. Tables

Table 9. Bonus-Malus Class at Year $t+1$ as a Function of the Number of Accidents at Year t.

Bonus-Malus Class Year t	0	1	2	3	4 or more
1	1	3	6	9	12
2	1	4	7	10	13
3	2	5	8	11	14
4	3	6	9	12	15
5	4	7	10	13	16
6	5	8	11	14	17
7	6	9	12	15	18
8	7	10	13	16	18
9	8	11	14	17	18
10	9	12	15	18	18
11	10	13	16	18	18
12	11	14	17	18	18
13	12	15	18	18	18
14	13	16	18	18	18
15	14	17	18	18	18
16	15	18	18	18	18
17	16	18	18	18	18
18	17	18	18	18	18

Table 10. Observable Characteristics-I

	Panel A						
	premium	discount	age	accidents on AR	bm class	man	switching rate
Market	457.70	92.39	51.96	0.16	1.92	0.59	0.12
A	473.75	115.45	53.15	0.17	1.86	0.59	0.12
B	498.07	70.55	53.00	0.12	1.82	0.61	0.12
C	461.16	73.48	52.56	0.16	1.90	0.58	0.09
D	378.54	106.37	49.61	0.18	1.88	0.63	0.09
Medium	447.15	88.73	51.07	0.17	2.04	0.58	0.13
Small	446.27	88.99	51.34	0.16	1.91	0.59	0.15
	Panel B: Clauses and Coverage						
	repair	increasing clause	exclusive dr.	expert dr.	free dr.	coverage	min coverage
Market	0.13	0.35	0.04	0.42	0.48	13.69	0.65
A	0.29	0.33	0.02	0.37	0.47	8.71	0.75
B	0.14	0.72	0.01	0.73	0.21	29.39	0.46
C	0.19	0.51	0.04	0.22	0.71	6.75	0.81
D	0.00	0.00	0.00	0.83	0.17	18.35	0.39
Medium	0.04	0.25	0.11	0.39	0.50	17.18	0.58
Small	0.05	0.28	0.02	0.35	0.60	8.17	0.72
	protected bonus	black box	No. installments				
Market	0.22	0.14	1.44				
A	0.43	0.35	1.46				
B	0.21	0.06	1.46				
C	0.02	0.15	1.53				
D	0.28	0.00	1.52				
Medium	0.08	0.03	1.42				
Small	0.24	0.08	1.37				
	Panel C: Car's Characteristics						
	car age	power	diesel	petrol	cubic cilinder		
Market	8.59	66.32	0.43	0.47	14.02		
A	8.65	65.05	0.42	0.47	13.87		
B	8.99	67.15	0.43	0.48	14.23		
C	8.61	65.17	0.39	0.50	13.81		
D	8.56	66.87	0.48	0.41	14.13		
Medium	8.37	66.97	0.43	0.47	14.07		
Small	8.55	66.99	0.44	0.45	14.12		

Note: This table reports the means of the variables using the sampling weights.

Table 11. Observable Characteristics-II

	Panel A: Accidents				
	size first accident	SOARF_SINDEN	acc. rate		
Market	2145.96	0.04	0.05		
A	2014.58	0.05	0.05		
B	2085.01	0.05	0.046		
C	2122.50	0.04	0.048		
D	2069.74	0.04	0.047		
Medium	2308.67	0.04	0.049		
Small	2148.37	0.04	0.051		
	Panel B: Local Markets				
	North-West	North-East	Center	South	Islands
Market	0.28	0.21.	0.21	0.20	0.10
A	0.26	0.18	0.20	0.24	0.12
B	0.25	0.21	0.15	0.28	0.11
C	0.29	0.23	0.22	0.19	0.07
D	0.23	0.13	0.31	0.20	0.13
Medium	0.32	0.20	0.21	0.17	0.10
Small	0.26	0.26	0.21	0.16	0.10
	Panel C: Subscriber's Location Characteristics				
	city density	non-mountain	partially mountain	totally mountain	
Market	1150.92	0.66	0.18	0.16	
A	1142.77	0.65	0.19	0.16	
B	1074.33	0.65	0.18	0.17	
C	1087.72	0.67	0.17	0.16	
D	1025.95	0.63	0.19	0.18	
Medium	1173.33	0.67	0.18	0.15	
Small	1243.17	0.65	0.20	0.15	
	Panel D: Altimeter Zone				
	internal mountain	coastal mountain	internal hill	coastal hill	lowland
Market	0.11	0.02	0.25	0.14	0.48
A	0.11	0.02	0.25	0.16	0.47
B	0.12	0.02	0.24	0.16	0.46
C	0.11	0.02	0.26	0.13	0.47
D	0.11	0.02	0.29	0.19	0.39
Medium	0.10	0.02	0.25	0.12	0.50
Small	0.11	0.03	0.23	0.14	0.50

Note: This table reports the means of the variables using the sampling weights.

Table 12. The Effect of the Driving Record on the Premium (Logs)

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
bm 1	-0.489***	-0.538***	-0.477***	-0.650***	-0.368***	-0.547***	-0.268***
	[0.004]	[0.009]	[0.013]	[0.018]	[0.012]	[0.007]	[0.006]
bm 2	-0.428***	-0.473***	-0.436***	-0.611***	-0.339***	-0.476***	-0.213***
	[0.004]	[0.010]	[0.015]	[0.019]	[0.016]	[0.009]	[0.007]
bm 3	-0.395***	-0.431***	-0.398***	-0.565***	-0.245***	-0.431***	-0.164***
	[0.004]	[0.010]	[0.015]	[0.019]	[0.016]	[0.009]	[0.007]
bm 4	-0.351***	-0.373***	-0.378***	-0.523***	-0.226***	-0.399***	-0.144***
	[0.004]	[0.011]	[0.016]	[0.020]	[0.018]	[0.009]	[0.008]
bm 5	-0.310***	-0.273***	-0.301***	-0.460***	-0.129***	-0.332***	-0.070***
	[0.004]	[0.010]	[0.015]	[0.020]	[0.017]	[0.009]	[0.008]
bm 6	-0.272***	-0.261***	-0.268***	-0.410***	-0.092***	-0.284***	-0.013
	[0.004]	[0.011]	[0.015]	[0.020]	[0.017]	[0.009]	[0.008]
bm 7	-0.231***	-0.213***	-0.266***	-0.406***	-0.014	-0.261***	0.024***
	[0.004]	[0.011]	[0.016]	[0.020]	[0.018]	[0.009]	[0.008]
bm 8	-0.192***	-0.169***	-0.177***	-0.379***	0.060***	-0.227***	0.055***
	[0.004]	[0.012]	[0.016]	[0.021]	[0.019]	[0.009]	[0.009]
bm 9	-0.156***	-0.172***	-0.176***	-0.322***	0.064***	-0.186***	0.110***
	[0.003]	[0.012]	[0.017]	[0.022]	[0.021]	[0.010]	[0.010]
bm 10	-0.110***	-0.120***	-0.081***	-0.241***	0.122***	-0.160***	0.139***
	[0.003]	[0.013]	[0.019]	[0.022]	[0.022]	[0.010]	[0.011]
bm 11	-0.066***	-0.049***	-0.048**	-0.168***	0.132***	-0.104***	0.172***
	[0.003]	[0.013]	[0.021]	[0.023]	[0.023]	[0.011]	[0.011]
bm 12	-0.024***	-0.056***	-0.003	-0.145***	0.166***	-0.066***	0.236***
	[0.003]	[0.014]	[0.020]	[0.024]	[0.024]	[0.011]	[0.012]
bm 13	0.017***	0.014	0.061***	-0.101***	0.242***	-0.004	0.262***
	[0.003]	[0.015]	[0.021]	[0.026]	[0.027]	[0.012]	[0.012]
bm 14	0.078***	-0.019**	0.056***	-0.094***	0.210***	-0.017**	0.253***
	[0.004]	[0.008]	[0.013]	[0.017]	[0.013]	[0.007]	[0.006]
1 acc on AR	0.104***	0.144***	0.256***	0.184***	0.150***	0.219***	0.250***
	[0.001]	[0.009]	[0.014]	[0.016]	[0.015]	[0.007]	[0.008]
2 acc on AR	0.188***	0.228***	0.355***	0.133***	0.206***	0.242***	0.358***
	[0.001]	[0.012]	[0.023]	[0.025]	[0.026]	[0.011]	[0.015]
R^2	0.412	0.414	0.414	0.414	0.414	0.414	0.414
N	4,057,822	4,057,822	4,057,822	4,057,822	4,057,822	4,057,822	4,057,822
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
previous year acc. FE	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: This table reports fixed-effect estimates of β_j^{AR} and β_j^{FE}–the effect of the bm class and of the number of accidents on the AR on the premium–as specified in equation (12). The dependent variable is the log of the premium. Column (1) contains the estimates of a restricted specification in which $\beta_j^{AR} = \beta^{AR}$ and $\beta_j^{BM} = \beta^{BM}$ for all j. Columns (2)-(7) contain the estimates of the company-specific parameters.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.
Source: IPER (contractual years 2013-2014, 2014-2015, 2015-2016, and 2016-2017).

Table 13. The Effect of the Driving Record on the Premium (Levels)

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
bm 1	-505.767***	-560.350***	-491.575***	-674.156***	-352.389***	-556.865***	-304.787***
	[1.870]	[4.580]	[6.697]	[9.382]	[6.436]	[3.829]	[2.874]
bm 2	-472.565***	-513.358***	-468.739***	-642.543***	-339.962***	-514.684***	-270.626***
	[1.866]	[5.310]	[7.863]	[10.147]	[8.092]	[4.513]	[3.889]
bm 3	-452.457***	-489.277***	-434.980***	-618.063***	-296.175***	-488.519***	-239.554***
	[1.855]	[5.345]	[7.777]	[10.077]	[8.330]	[4.571]	[3.907]
bm 4	-425.472***	-455.089***	-431.649***	-596.094***	-283.417***	-473.130***	-238.165***
	[1.851]	[5.817]	[8.162]	[10.455]	[9.123]	[4.783]	[4.413]
bm 5	-398.496***	-387.577***	-380.017***	-554.906***	-228.872***	-432.663***	-188.349***
	[1.844]	[5.465]	[7.899]	[10.363]	[8.758]	[4.606]	[4.123]
bm 6	-371.241***	-374.342***	-352.143***	-521.483***	-211.451***	-398.192***	-145.972***
	[1.839]	[5.527]	[7.909]	[10.328]	[9.049]	[4.591]	[4.268]
bm 7	-339.642***	-327.654***	-341.993***	-509.886***	-153.368***	-374.858***	-116.171***
	[1.834]	[5.642]	[8.149]	[10.543]	[9.631]	[4.703]	[4.404]
bm 8	-304.697***	-285.562***	-268.405***	-482.728***	-106.640***	-344.527***	-85.054***
	[1.831]	[6.056]	[8.411]	[10.779]	[9.984]	[4.884]	[4.764]
bm 9	-269.909***	-285.509***	-249.620***	-439.204***	-85.683***	-314.370***	-43.553***
	[1.828]	[6.240]	[8.921]	[11.424]	[11.156]	[5.056]	[5.128]
bm 10	-225.994***	-231.408***	-193.094***	-361.981***	-50.063***	-284.954***	-5.183
	[1.826]	[6.547]	[9.965]	[11.704]	[11.443]	[5.390]	[5.489]
bm 11	-178.959***	-159.489***	-149.726***	-296.153***	-42.187***	-234.707***	29.434***
	[1.821]	[6.875]	[11.107]	[11.925]	[11.820]	[5.551]	[5.723]
bm 12	-128.702***	-142.840***	-99.095***	-250.999***	19.276	-193.642***	102.850***
	[1.829]	[7.378]	[10.388]	[12.641]	[12.522]	[5.910]	[6.078]
bm 13	-67.274***	-72.517***	-1.346	-178.116***	108.922***	-132.851***	158.095***
	[1.829]	[7.568]	[11.180]	[13.336]	[14.085]	[6.355]	[6.445]
bm 14	29.174***	-64.451***	31.087***	-148.285***	116.496***	-82.438***	188.156***
	[1.858]	[4.168]	[6.673]	[8.832]	[6.939]	[3.555]	[3.341]
1 acc on AR	47.461***	78.127***	203.875***	156.318***	78.175***	147.485***	173.721***
	[0.270]	[4.499]	[7.513]	[8.273]	[7.611]	[3.779]	[4.394]
2 acc on AR	103.520***	155.979***	329.797***	87.932***	48.733***	142.689***	300.931***
	[0.628]	[6.467]	[12.067]	[12.965]	[13.748]	[5.701]	[7.625]
R^2	0.413	0.416	0.416	0.416	0.416	0.416	0.416
N	4,057,822	4,057,822	4,057,822	4,057,822	4,057,822	4,057,822	4,057,822
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
previous year acc. FE	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: This table reports fixed-effect estimates of β_j^{AR} and β_j^{FE}–the effect of the bm class and of the number of accidents on the AR on the premium–as specified in equation (12). The dependent variable is the premium in euros. Column (1) contains the estimates of a restricted specification in which $\beta_j^{AR} = \beta^{AR}$ and $\beta_j^{BM} = \beta^{BM}$ for all j. Columns (2)-(7) contain the estimates of the company-specific parameters.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

Source: IPER (contractual years 2013-2014, 2014-2015, 2015-2016, and 2016-2017).

Table 14. Penalties Across Companies

	Panel A: Zero Accidents on AR						
	Market	A	B	C	D	Medium	Small
BM Class							
1	100.771	149.2	260.47	212.411	134.389	215.831	238.954
2	127.756	183.388	263.801	234.38	147.147	231.22	240.343
3	121.53	203.908	292.597	243.955	189.265	229.506	255.998
4	128.677	193.062	286.712	252.898	162.899	237.812	267.303
5	133.291	205.562	293.531	242.526	208.224	245.757	295.715
6	141.26	180.142	315.487	228.496	200.407	235.621	277.016
7	148.793	166.96	306.398	238.597	203.943	231.307	276.14
8	161.109	174.373	352.774	304.223	181.48	237.389	284.709
9	173.199	204.2	322.554	342.893	142.628	257.305	288.209
10	188.668	220.796	354.4	344.523	183.134	268.213	320.124
11	206.181	237.018	395.623	340.183	237.16	299.588	336.999
12	255.594	173.165	384.688	304.186	236.858	299.754	332.443
	Panel B: One Accident on AR						
	Market	A	B	C	D	Medium	Small
BM Class							
1	109.369	148.925	182.517	-12.293	26.772	63.55	192.443
2	136.354	183.113	185.848	9.676	39.53	78.939	193.832
3	130.128	203.633	214.644	19.251	81.648	77.225	209.487
4	137.275	192.787	208.759	28.194	55.282	85.531	220.792
5	141.889	205.287	215.578	17.822	100.607	93.476	249.204
6	149.858	179.867	237.534	3.792	92.79	83.34	230.505
7	157.391	166.685	228.445	13.893	96.326	79.026	229.629
8	169.707	174.098	274.821	79.519	73.863	85.108	238.198
9	181.797	203.925	244.601	118.189	35.011	105.024	241.698
10	197.266	220.521	276.447	119.819	75.517	115.932	273.613
11	214.779	236.743	317.67	115.479	129.543	147.307	290.488
12	264.192	172.89	306.735	79.482	129.241	147.473	285.932

Note: Panels A and B show the penalty in euros after one accident as a function of the bm class, conditional on having one and two accidents on the AR, respectively. These estimates are obtained using the coefficients related to the driving record in the estimating equation (12) reported in table 13, and the evolution of the bm class described in table 9.

Table 15. The Effect of the Driving Record on the Accident Probability Conditional on Zero Accidents on the AR (Arellano-Bond)

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
L.ACC	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
bm 1 and zero acc on AR	0.537***	0.538***	0.539***	0.519***	0.541***	0.582***	0.483***
	[0.005]	[0.009]	[0.014]	[0.015]	[0.017]	[0.009]	[0.010]
bm 2 and zero acc on AR	0.497***	0.497***	0.497***	0.479***	0.506***	0.544***	0.439***
	[0.006]	[0.010]	[0.015]	[0.015]	[0.018]	[0.009]	[0.010]
bm 3 and zero acc on AR	0.467***	0.469***	0.465***	0.451***	0.468***	0.513***	0.408***
	[0.006]	[0.010]	[0.015]	[0.016]	[0.019]	[0.009]	[0.010]
bm 4 and zero acc on AR	0.445***	0.446***	0.434***	0.427***	0.449***	0.494***	0.390***
	[0.006]	[0.010]	[0.015]	[0.016]	[0.019]	[0.009]	[0.011]
bm 5 and zero acc on AR	0.422***	0.425***	0.418***	0.409***	0.431***	0.466***	0.362***
	[0.006]	[0.010]	[0.015]	[0.016]	[0.019]	[0.010]	[0.011]
bm 6 and zero acc on AR	0.401***	0.400***	0.392***	0.383***	0.411***	0.448***	0.343***
	[0.006]	[0.010]	[0.015]	[0.016]	[0.020]	[0.010]	[0.011]
bm 7 and zero acc on AR	0.378***	0.382***	0.375***	0.355***	0.397***	0.417***	0.323***
	[0.007]	[0.011]	[0.016]	[0.017]	[0.022]	[0.010]	[0.012]
bm 8 and zero acc on AR	0.352***	0.347***	0.347***	0.317***	0.381***	0.395***	0.306***
	[0.007]	[0.012]	[0.017]	[0.017]	[0.023]	[0.011]	[0.012]
bm 9 and zero acc on AR	0.333***	0.343***	0.340***	0.301***	0.357***	0.371***	0.272***
	[0.008]	[0.012]	[0.017]	[0.019]	[0.024]	[0.012]	[0.013]
bm 10 and zero acc on AR	0.313***	0.320***	0.319***	0.284***	0.338***	0.348***	0.257***
	[0.008]	[0.013]	[0.019]	[0.019]	[0.024]	[0.012]	[0.014]
bm 11 and zero acc on AR	0.295***	0.302***	0.301***	0.266***	0.326***	0.335***	0.227***
	[0.009]	[0.014]	[0.019]	[0.020]	[0.026]	[0.013]	[0.015]
bm 12 and zero acc on AR	0.276***	0.277***	0.292***	0.259***	0.283***	0.312***	0.210***
	[0.010]	[0.015]	[0.020]	[0.022]	[0.026]	[0.014]	[0.016]
bm 13 and zero acc on AR	0.252***	0.250***	0.285***	0.235***	0.273***	0.286***	0.181***
	[0.011]	[0.017]	[0.023]	[0.026]	[0.029]	[0.016]	[0.018]
bm 14 and zero acc on AR	0.215***	0.231***	0.200***	0.071	0.217***	0.222***	0.178***
	[0.019]	[0.025]	[0.041]	[0.102]	[0.083]	[0.057]	[0.063]
N	1,142,797	1,142,797	1,142,797	1,142,797	1,142,797	1,142,797	1,142,797
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: The dependent variable is a dummy taking value one if one or more accidents are provoked during the year, and zero otherwise. The coefficients are obtained by estimating the accident probability specified in equation (13) by the AB estimator. In column (1), the estimates of a restricted specification–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ for all j–are presented. The estimates of the company-specific parameters ($\alpha^{dr}_{j,k-n}$) of the baseline specification, are presented in columns (2)-(7). Robust standard errors are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contracts starting in 2013, 2014, 2015, and in the first quarter of 2016).

Table 16. The Effect of the Driving Record on the Accident Probability Conditional on One Accident on the AR (Arellano-Bond)-Cont.

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
bm 1 and one acc on AR	0.374***	0.380***	0.368***	0.360***	0.370***	0.412***	0.329***
	[0.005]	[0.009]	[0.014]	[0.015]	[0.018]	[0.009]	[0.010]
bm 2 and one acc on AR	0.243***	0.254***	0.246***	0.226***	0.220***	0.279***	0.193***
	[0.005]	[0.009]	[0.015]	[0.015]	[0.018]	[0.009]	[0.010]
bm 3 and one acc on AR	0.119***	0.133***	0.111***	0.098***	0.098***	0.158***	0.068***
	[0.006]	[0.010]	[0.016]	[0.016]	[0.019]	[0.009]	[0.011]
bm 4 and one acc on AR	0.142***	0.149***	0.122***	0.138***	0.111***	0.180***	0.101***
	[0.007]	[0.014]	[0.022]	[0.022]	[0.024]	[0.013]	[0.015]
bm 5 and one acc on AR	0.145***	0.141***	0.149***	0.142***	0.141***	0.191***	0.081***
	[0.008]	[0.015]	[0.023]	[0.023]	[0.028]	[0.013]	[0.016]
bm 6 and one acc on AR	0.148***	0.153***	0.142***	0.116***	0.165***	0.192***	0.094***
	[0.008]	[0.015]	[0.023]	[0.022]	[0.029]	[0.014]	[0.017]
bm 7 and one acc on AR	0.136***	0.160***	0.097***	0.148***	0.144***	0.171***	0.060***
	[0.009]	[0.016]	[0.024]	[0.022]	[0.028]	[0.014]	[0.017]
bm 8 and one acc on AR	0.134***	0.159***	0.116***	0.141***	0.164***	0.162***	0.052***
	[0.009]	[0.016]	[0.025]	[0.023]	[0.030]	[0.014]	[0.017]
bm 9 and one acc on AR	0.121***	0.132***	0.078***	0.120***	0.137***	0.156***	0.066***
	[0.009]	[0.017]	[0.027]	[0.023]	[0.033]	[0.014]	[0.019]
bm 10 and one acc on AR	0.096***	0.096***	0.093***	0.075***	0.087**	0.137***	0.045**
	[0.010]	[0.018]	[0.032]	[0.027]	[0.036]	[0.016]	[0.021]
bm 11 and one acc on AR	0.056***	0.079***	0.041	0.048	0.049	0.088***	-0.017
	[0.012]	[0.023]	[0.036]	[0.035]	[0.044]	[0.018]	[0.024]
bm 12 and one acc on AR	0.017	0.064**	-0.05	0.024	-0.034	0.048**	-0.063**
	[0.014]	[0.026]	[0.052]	[0.037]	[0.054]	[0.021]	[0.027]
bm 13 and one acc on AR	-0.057***	0.012	-0.101**	-0.001	-0.058	-0.055**	-0.160***
	[0.017]	[0.032]	[0.050]	[0.046]	[0.063]	[0.025]	[0.036]
bm 14 and one acc on AR	-0.059***	0.023	-0.072	0.033	-0.039	-0.078***	-0.181***
	[0.018]	[0.036]	[0.053]	[0.063]	[0.066]	[0.028]	[0.035]
N	1,142,797	1,142,797	1,142,797	1,142,797	1,142,797	1,142,797	1,142,797
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
previous year acc. FE	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: The dependent variable is a dummy taking value one if one or more accidents are provoked during the year, and zero otherwise. The coefficients are obtained by estimating the accident probability specified in equation (13) by the AB estimator. In column (1), the estimates of a restricted specification–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ for all j–are presented. The estimates of the company-specific parameters ($\alpha^{dr}_{j,k-n}$) of the baseline specification, are presented in columns (2)-(7). Robust standard errors are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contracts starting in 2013, 2014, 2015, and in the first quarter of 2016).

TABLE 17. The Association between Penalties and Accident Probabilities

	Panel A: Zero Accidents on the AR					Panel B: One Accident on the AR				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No. of Pairs	AB	AB-CS	LPM	FE Logit	No. of Pairs	AB	AB-CS	LPM	FE Logit
All Companies	72	-0.509		-0.499	-0.522	60	-0.398		-0.334	-0.125
A	22	-0.421	-0.972	-0.421	-0.426	20	-0.774	-0.742	-0.774	-0.512
B	22	-0.931	-0.885	-0.946	-0.897	20	-0.713	-0.721	-0.514	-0.751
C	22	-0.864	-0.902	-0.871	-0.881	20	-0.546	-0.609	-0.230	-0.238
D	22	-0.666	-0.816	-0.632	-0.653	20	-0.662	-0.726	-0.422	-0.647
Medium	22	-0.847	-0.935	-0.881	-0.886	20	-0.677	-0.676	-0.473	-0.605
Small	22	-0.936	-0.914	-0.943	-0.952	20	-0.739	-0.628	-0.429	-0.516
Restricted Spec.	24	-0.915		-0.936	-0.919	20	-0.785		-0.704	-0.752

Note: This table reports the coefficient of correlation (ρ) between the penalties and the accident probabilities ($\alpha^{dr}_{j,k-n}$) estimated by each of the three estimators and the penalties ($\Delta p_{j,k-n}$)–presented in table 14–across bm classes. Columns (2), (4) and (5) contain ρ conditional on $n = 0$. Columns (7), (9) and (10) present ρ condtional on $n = 1$. The first row contains the correlation using all the pairs associated with the six companies. Rows 2-7 contain present ρ using the company-specific pairs. In the last row the correlation between penalties and accident probabilities estimated using the restricted specifications–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ and $\Delta p_{j,k-n} = \Delta p_{k-n}$ for all j and driving records (k, n)–are presented.

TABLE 18. Jumps the Baseline Hazard Rate

	(1)	(2)	(3)	(4)	(5)	(6)
	All Sample	Stayers	Switchers	All Sample	Stayers	Switchers
	Jumps in the Baseline Hazard Rate			P-values of the Test $\Delta_j = 0$		
Δ_2	-0.70	-0.10	-1.29	0.545	0.923	0.765
Δ_3	1.01	-1.98	-7.41	0.399	0.183	0.061
Δ_4	-2.57	-2.86	8.33	0.054	0.094	0.039
Δ_5	2.02	3.25	-0.40	0.094	0.011	0.937
Δ_5	1.51	0.60	2.63	0.230	0.713	0.591
Δ_7	-4.40	-1.78	-0.50	0.003	0.234	0.892
Δ_8	2.63	1.92	13.09	0.023	0.234	0.000
Δ_9	-0.30	-0.70	3.15	0.803	0.672	0.369
Δ_{10}	0.50	-1.29	20.08	0.630	0.318	0.000
Δ_{11}	3.56	-0.50	14.80	0.034	0.758	0.000
Δ_{12}	16.42	4.81	56.99	0.000	0.005	0.000
AMH	21.17	2.84	116.41			

Note: Columns (1)-(3) reports the estimates jumps of the interval-specific baseline hazard rates–the Δ_j's defined in the main text–for each sample.
Columns (4)-(6) contain the p-values of a t-test of the null hypothesis that $\Delta_j = 0$.

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9. Online Appendix

10. The Effect of the Grace Period on the Severity of Accidents

A common assumption in the literature is that careless driving only affects the frequency of accidents, not their severity. This assumption is for convenience, as it allows one to distinguish ex-ante from ex-post moral hazard. Recent evidence from insurance telematics data, however, suggests that driving style does play a role.[34] For example, "distracted driving"–driving while doing another activity that takes your attention away from driving, such as talking on the phone or texting–contributes to both the number of accidents and their seriousness. Notice that because the size of the damage does not affect insurance rates–true in the data–the causal effect of the grace period on the severity of accidents cannot be rationalized by self-insurance and can be attributed to moral hazard. I estimate by OLS the following specification:

$$\log(s_{ijt}) = \alpha_0 g_i + \alpha_1 res\_g_i + \alpha_2 res\_ng_i + \beta X_{ijt} + \epsilon_{ijt} \tag{20}$$

where s_{ijt} measures the total indemnity received by the parties not at fault as a consequence of the first accident driver i covered by company j is liable for during contractual year t.[35] The indicator g_i takes value one if the first accident happened during the grace period, res_i measures the residual days left before the contracts expires from the day of the accident (if any), $res_i\_g_i(= res \times g_i)$ and $res_i\_ng_i(= res \times (1 - g_i))$ are interaction terms. This specification allows me to flexibly capture the effect of the residual days left on the size of the damage. I restrict the sample to claims related to accidents of the first and second contractual years to minimize the proportion of claims whose final indemnity has not been liquidated.[36] The vector X_{ijt} contains a number of controls described at the bottom of table 29. In particular I control for car characteristics, province, company fixed effects and characteristics of the city. I also control for $SOARF\_SINDEN$–the proportion of claims over which, in a given province

[34] Insurance telematics allow the company to monitor the driving style of the insuree and condition the premium on a host of variables, such as miles driven, frequency of brakes, speed, and miles driven on the highway versus other types of roads.

[35] I do not consider second and third accidents as there are few observations. The original distribution of the indemnity has been trimmed using the 99^{th}-percentile of the contractual year-specific distribution

[36] About 96.5 percent and 96 percent of the claims of the first and second contractual year are not on-hold.

and year, an auditing procedure started–my proxy for province-level incidence of frauds.

Table 29 presents the estimates of the effect using the all sample (panel A1) and the sample of switchers (panel A2). Given the great dispersion of the size of the damage, I analyze the effect on various part of the distribution. I focus on the first (Q1), second (median), and third quartile (Q3) by means of quantile regression as well as on the conditional mean (OLS). Columns (1) and (5) present the estimates by OLS, columns (2) and (6) the effect on Q1, columns (3) and (7) on the median, and columns (4) and (8) on Q3. I find that, all else being equal, the grace period implies an increase of the conditional mean of about 10 percent; moreover, the closer the accident is to the expiration date within the grace period, the higher the associated damage (res_g_i is statistically significant). The grace period effect on the mean/median is more pronounced across switchers: damage increases 19 percent, and the effect of the residual days left is also higher. The effects on the different quantiles are similar and slightly stronger on the higher quantiles, suggesting that the grace period implies a positive location-shift of the distribution. All in all, these findings reinforce the moral hazard story and understate the role of self-insurance.
To detect systematic variation across companies, I estimate the following specification:

$$\log(s_{ijt}) = \sum_j \alpha_{0j} g_i \times c_j + \sum_j \alpha_{1j} res\_g_i \times c_j + \alpha_{2j} res\_g_i \times c_j + \beta X_{ijt} + \epsilon_{it} \tag{21}$$

where c_j is a company j dummy, with $j \in \langle A, B, C, D, Medium, Small \rangle$. The results, presented in table 31, indicate no statistically significant effect of the grace period on the conditional mean for companies A, B, C and D. The same is true for the effect on the median, with the exception of the sample of switchers covered by company A. The hypothesis that moral hazard is heterogeneous across companies is confirmed by these findings. There is no obvious explanation to reconcile this result–the bulk of the grace period effect comes from the set of medium and small companies–with the fact that AMH is lower in those companies (see table 8). One possible story is that effort is multidimensional: drivers choose speed and miles, say. Speed and miles have a different effect on the accident probability versus the severity of the accidents and they are heterogeneous across companies.[37]

Frauds The positive effect of the grace period on the size of damage could be justified by fraudulent claims. There are two relevant types of frauds; the first is when the accident is real (not organized ex-ante) and the driver who is not responsible "simply" overreports the size of the damage. One reason there can be overreporting during the grace period of the contract subscribed by the liable driver has to do with possible "bargaining" on the individual percentage of fault. As the received indemnity is proportional to the percentage of fault, it is possible that liable drivers in the grace period are more prone to overstating their percentage of fault, thereby increasing the indemnity received by third parties. As for this type of fraud–parties agree to misreport their percentage of fault but not the occurrence of the accident–its presence still allows one to interpret the grace period effect on the hazard rate as true ex-ante moral hazard.[38]

The second type of fraud–two drivers set up a fake accident and agree to split the indemnity of the non "liable" party–is more problematic. Clearly, the incentive to arrange fake accidents is more pronounced during the grace period of one of the contracts, as the penalties are postponed or eliminated. As by law bodily injuries have to be certified at a public hospital to obtain an indemnity–this idea was first proposed by Chiappori and Salaniè (2000) to detect ex-post moral hazard–it is unlikely that fake accidents involve bodily injuries as they imply too-high non-monetary costs.[39] Thus, the absence of a statistically different effect of the grace period on the two types of claims makes the fake accident story less plausible.[40]

[37] Certainly, further analysis using actual data from insurance telematics–data on distance driven and driving styles–is in order to shed light on the actual mechanism through which the various forms of driving effort affect the likelihood of an accident.

[38] Recall that a driver is at fault if her percentage of fault is higher than 50 percent.

[39] Chiappori and Salaniè (2000) argue that ex-post moral hazard should be absent in claims with bodily injuries, as filing the claim is mandatory, but they could not pursue this strategy to check for ex-post moral hazard because their sample was too small.

[40] Fraudulent claims with bodily injuries were thought to be pervasive among whiplash claims in Italy and elsewhere. To combat this type of fraud, a recent law ("decreto Monti") establishes that to receive any indemnity, the bodily injuries of a small entity have to be documented by a clinical visual assessment (MRI)–the simple medical certificate does not suffice. There is evidence that the law drastically decreased the incidence of whiplash claims.

In my sample, about 15 percent of claims involve bodily injury. I estimate the specification in (20) on the sample of claims with and without bodily injuries. The estimates for these two types of claims are presented in panels A and B of table 30. As can be seen from panel A, the effect among claims without bodily injuries both in terms of mean and median is similar to the one obtained using the sample with all types of claims, regardless of the switching decision. Interestingly, when I employ the sample of claims with bodily injuries, the effect on the conditional mean vanishes, but the effect on the median is analogous to the one obtained using all/the bodily injuries claims.

As the qualitative results using the two types of claims change little, the positive association damage-grace period is unlikely to be driven by a pure fraud effect. As a further robustness check, in figure 11 the hazard rates of claims with and without bodily injuries, conditional on being responsible for at least one accident, are shown. Both types of accidents are characterized by a very similar hazard rate, with a peak corresponding with the grace period.

Ex-post Moral Hazard In at-fault insurance regimes, ex-post moral hazard occurs when, after comparing the increase in the premium and the cost directly compensating the non-liable parties, the policyholder at fault persuades the third parties to not file the claim. The general idea, summarized by Chiappori and Salaniè (2000) is that these kind of "street" arrangements are unlikely to arise in accidents involving multiple drivers because parties cannot commit.[41] However, under the assumption that the severity of the accidents does not depend on driving effort, in the presence of ex-post moral hazard one would expect a negative effect of the grace period on the size of the damage because also small claims are filed. This effect is contrary to the results I obtained by estimating specification 20. As much as for the possible presence of fraudulent claims, the comparison of the size of the claims with and without bodily injuries–as proposed by Chiappori and Salaniè (2000), though it could not be implemented because of the small sample size of their data–also indicates that ex-post moral is of second order.

[41] Jeziorskiy, Krasnokutskaya, and Ceccarini (2017) also abstract from ex-post moral hazard within the Portuguese auto insurance market.

10.1. **Further Robustness Checks.** I now analyze three confounding factors: misreporting, learning and seasonality effects.

Misreporting As the identification comes from the date of the accident within a contractual year, one may worry that many accidents that are reported to have happened during the grace period in fact happened before. However, accidents at fault–the ones under examination in this study–always involve third parties. For misreporting to happen, drivers not at fault have to be persuaded to lie about the real date. In other words, a fraud has to be organized. It is reasonable that the expected cost of such a fraud–the expected legal sanctions–is increasing in the distance between the actual date of the accident and the reported one. If the cost is small enough, and accidents right before the grace period are inputted to a day right after, one should observe a decrease of the hazard rate right before the grace period. However, figure 8 shows a sharp increase before day 305. As an additional placebo test, it is comforting that the hazard rate is characterized by a grace period effect regardless of the presence of bodily injuries (see figure 11).

Learning Although it is reasonable that drivers improve their driving skills over time, the following observations suggest that such a mechanism is of second order. First, if lower uncertainty leads to better driving, one would expect the hazard rate to decline over time, contrary to what we observe. Second, a grace period effect also exists among more experienced drivers (age ≥ 55), a group typically characterized by little learning. Finally, if learning occurs smoothly over time, the rate at which the hazard rate increases should be constant. In the data, the second derivative of the hazard rate increases in correspondence of the grace period.

Seasonality It is well known that accidents are more likely to occur in winter. At first blush, one may suspect that the grace period effect is an artifact of seasonality. Figure 10 depicts the pattern of the hazard rate, conditional on the starting quarter of contract. The grace period effects appear regardless of the season in which the contract ends.

10.2. **The Effect of the Driving Record on the Switching Probability.** To investigate the effect of the driving record on the decision to switch I specify the following reduced-form regression:

$$\Pr(s_{ijkt} = 1) = \Lambda(c_{jt} + \sum_{k=1}^{14} \beta_k^{bm} bm_k + \sum_{n \in \{1,2\}} \beta_n^{AR} accAR_n + \beta^Z Z_{it} + \gamma_t + \eta_i), \tag{22}$$

where the dependent variable s_{ijkt} takes value one if driver i assigned to driving category k is covered by company j during year t and zero otherwise, bm_k and $accAR_n$ are an indicators taking value one if the policyholder is assigned to class k and has n accidents on record, respectively, and zero otherwise; Z_{it} is a large set of controls included in the regression equation 13, γ_t is a contractual year indicator, η_i is an unobservable fixed-effect, and c_{jt} is a company indicator taking value one if the driver is covered by company j in year t, and zero otherwise.

I am primarily interested in identifying β_k^{bm} and β_n^{AR}, the average effect of the driving category on the switching probability. Table 32 presents the estimates using different specification; column (1) and column (2) contain the estimates of a logit model–η_i is ignored–and of a fixed effect model, respectively; in column (3) the results obtained by applying a fixed-effect estimator to a linear probability model are shown. The effect of bm classes 1-8 is not statistically significant, once unobserved heterogeneity is accounted for; on the contrary classes 9-14 are statistically significant with a negative sign indicating a lower propensity to change companies with respect to the omitted category (classes 15-18). Furthermore, having one and two accident on record increases the chances to leave the company. The difference in the sign and the magnitude of the coefficients in column (1) with respect to column (2) suggest the presence of unobervable preferences for risk correlated with the driving record. Taken together, these findings suggest that better types are overrepresented in company-specific panel data as a consequence of the dynamic selection mechanism. Therefore, the data do not support the assumption of that company-specific samples are random *at all points in time* (RS).

11. Sampling the core sample

The core sample has been extracted from the universe of individuals subscribing one or more auto insurance contracts in 2013, the universe of subscribers in 2013. Contracts for motorcycles or car fleets are not considered. The survey design is stratified single-stage (see Cochran (1977)). The stratification variables are region (20), city size (small, medium, large) and age group ($<$ 25, [25,35), [35,45), [45,60), and $\geq$ 60). The combination of these variables generates 300 theoretical cells, of which only 240 contain some elements of the population. The sum of the survey weights reproduces the population size of the 2013 subscribers within each cell. The total sample size is divided among the cells according to the population distribution (proportional sampling), with the exception of the age class, for which the younger classes are oversampled according to the following criterion:

- < 25: sampling probability is 5 percent, 1.78 in the population
- $[25, 35)$: sampling probability is 20 percent, 11.62 in the population
- $[35, 45)$: sampling probability is 25 percent, 21.88 in the population
- $[45, 60)$: sampling probability is 30 percent, 34.18 in the population
- ≥ 60: sampling probability is 20 percent, 30.54 in the population

From the second year on, the sampling weights attached to each contract are updated dynamically by considering as a population of interest the universe of subscribers at each quarter of the calendar year.

11.1. **Description of the Variables.** I now describe in detail variables I use in the empirical analysis and whose means are shown in tables 10 and 11:

- premium (in euros): yearly premium paid for the third-party liability insurance
- discount (in euros): discount on the theoretical tariff applied by the agent/broker, if any. The theoretical tariff by definition equals premium+discount
- installments: number of chunks the premium is split in: 0 (the entire amount is paid when subscribing the contract), 2, 3, or 4 payments. Dummy variables have been constructed.
- age (in years): age of the subscriber at the time of underwriting date of the contract. Depending on the specification, I either use the variable as it is or dummies for the following age groups: [18;25), [25;34), [35;44), [45;60), and $\geq$ 60.
- accidents on AR: number of accident at fault (percentage of fault $>$ 50) over the past five years reported on the AR ("*Attestato di Rischio*")
- bm class: bonus-malus class (1-18)
- man: indicator for whether the subscriber is a male

- switching rate: mean of the indicator *change*, taking value one if the subscriber switches at the end of the contractual year and zero is she stays.
- clauses
  - repair: indicator taking value one if the clause "*risarcimento in forma specifica*" is active. The clause establishes that if an accident not at fault occurs, the vehicle has to be repaired by a specified list of body shops. Typically, companies have agreements with those body shops to minimize expenses.
  - black box: indicator for whether the so-called black box, a device able to record a variety of behaviors (e.g., km driven and whether there has been a "crash"), has been installed and guarantees a reduction of the base premium.
  - driving clauses: this clause conditions the indemnity on the identity of the driver. In particular, if restrictions on the drivers are present, in case an accident is provoked and the restrictions are not met the company refunds whoever is not at fault and recoups the damage from the subscriber of the contract. There are four mutually exclusive alternatives generating the following dummies
    - free driving: indicator taking value one if there is no restriction on the driver's identity
    - expert driving: indicator taking value one if only individuals with a certain driving experience can drive
    - exclusive driving: indicator taking value one if only individuals with a certain driving experience can drive
    - other: other types of driving clauses are present (the omitted category is "other")
  - protected bonus: indicator taking value one if the so called "*bonus protetto*" clause is active on the contract. Such a clause allows me to eliminate/diminish the increase in the premium in case of an accident.
- increasing clause: indicator taking value one if there are other clauses that i) imply an increase in the premium, or ii) are different than the ones listed that are active on the contract

- coverage (in euros): upper limit on the amount the company will pay for accidents at fault. The insured driver is responsible if the damage exceeds the specified liability limit
- min coverage: indicator taking value one if the coverage equals the minimum mandatory liability limit of 6 million (1 million for property damage and 5 million for health damage)
- car's characteristics:
  - type of fuel supply. The categories are diesel, fuel, electric, gpl, hybrid diesel/electric, hybrid petrol/electric, methane, mixture, particulate filter, petrol, petrol/ethanol, petrol/lpg, petrol/wank, and petrol/methane.

    I constructed two dummies, petrol and diesel–taking value one if the fuel supply is diesel or petrol, respectively, and zero otherwise. The omitted category is other types of fuel supply.
  - car's age: year of registry of the vehicle
  - cc: cubic cylinder of the vehicle, ranging from 1 to 100. I constructed dummies for the following groups: [10, 12), [12, 13), [13, 15), [15, 22), [22, 100]. The omitted category is [1, 10).
  - power of the vehicle (in KW) ranging from 1 to 585
- size first accident (in euros): total indemnity obtained by the third parties for the first accident the policyholder is responsible for
- $SOARF\_SINDEN$: fraction of claims in the province of residence of the subscriber over which an investigation for possible fraud has started. Available for years 2013 and 2014
- acc rate: mean of the indicator ACC, taking value one if the driver is responsible for one or more accident during the year
- 5 dummies taking value one if the subscriber resides in one of the five macroregions of Italy: North-East, North-West, Center, South, Islands
- city density: number of people living in the province the subscriber lives in divided by the area (in square KM) of the province
- type of city: non-mountain, partially mountain, totally mountain
- altimeter zone: altitude of the province of residence of the subscriber according the classification provided by ISTAT, the Italian Institute of Statistics. There are five groups in descending order with respect to altitude: internal mountain, coastal mountain, internal hill, coastal hill, lowland

- geomorphological classification: ISTAT divides location in three groups: non-mountain, partially mountain, totally mountain

TABLE 19. Baseline Hazard Rate

	(1) All Sample	(2) Stayers	(3) Switchers
hr_1_30	-8.012***	-8.141***	-8.355***
	(0.066)	(0.080)	(0.162)
hr_30_60	-8.019***	-8.142***	-8.368***
	(0.066)	(0.078)	(0.168)
hr_60_90	-8.009***	-8.162***	-8.445***
	(0.066)	(0.080)	(0.170)
hr_90_120	-8.035***	-8.191***	-8.365***
	(0.064)	(0.076)	(0.163)
hr_120_150	-8.015***	-8.159***	-8.369***
	(0.061)	(0.077)	(0.163)
hr_150_180	-8.000***	-8.153***	-8.343***
	(0.058)	(0.077)	(0.152)
hr_180_210	-8.045***	-8.171***	-8.348***
	(0.065)	(0.080)	(0.150)
hr_210_240	-8.019***	-8.152***	-8.225***
	(0.064)	(0.077)	(0.155)
hr_240_270	-8.022***	-8.159***	-8.194***
	(0.063)	(0.078)	(0.147)
hr_270_305	-8.017***	-8.172***	-8.011***
	(0.062)	(0.080)	(0.142)
hr_305_335	-7.982***	-8.177***	-7.873***
	(0.056)	(0.076)	(0.133)
hr_335_365	-7.830***	-8.130***	-7.422***
	(0.059)	(0.076)	(0.128)
bm class FE	Yes	Yes	Yes
no. of accidents on AR FE	Yes	Yes	Yes
policyholder char.	Yes	Yes	Yes
car char.	Yes	Yes	Yes
clauses	Yes	Yes	Yes
city char.	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes
company FE	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes
province FE	Yes	Yes	Yes
N	37,208,804	26,514,671	4,050,172

Note: This table reports the estimates of the bhr's–λ_j's–obtained by estimating the Cox model specified in equation (16) on each sample. hr_1_30 denotes the logarithm of the bhr in the interval $[1; 30)$; the other parameters are defined analogously. N denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.
Source: IPER (contr. years 2013-2014, 2014-2015, and 2015-2016).

12. Tables

Table 20. The Effect of the Driving Record on the Accident Probability Conditional on Zero Accidents on the AR (FE-LPM)

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
L.ACC	-0.390***	-0.390***	-0.390***	-0.390***	-0.390***	-0.390***	-0.390***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
bm 1 and zero acc on AR	0.417***	0.416***	0.423***	0.397***	0.420***	0.456***	0.374***
	[0.003]	[0.004]	[0.007]	[0.007]	[0.009]	[0.004]	[0.005]
bm 2 and zero acc on AR	0.386***	0.384***	0.392***	0.366***	0.389***	0.427***	0.339***
	[0.003]	[0.005]	[0.008]	[0.008]	[0.010]	[0.005]	[0.005]
bm 3 and zero acc on AR	0.367***	0.365***	0.371***	0.348***	0.372***	0.406***	0.321***
	[0.003]	[0.005]	[0.008]	[0.008]	[0.011]	[0.005]	[0.006]
bm 4 and zero acc on AR	0.350***	0.348***	0.346***	0.329***	0.365***	0.390***	0.307***
	[0.003]	[0.005]	[0.008]	[0.009]	[0.011]	[0.005]	[0.006]
bm 5 and zero acc on AR	0.331***	0.331***	0.332***	0.315***	0.346***	0.369***	0.282***
	[0.003]	[0.006]	[0.008]	[0.009]	[0.011]	[0.005]	[0.006]
bm 6 and zero acc on AR	0.314***	0.310***	0.312***	0.295***	0.328***	0.356***	0.267***
	[0.003]	[0.006]	[0.008]	[0.009]	[0.012]	[0.005]	[0.006]
bm 7 and zero acc on AR	0.299***	0.301***	0.302***	0.276***	0.316***	0.334***	0.253***
	[0.004]	[0.006]	[0.009]	[0.010]	[0.013]	[0.006]	[0.007]
bm 8 and zero acc on AR	0.282***	0.279***	0.285***	0.248***	0.301***	0.320***	0.239***
	[0.004]	[0.007]	[0.010]	[0.011]	[0.014]	[0.006]	[0.007]
bm 9 and zero acc on AR	0.265***	0.274***	0.277***	0.234***	0.271***	0.296***	0.217***
	[0.004]	[0.008]	[0.011]	[0.011]	[0.015]	[0.007]	[0.008]
bm 10 and zero acc on AR	0.246***	0.253***	0.258***	0.209***	0.254***	0.276***	0.202***
	[0.005]	[0.008]	[0.012]	[0.012]	[0.015]	[0.007]	[0.008]
bm 11 and zero acc on AR	0.226***	0.233***	0.231***	0.197***	0.243***	0.259***	0.172***
	[0.005]	[0.009]	[0.012]	[0.013]	[0.016]	[0.008]	[0.009]
bm 12 and zero acc on AR	0.207***	0.211***	0.228***	0.193***	0.209***	0.233***	0.155***
	[0.006]	[0.010]	[0.013]	[0.014]	[0.018]	[0.009]	[0.010]
bm 13 and zero acc on AR	0.182***	0.189***	0.207***	0.169***	0.209***	0.205***	0.121***
	[0.007]	[0.012]	[0.015]	[0.016]	[0.021]	[0.010]	[0.011]
bm 14 and zero acc on AR	0.157***	0.178***	0.140***	0.029	0.158**	0.156***	0.120**
	[0.014]	[0.019]	[0.044]	[0.070]	[0.071]	[0.039]	[0.048]
N	2,179,729	2,179,729	2,179,729	2,179,729	2,179,729	2,179,729	2,179,729
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
previous year acc. FE	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: The dependent variable is a dummy taking value one if one or more accidents are provoked during the year, and zero otherwise. The coefficients are obtained by estimating the accident probability specified in equation (13) by the WG estimator applied to a linear probability model. In column (1), the estimates of a restricted specification–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ for all j–are presented. The estimates of the company-specific parameters ($\alpha^{dr}_{j,k-n}$) of the baseline specification, are presented in columns (2)-(7).
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.
Source: IPER (contracts starting in 2013, 2014, 2015 and in the first quarter of 2016.)

Table 21. The Effect of the Driving Record on the Accident Probability Conditional on One Accident on the AR (FE-LPM)

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
bm 1 and one acc on AR	0.240***	0.244***	0.258***	0.218***	0.222***	0.268***	0.206***
	[0.003]	[0.005]	[0.007]	[0.007]	[0.009]	[0.004]	[0.005]
bm 2 and one acc on AR	0.089***	0.097***	0.103***	0.074***	0.059***	0.115***	0.050***
	[0.003]	[0.005]	[0.008]	[0.008]	[0.010]	[0.005]	[0.005]
bm 3 and one acc on AR	0.180***	0.188***	0.175***	0.168***	0.168***	0.213***	0.137***
	[0.003]	[0.005]	[0.008]	[0.008]	[0.009]	[0.005]	[0.005]
bm 4 and one acc on AR	0.156***	0.153***	0.153***	0.144***	0.134***	0.188***	0.127***
	[0.004]	[0.008]	[0.012]	[0.012]	[0.015]	[0.007]	[0.008]
bm 5 and one acc on AR	0.147***	0.147***	0.144***	0.141***	0.132***	0.183***	0.104***
	[0.004]	[0.008]	[0.013]	[0.013]	[0.016]	[0.007]	[0.009]
bm 6 and one acc on AR	0.144***	0.139***	0.151***	0.114***	0.155***	0.175***	0.116***
	[0.004]	[0.009]	[0.014]	[0.013]	[0.017]	[0.007]	[0.009]
bm 7 and one acc on AR	0.133***	0.149***	0.125***	0.147***	0.125***	0.154***	0.080***
	[0.005]	[0.009]	[0.014]	[0.012]	[0.017]	[0.007]	[0.009]
bm 8 and one acc on AR	0.125***	0.135***	0.121***	0.153***	0.137***	0.142***	0.067***
	[0.005]	[0.009]	[0.014]	[0.013]	[0.017]	[0.008]	[0.010]
bm 9 and one acc on AR	0.129***	0.127***	0.117***	0.140***	0.161***	0.155***	0.077***
	[0.005]	[0.009]	[0.016]	[0.014]	[0.018]	[0.008]	[0.011]
bm 10 and one acc on AR	0.119***	0.110***	0.119***	0.111***	0.094***	0.157***	0.081***
	[0.006]	[0.011]	[0.019]	[0.016]	[0.022]	[0.009]	[0.012]
bm 11 and one acc on AR	0.086***	0.095***	0.075***	0.083***	0.089***	0.117***	0.024*
	[0.007]	[0.013]	[0.022]	[0.019]	[0.024]	[0.010]	[0.014]
bm 12 and one acc on AR	0.057***	0.087***	-0.009	0.060***	0.044*	0.076***	0.01
	[0.008]	[0.015]	[0.027]	[0.022]	[0.026]	[0.012]	[0.016]
bm 13 and one acc on AR	-0.008	0.032*	-0.01	0.051*	-0.015	-0.012	-0.076***
	[0.009]	[0.017]	[0.030]	[0.027]	[0.031]	[0.014]	[0.019]
bm 14 and one acc on AR	-0.021**	0.007	-0.038	0.051	0.026	-0.024	-0.101***
	[0.009]	[0.018]	[0.034]	[0.032]	[0.034]	[0.015]	[0.021]
N	2,179,729	2,179,729	2,179,729	2,179,729	2,179,729	2,179,729	2,179,729
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
previous year acc. FE	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: The dependent variable is a dummy taking value one if one or more accidents are provoked during the year, and zero otherwise. The coefficients are obtained by estimating the accident probability specified in equation (13) by the WG estimator applied to a linear probability model. In column (1), the estimates of a restricted specification–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ for all j–are presented. The estimates of the company-specific parameters ($\alpha^{dr}_{j,k-n}$) of the baseline specification, are presented in columns (2)-(7).

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

Source: IPER (contracts starting in 2013, 2014, 2015 and in the first quarter of 2016.).

Table 22. The Effect of the Driving Record on the Accident Probability Conditional on Zero Accidents on the AR (FE Logit)

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
L.ACC	-4.193***	-4.203***	-4.203***	-4.203***	-4.203***	-4.203***	-4.203***
	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]
bm 1 and zero acc on AR	7.403***	7.511***	7.646***	6.547***	7.521***	7.905***	6.991***
	[0.086]	[0.142]	[0.230]	[0.205]	[0.267]	[0.134]	[0.148]
bm 2 and zero acc on AR	6.764***	6.914***	7.010***	5.909***	6.627***	7.296***	6.312***
	[0.097]	[0.181]	[0.270]	[0.260]	[0.350]	[0.159]	[0.179]
bm 3 and zero acc on AR	6.411***	6.575***	6.400***	5.738***	6.424***	6.882***	6.011***
	[0.103]	[0.187]	[0.276]	[0.268]	[0.370]	[0.164]	[0.189]
bm 4 and zero acc on AR	6.169***	6.315***	6.078***	5.489***	6.766***	6.562***	5.772***
	[0.109]	[0.191]	[0.283]	[0.274]	[0.377]	[0.168]	[0.196]
bm 5 and zero acc on AR	5.874***	6.013***	5.884***	5.432***	6.537***	6.204***	5.352***
	[0.114]	[0.194]	[0.286]	[0.282]	[0.393]	[0.171]	[0.201]
bm 6 and zero acc on AR	5.627***	5.684***	5.583***	5.118***	5.835***	6.039***	5.189***
	[0.121]	[0.204]	[0.290]	[0.294]	[0.416]	[0.179]	[0.212]
bm 7 and zero acc on AR	5.647***	5.936***	5.654***	5.067***	5.962***	5.943***	5.122***
	[0.131]	[0.218]	[0.309]	[0.317]	[0.434]	[0.191]	[0.227]
bm 8 and zero acc on AR	5.564***	5.677***	5.692***	4.760***	5.780***	5.950***	5.032***
	[0.143]	[0.239]	[0.349]	[0.360]	[0.466]	[0.205]	[0.246]
bm 9 and zero acc on AR	5.412***	5.818***	5.855***	4.613***	5.355***	5.575***	4.906***
	[0.158]	[0.270]	[0.389]	[0.371]	[0.518]	[0.226]	[0.267]
bm 10 and zero acc on AR	5.030***	5.400***	5.238***	3.762***	5.309***	5.301***	4.571***
	[0.174]	[0.300]	[0.415]	[0.415]	[0.558]	[0.240]	[0.288]
bm 11 and zero acc on AR	4.606***	4.879***	4.766***	3.803***	4.950***	4.858***	3.979***
	[0.194]	[0.322]	[0.454]	[0.433]	[0.576]	[0.262]	[0.314]
bm 12 and zero acc on AR	4.410***	4.484***	4.886***	4.183***	4.421***	4.524***	3.800***
	[0.213]	[0.356]	[0.505]	[0.437]	[0.701]	[0.286]	[0.343]
bm 13 and zero acc on AR	4.206***	4.394***	4.653***	4.115***	4.476***	4.080***	3.685***
	[0.235]	[0.422]	[0.577]	[0.489]	[0.815]	[0.338]	[0.392]
bm 14 and zero acc on AR	3.654***	4.600***	-9.109	-9.663	-9.816	3.048***	2.354
	[0.626]	[0.824]	[2251.854]	[1508.529]	[1760.053]	[1.146]	[3.122]
N	212,052	212,052	212,052	212,052	212,052	212,052	212,052
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
previous year acc. FE	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. Year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: The dependent variable is a dummy taking value one if one or more accidents are provoked during the year, and zero otherwise. The coefficients are obtained by estimating the accident probability specified in equation (13) by the FE logit estimator applied to a linear probability model. In column (1), the estimates of a restricted specification–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ for all j–are presented. The estimates of the company-specific parameters ($\alpha^{dr}_{j,k-n}$) of the baseline specification, are presented in columns (2)-(7).

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

Source: IPER (contracts starting in 2013, 2014, 2015, and in the first quarter of 2016.).

TABLE 23. The Effect of the Driving Record on the Accident Probability Conditional on One Accident on the AR (FE Logit)-Cont.

	(1) Market	(2) A	(3) B	(4) C	(5) D	(6) Medium	(7) Small
bm 1 and one acc on AR	5.089***	5.243***	5.593***	4.102***	4.888***	5.464***	4.806***
	[0.089]	[0.155]	[0.252]	[0.226]	[0.302]	[0.148]	[0.164]
bm 2 and one acc on AR	2.882***	3.018***	3.358***	2.138***	2.703***	3.254***	2.497***
	[0.082]	[0.147]	[0.248]	[0.215]	[0.284]	[0.139]	[0.158]
bm 3 and one acc on AR	3.921***	4.016***	4.107***	3.398***	3.739***	4.352***	3.533***
	[0.082]	[0.145]	[0.248]	[0.218]	[0.275]	[0.138]	[0.158]
bm 4 and one acc on AR	3.033***	2.796***	3.232***	2.662***	2.436***	3.486***	2.901***
	[0.123]	[0.238]	[0.416]	[0.378]	[0.480]	[0.219]	[0.251]
bm 5 and one acc on AR	2.855***	2.778***	2.987***	2.170***	2.239***	3.441***	2.373***
	[0.131]	[0.256]	[0.438]	[0.371]	[0.518]	[0.215]	[0.287]
bm 6 and one acc on AR	2.671***	2.382***	2.836***	1.371***	3.059***	3.006***	2.668***
	[0.135]	[0.285]	[0.450]	[0.420]	[0.486]	[0.213]	[0.273]
bm 7 and one acc on AR	2.499***	2.571***	2.955***	2.292***	2.515***	2.594***	2.184***
	[0.140]	[0.269]	[0.428]	[0.401]	[0.550]	[0.224]	[0.289]
bm 8 and one acc on AR	2.325***	2.447***	2.690***	2.511***	2.728***	2.368***	1.707***
	[0.144]	[0.264]	[0.426]	[0.410]	[0.493]	[0.231]	[0.308]
bm 9 and one acc on AR	2.455***	2.389***	2.985***	2.422***	2.824***	2.499***	2.257***
	[0.154]	[0.279]	[0.482]	[0.446]	[0.559]	[0.251]	[0.315]
bm 10 and one acc on AR	2.556***	2.076***	2.057***	2.093***	2.407***	2.921***	2.875***
	[0.173]	[0.325]	[0.613]	[0.477]	[0.682]	[0.272]	[0.349]
bm 11 and one acc on AR	2.235***	2.366***	2.000***	2.263***	1.477**	2.506***	1.726***
	[0.192]	[0.343]	[0.766]	[0.525]	[0.684]	[0.294]	[0.459]
bm 12 and one acc on AR	1.898***	2.769***	0.638	1.579**	2.326***	1.861***	1.032*
	[0.225]	[0.422]	[0.841]	[0.716]	[0.692]	[0.341]	[0.540]
bm 13 and one acc on AR	0.879***	1.778***	0.009	1.125	1.289	0.56	0.358
	[0.267]	[0.492]	[0.843]	[0.815]	[0.903]	[0.405]	[0.601]
bm 14 and one acc on AR	0.827***	1.011**	0.048	1.882**	1.701	1.018**	-0.937
	[0.279]	[0.501]	[0.930]	[0.803]	[1.104]	[0.427]	[0.687]
N	212,052	212,052	212,052	212,052	212,052	212,052	212,052
policyholder char.	yes	yes	yes	yes	yes	yes	yes
car char.	yes	yes	yes	yes	yes	yes	yes
clauses	yes	yes	yes	yes	yes	yes	yes
city char.	yes	yes	yes	yes	yes	yes	yes
previous year acc. FE	yes	yes	yes	yes	yes	yes	yes
closed claim FE	yes	yes	yes	yes	yes	yes	yes
no. of installments FE	yes	yes	yes	yes	yes	yes	yes
company FE	yes	yes	yes	yes	yes	yes	yes
contr. year FE	yes	yes	yes	yes	yes	yes	yes
province FE	yes	yes	yes	yes	yes	yes	yes

Note: The dependent variable is a dummy taking value one if one or more accidents are provoked during the year, and zero otherwise. The coefficients are obtained by estimating the accident probability specified in equation (13) by the FE logit estimator applied to a linear probability model. In column (1), the estimates of a restricted specification–$\alpha^{dr}_{j,k-n} = \alpha^{dr}_{k-n}$ for all j–are presented. The estimates of the company-specific parameters ($\alpha^{dr}_{j,k-n}$) of the baseline specification, are presented in columns (2)-(7).

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

Source: IPER (contracts starting in 2013, 2014, 2015, and in the first quarter of 2016.).

Table 24. The Effect of the Driving Record on the Premium (Levels) Using Company-Specific Sample of Contracts

	(1) A	(2) B	(3) C	(4) D	(5) Medium	(6) Small
bm 1	-449.632***	-626.897***	-619.858***	-579.549***	-753.785***	-323.740***
	(4.167)	(8.151)	(7.333)	(8.368)	(3.823)	(2.723)
bm 2	-423.997***	-596.829***	-592.065***	-548.971***	-725.613***	-292.942***
	(4.149)	(8.123)	(7.309)	(8.343)	(3.804)	(2.733)
bm 3	-412.598***	-570.843***	-570.463***	-523.882***	-704.322***	-271.887***
	(4.124)	(8.089)	(7.281)	(8.302)	(3.779)	(2.722)
bm 4	-388.545***	-544.571***	-548.411***	-505.932***	-680.505***	-251.210***
	(4.101)	(8.057)	(7.252)	(8.274)	(3.757)	(2.741)
bm 5	-369.066***	-515.521***	-526.178***	-477.864***	-653.571***	-226.864***
	(4.078)	(8.024)	(7.222)	(8.241)	(3.733)	(2.749)
bm 6	-349.645***	-486.178***	-505.234***	-445.709***	-625.228***	-201.576***
	(4.055)	(7.990)	(7.193)	(8.212)	(3.710)	(2.766)
bm 7	-325.843***	-451.566***	-482.083***	-414.461***	-593.815***	-173.403***
	(4.026)	(7.950)	(7.159)	(8.170)	(3.683)	(2.795)
bm 8	-297.948***	-415.407***	-454.955***	-390.618***	-559.481***	-143.064***
	(3.994)	(7.894)	(7.116)	(8.122)	(3.654)	(2.846)
bm 9	-273.717***	-381.550***	-420.634***	-364.186***	-521.888***	-114.963***
	(3.954)	(7.826)	(7.064)	(8.065)	(3.616)	(2.907)
bm 10	-244.077***	-326.111***	-384.270***	-333.827***	-474.699***	-79.072***
	(3.897)	(7.738)	(7.000)	(7.985)	(3.575)	(2.979)
bm 11	-211.380***	-282.851***	-342.908***	-297.537***	-420.486***	-34.241***
	(3.832)	(7.606)	(6.923)	(7.898)	(3.520)	(3.059)
bm 12	-177.190***	-242.741***	-307.579***	-254.284***	-369.264***	17.015***
	(3.775)	(7.540)	(6.843)	(7.831)	(3.479)	(3.163)
bm 13	-137.972***	-189.910***	-248.249***	-202.387***	-295.447***	63.204***
	(3.682)	(7.399)	(6.711)	(7.703)	(3.407)	(3.282)
bm 14	-97.890***	-61.033***	-169.557***	-116.363***	-195.353***	144.993***
	(3.595)	(7.365)	(6.693)	(7.640)	(3.367)	(3.483)
1 acc on AR	35.847***	51.899***	38.740***	15.429***	41.978***	51.074***
	(0.464)	(0.788)	(0.662)	(0.809)	(0.458)	(0.550)
2 acc on AR	109.780***	75.893***	94.349***	34.715***	87.507***	105.991***
	(1.061)	(1.958)	(1.570)	(1.843)	(1.041)	(1.278)
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes
city char.	Yes	Yes	Yes	Yes	Yes	Yes
previous year acc. FE	Yes	Yes	Yes	Yes	Yes	Yes
closed claim FE	Yes	Yes	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.330	0.279	0.356	0.435	0.420	0.397

Note: This table reports fixed-effect estimates of β_j^{AR} and β_j^{FE}–the effect of the bm class and of the number of accidents on the AR on the premium–as specified in equation (12). The dependent variable is the log of the premium. The coefficients reported in each column are obtained estimating equation (12) on the company-specific sample of contracts.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard error are reported in parentheses.

Source: IPER (contractual years 2013-2014, 2014-2015, 2015-2016, and 2016-2017.).

Table 25. Penalties Across Companies Using Company-Specific Sample of Contracts

	A	B	C	D	Medium	Small
	Panel A: Zero Accidents on AR					
BM Class						
1	72.881	107.953	88.135	71.096	91.441	102.927
2	96.934	134.225	110.187	89.046	115.258	123.604
3	90.778	133.207	104.627	86.536	114.02	117.152
4	98.8	136.564	103.969	93.602	121.072	121.385
5	98.549	144.904	105.068	106.9	128.668	128.881
6	106.965	152.013	109.963	102.675	136.068	134.874
7	111.775	156.527	123.34	96.952	145.318	137.687
8	117.613	177.354	136.553	96.063	161.094	145.405
9	122.415	184.455	150.787	108.51	180.973	159.897
10	132.374	190.708	151.795	125.331	194.602	183.052
11	141.952	188.1	174.761	146.869	221.23	193.35
12	149.337	273.717	212.091	196.603	267.111	230.308
	Panel B: One Accident on AR					
	A	B	C	D	Medium	Small
BM Class						
1	110.967	80.048	105.004	74.953	68.749	106.77
2	135.02	106.32	127.056	92.903	92.566	127.447
3	128.864	105.302	121.496	90.393	91.328	120.995
4	136.886	108.659	120.838	97.459	98.38	125.228
5	136.635	116.999	121.937	110.757	105.976	132.724
6	145.051	124.108	126.832	106.532	113.376	138.717
7	149.861	128.622	140.209	100.809	122.626	141.53
8	155.699	149.449	153.422	99.92	138.402	149.248
9	160.501	156.55	167.656	112.367	158.281	163.74
10	170.46	162.803	168.664	129.188	171.91	186.895
11	180.038	160.195	191.63	150.726	198.538	197.193
12	187.423	245.812	228.96	200.46	244.419	234.151

Note: Panels A and B show the penalty in euros after one accident as a function of the bm class, conditional on having one and two accidents on the AR, respectively. These estimates are obtained using the coefficients related to the driving record in the estimating equation (12) on the company-specific sample of contracts, reported in table 13, and the evolution of the bm class described in table 9.

Table 26. Baseline Hazard Rate Among Different Groups of Switchers

	(1) All	(2) G10	(3) G20	(4) G30	(5) G50	(6) G70	(7) G80	(8) G100
hr_1_30	-8.355***	-10.624***	-8.891***	-8.447***	-8.904***	-8.813***	-8.635***	-7.407***
	(0.162)	(0.582)	(0.615)	(0.582)	(0.393)	(0.337)	(0.486)	(0.246)
hr_30_60	-8.368***	-10.422***	-9.058***	-8.219***	-8.877***	-8.765***	-8.854***	-7.461***
	(0.168)	(0.582)	(0.629)	(0.566)	(0.391)	(0.364)	(0.488)	(0.240)
hr_60_90	-8.445***	-10.772***	-9.095***	-8.378***	-8.863***	-8.965***	-8.899***	-7.484***
	(0.170)	(0.554)	(0.601)	(0.567)	(0.404)	(0.332)	(0.490)	(0.251)
hr_90_120	-8.365***	-10.465***	-8.906***	-8.352***	-8.738***	-8.735***	-8.865***	-7.500***
	(0.163)	(0.553)	(0.613)	(0.598)	(0.394)	(0.331)	(0.473)	(0.239)
hr_120_150	-8.369***	-10.813***	-8.671***	-8.277***	-8.824***	-8.710***	-8.935***	-7.484***
	(0.163)	(0.511)	(0.607)	(0.598)	(0.417)	(0.345)	(0.493)	(0.236)
hr_150_180	-8.343***	-10.218***	-8.709***	-8.521***	-8.877***	-8.765***	-8.719***	-7.461***
	(0.152)	(0.541)	(0.591)	(0.559)	(0.399)	(0.334)	(0.490)	(0.240)
hr_180_210	-8.348***	-10.230***	-8.709***	-8.142***	-8.762***	-8.720***	-8.653***	-7.613***
	(0.150)	(0.509)	(0.618)	(0.592)	(0.379)	(0.340)	(0.485)	(0.236)
hr_210_240	-8.225***	-10.152***	-8.383***	-7.986***	-8.591***	-8.539***	-8.575***	-7.571***
	(0.155)	(0.512)	(0.612)	(0.574)	(0.380)	(0.327)	(0.478)	(0.237)
hr_240_270	-8.194***	-10.089***	-8.365***	-8.023***	-8.385***	-8.498***	-8.434***	-7.654***
	(0.147)	(0.541)	(0.594)	(0.551)	(0.374)	(0.326)	(0.473)	(0.239)
hr_270_305	-8.011***	-9.834***	-8.038***	-7.732***	-8.235***	-8.260***	-8.338***	-7.554***
	(0.142)	(0.567)	(0.599)	(0.580)	(0.374)	(0.331)	(0.494)	(0.229)
hr_305_335	-7.873***	-9.615***	-7.978***	-7.614***	-8.060***	-8.161***	-8.230***	-7.394***
	(0.133)	(0.564)	(0.588)	(0.569)	(0.368)	(0.305)	(0.476)	(0.228)
hr_335_365	-7.422***	-9.049***	-7.449***	-7.120***	-7.462***	-7.795***	-7.770***	-7.078***
	(0.128)	(0.568)	(0.598)	(0.531)	(0.366)	(0.295)	(0.506)	(0.232)
bm class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
no. of acc on AR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
car char	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
city char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,050,172	432,378	432,308	425,985	828,194	774,995	379,016	777,296

Note: This table reports the estimates of the baseline hazard rates (λ_j), obtained by fitting the Cox model specified in equation (16) on the sample of groups G10-G10, as defined in the text. *hr_1_30* denotes the logarithm of the baseline hazard rate function in the interval $[1; 30)$. The other parameters are defined analogously. N denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.
Source: IPER (contractual years 2013-2014, 2014-2015, and 2015-2016).

TABLE 27. Estimates of the Company-Specific BHR–All Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	(A)	(B)	(C)	(D)	(Medium)	(Small)
hr_1_30	-7.992***	-8.038***	-8.071***	-7.993***	-7.912***	-7.777***
	[0.074]	[0.068]	[0.074]	[0.082]	[0.068]	[0.616]
hr_30_60	-7.999***	-8.027***	-8.006***	-7.983***	-7.936***	-7.814***
	[0.070]	[0.072]	[0.067]	[0.077]	[0.071]	[0.620]
hr_60_90	-7.985***	-8.026***	-8.012***	-7.950***	-7.914***	-7.816***
	[0.065]	[0.074]	[0.071]	[0.097]	[0.069]	[0.612]
hr_90_120	-8.041***	-8.022***	-7.988***	-8.010***	-7.975***	-7.799***
	[0.066]	[0.073]	[0.074]	[0.079]	[0.064]	[0.618]
hr_120_150	-8.024***	-8.037***	-7.986***	-7.910***	-7.934***	-7.789***
	[0.063]	[0.068]	[0.066]	[0.082]	[0.062]	[0.610]
hr_150_180	-8.012***	-7.978***	-7.951***	-7.920***	-7.907***	-7.815***
	[0.056]	[0.069]	[0.067]	[0.081]	[0.063]	[0.616]
hr_180_210	-8.037***	-8.066***	-8.078***	-7.977***	-7.946***	-7.825***
	[0.066]	[0.079]	[0.074]	[0.071]	[0.069]	[0.614]
hr_210_240	-8.011***	-8.073***	-8.022***	-7.919***	-7.913***	-7.813***
	[0.068]	[0.073]	[0.062]	[0.078]	[0.074]	[0.616]
hr_240_270	-8.047***	-7.980***	-8.053***	-7.996***	-7.933***	-7.776***
	[0.063]	[0.069]	[0.076]	[0.086]	[0.066]	[0.615]
hr_270_305	-8.003***	-7.984***	-8.003***	-7.990***	-7.961***	-7.787***
	[0.063]	[0.067]	[0.067]	[0.080]	[0.069]	[0.613]
hr_305_335	-7.999***	-7.918***	-7.998***	-7.869***	-7.889***	-7.785***
	[0.053]	[0.059]	[0.058]	[0.081]	[0.065]	[0.614]
hr_335_365	-7.854***	-7.726***	-7.861***	-7.820***	-7.745***	-7.610***
	[0.063]	[0.079]	[0.058]	[0.071]	[0.058]	[0.611]
bm class FE	Yes	Yes	Yes	Yes	Yes	Yes
no. of acc. on AR FE	Yes	Yes	Yes	Yes	Yes	Yes
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes
car char	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes
city char.	Yes	Yes	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	37,208,804	37,208,804	37,208,804	37,208,804	37,208,804	37,208,804

Note: This table reports the estimates of the company-specific baseline hazard rates (λ_{jk}), obtained by fitting the Cox model specified in equation (19) on the all sample. hr_1_30 denotes the logarithm of the baseline hazard rate function in the interval $[1; 30)$. The other parameters are defined analogously. N denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contractual years 2013-2014, 2014-2015, and 2015-2016).

Table 28. Estimates of the Company-Specific BHR–Switchers

	(1) (A)	(2) (B)	(3) (C)	(4) (D)	(5) (Medium)	(6) (Small)
hr_1_30	-8.316***	-8.254***	-8.177***	-8.422***	-8.443***	-7.669***
	[0.181]	[0.177]	[0.209]	[0.246]	[0.175]	[1.031]
hr_30_60	-8.363***	-8.175***	-8.003***	-8.393***	-8.534***	-7.688***
	[0.174]	[0.226]	[0.180]	[0.251]	[0.187]	[1.039]
hr_60_90	-8.444***	-8.305***	-8.226***	-8.452***	-8.581***	-7.718***
	[0.173]	[0.196]	[0.198]	[0.253]	[0.192]	[1.036]
hr_90_120	-8.416***	-8.145***	-8.104***	-8.187***	-8.537***	-7.637***
	[0.181]	[0.236]	[0.184]	[0.215]	[0.179]	[1.033]
hr_120_150	-8.367***	-8.145***	-8.086***	-8.12***	-8.581***	-7.659***
	[0.176]	[0.207]	[0.193]	[0.225]	[0.177]	[1.032]
hr_150_180	-8.434***	-8.183***	-8.131***	-8.037***	-8.402***	-7.678***
	[0.158]	[0.168]	[0.196]	[0.236]	[0.168]	[1.046]
hr_180_210	-8.244***	-8.145***	-8.122***	-8.099***	-8.515***	-7.735***
	[0.164]	[0.184]	[0.166]	[0.180]	[0.171]	[1.031]
hr_210_240	-8.214***	-8.175***	-7.89***	-7.997***	-8.31***	-7.592***
	[0.152]	[0.197]	[0.183]	[0.164]	[0.180]	[1.027]
hr_240_270	-8.218***	-7.994***	-8.104***	-8.187***	-8.205***	-7.568***
	[0.159]	[0.164]	[0.152]	[0.218]	[0.179]	[1.045]
hr_270_305	-7.988***	-7.788***	-7.873***	-7.538***	-8.093***	-7.44***
	[0.148]	[0.148]	[0.177]	[0.196]	[0.161]	[1.037]
hr_305_335	-7.839***	-7.652***	-7.775***	-7.715***	-7.937***	-7.262***
	[0.139]	[0.146]	[0.137]	[0.203]	[0.164]	[1.032]
hr_335_365	-7.461***	-7.00***	-7.306***	-7.128***	-7.512***	-6.858***
	[0.129]	[0.166]	[0.153]	[0.161]	[0.137]	[1.034]
bm class FE	Yes	Yes	Yes	Yes	Yes	Yes
no. of acc. on AR FE	Yes	Yes	Yes	Yes	Yes	Yes
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes
city char.	Yes	Yes	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,050,172	4,050,172	4,050,172	4,050,172	4,050,172	4,050,172

Note: This table reports the estimates of the company-specific baseline hazard rates (λ_{jk}), obtained by fitting the Cox model specified in equation (19) on the sample of switchers. *hr_1_30* denotes the logarithm of the baseline hazard rate function in the interval $[1; 30)$. The other parameters are defined analogously. N denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contractual years 2013-2014, 2014-2015, and 2015-2016).

Table 29. The Effect of the Grace Period on the Size of Damage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Q25	Median	Q75	OLS	Q25	Median	Q75
	Panel A: All Claims							
	A1-All Sample				A2-Switchers			
g	0.100***	0.087***	0.111***	0.112***	0.188***	0.199***	0.215***	0.174***
	(0.028)	(0.021)	(0.020)	(0.022)	(0.042)	(0.038)	(0.041)	(0.038)
res_g	-0.002***	-0.002***	-0.002***	-0.003***	-0.004***	-0.003***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
nores_g	-0.000	-0.000	-0.000**	-0.000*	-0.000**	-0.000**	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	87,847	87,847	87,847	87,847	9,813	9,813	9,813	9,813
R^2	0.034			0.022	0.079			
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
bm class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
no. of acc. on AR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
city's char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOARF_SINDEN	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the logarithm of the total indemnity (in euros) received by the third parties involved in the first accident of the contractual year the driver is liable of. The sample is restricted to claims not on hold. The distribution of the indemnity has been trimmed using the 99^{th} percentile. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contractual years 2013-2014 and 2014-2015).

Table 30. The Effect of the Grace Period on the Size of Damage–Claims with and without Bodily Injuries

	Panel A: Claims Without Bodily Injuries							
	A1-All Sample				A2-Switchers			
g	0.130***	0.088***	0.135***	0.161***	0.298***	0.230***	0.330***	0.315***
	(0.030)	(0.022)	(0.019)	(0.021)	(0.052)	(0.037)	(0.039)	(0.036)
res_g	-0.003***	-0.002***	-0.003***	-0.004***	-0.006***	-0.004***	-0.006***	-0.008***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
nores_g	-0.000	-0.000	-0.000**	-0.000*	-0.000**	-0.000**	-0.000***	-0.000**
	-0.000**	-0.000	-0.000	-0.000**	-0.000*	-0.000**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	74,953	74,953	74,953	74,953	8,247	8,247	8,247	8,247
R^2	0.037				0.086			
	Panel B: Claims With Bodily Injuries							
	B1-All Sample				B2-Switchers			
g	0.056*	0.042	0.103***	0.044*	0.157	0.079	0.211**	0.192***
	(0.032)	(0.048)	(0.038)	(0.026)	(0.099)	(0.130)	(0.091)	(0.061)
res_g	-0.001	-0.002	-0.002	-0.000	-0.004*	-0.004	-0.004	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)
nores_g	-0.000	-0.000	0.000	-0.000	-0.000**	-0.001*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	12,894	12,894	12,894	12,894	1,668	1,668	1,668	1,668
R^2	0.049				0.184			
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
bm class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
no. of acc. on AR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
city char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOARF_SINDEN	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the logarithm of the total indemnity (in euros) received by the third parties involved in the first accident of the contractual year the driver is liable of. The sample is restricted to claims not on hold. The distribution of the indemnity has been trimmed using the 99^{th} percentile. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contractual years 2013-2014 and 2014-2015).

Table 31. OLS Regression on the Impact of the Grace Period on the Size of Damage Across Companies

	(1) OLS (Stayers)	(2) Median Regr. (Stayers)	(3) OLS (Switchers)	(4) Median Regr.(Switchers)
G×A	0.041	0.042	0.137*	0.263***
	(0.041)	(0.042)	(0.081)	(0.096)
G×B	0.143**	0.135***	0.133	0.161
	(0.057)	(0.051)	(0.110)	(0.148)
G×C	0.074	0.073	0.202	0.169*
	(0.059)	(0.080)	(0.127)	(0.099)
G×D	0.072	0.041	-0.076	0.088
	(0.071)	(0.092)	(0.203)	(0.284)
G×Medium	0.114***	0.123***	0.262***	0.247***
	(0.031)	(0.044)	(0.077)	(0.073)
G×Small	0.151***	0.163***	0.253***	0.295***
	(0.049)	(0.038)	(0.083)	(0.062)
policyholder char.	Yes	Yes	Yes	Yes
bm class FE	Yes	Yes	Yes	Yes
no of acc. on AR FE	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes
city char.	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes
company FE	Yes	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes
SOARF_SINDEN	Yes	Yes	Yes	Yes
N	87,849	87,849	9,915	9,915
R^2	0.034		0.080	

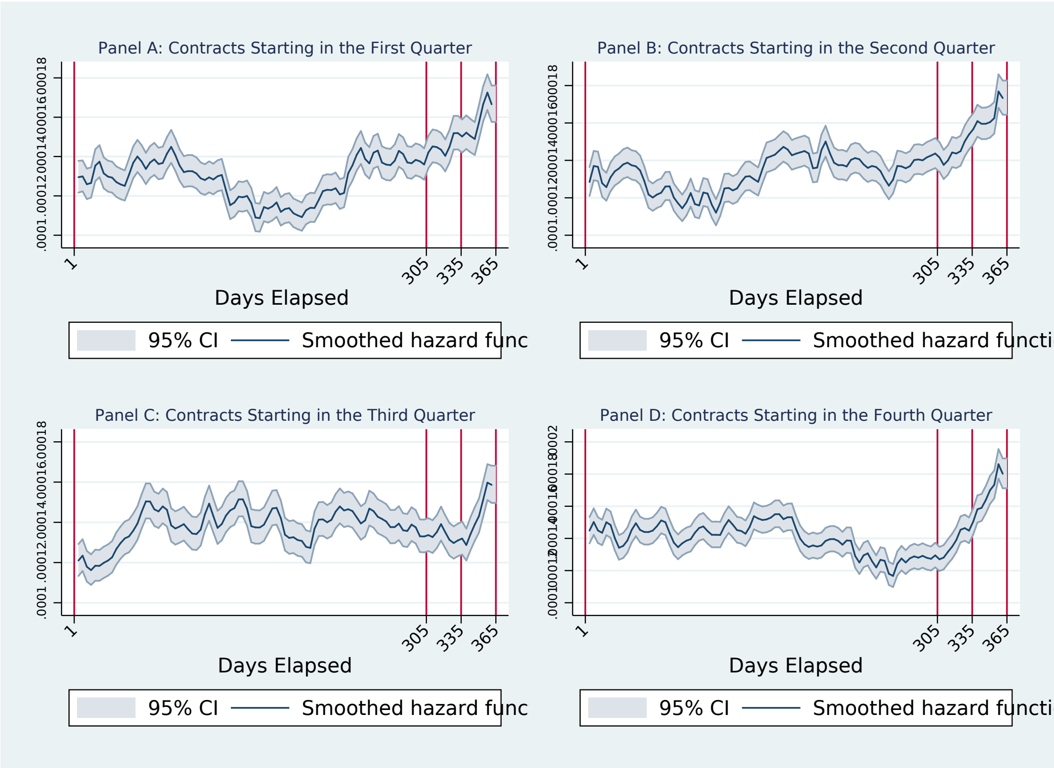
Note: The dependent variable is the logarithm of the total indemnity (in euros) received by the third parties involved in the first accident of the contractual year for which the driver is liable. The sample is restricted to claims not on hold. The distribution of the indemnity has been trimmed using the 99^{th} percentile. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contractual years 2013-2014, and 2014-2015).

13. Figures

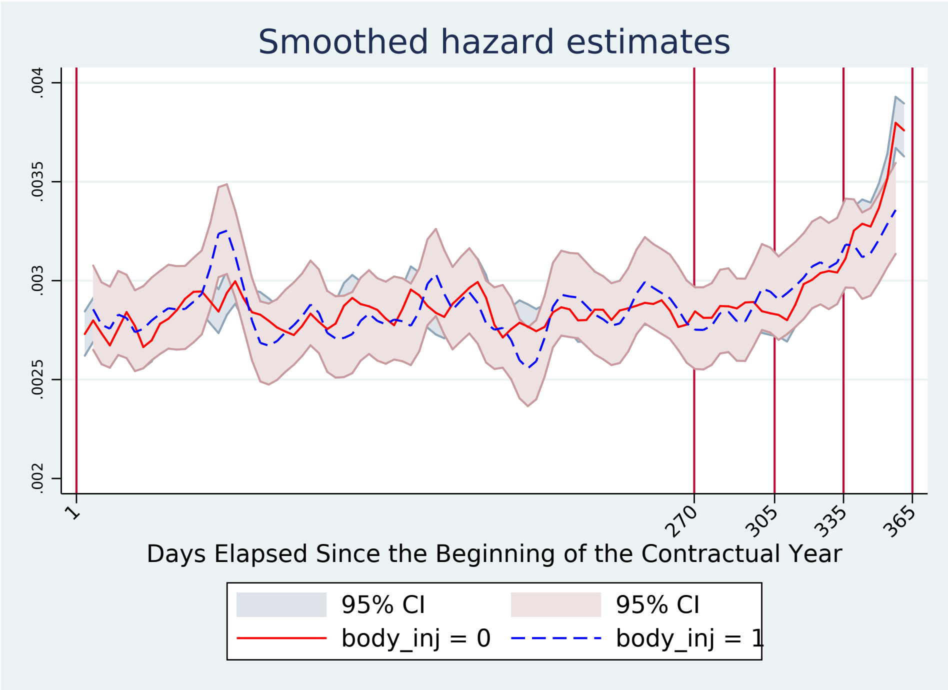
Figure 10. Hazard Rate Conditional on the Quarter



Note. This graph depicts the hazard rate of accidents conditional on the starting quarter of the contract. The hazard rate is bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rate. A PWP gap-time model has been adopted to take into account the correlation across multiple accidents.

Source: IPER (contractual years 2013-2014, 2014-2015, and 2015-2016)

FIGURE 11. Hazard Rate During the Contractual Year Conditional on the Presence of Bodily Injuries



Note. The hazard rates are bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rates. The sample is restricted to contracts associated with one or more claims during the contractual year. The continuous (dotted) line represents the hazard rate of claims with (without) bodily injuries.

Source: IPER (contracts covering years 2013-2014 and 2014-2015).

Table 32. Switching Probability

	(1) Logit	(2) FE Logit	(3) LPM
bm 1	0.069	-0.106	-0.004
	(0.060)	(0.095)	(0.010)
bm 2	0.257***	-0.054	-0.001
	(0.062)	(0.095)	(0.010)
bm 3	0.162***	-0.139	-0.011
	(0.057)	(0.094)	(0.010)
bm 4	0.301***	-0.094	-0.006
	(0.054)	(0.094)	(0.010)
bm 5	0.301***	-0.091	-0.007
	(0.054)	(0.093)	(0.010)
bm 6	0.309***	-0.103	-0.009
	(0.053)	(0.093)	(0.010)
bm 7	0.341***	-0.096	-0.009
	(0.056)	(0.093)	(0.010)
bm 8	0.336***	-0.153*	-0.018*
	(0.056)	(0.092)	(0.010)
bm 9	0.397***	-0.176*	-0.022**
	(0.057)	(0.092)	(0.010)
bm 10	0.416***	-0.196**	-0.024**
	(0.061)	(0.092)	(0.010)
bm 11	0.443***	-0.243***	-0.029***
	(0.057)	(0.092)	(0.010)
bm 12	0.461***	-0.298***	-0.038***
	(0.062)	(0.092)	(0.010)
bm 13	0.497***	-0.269***	-0.033***
	(0.059)	(0.092)	(0.010)
bm 14	0.661***	-0.090	-0.012
	(0.058)	(0.094)	(0.010)
1 acc on AR	-0.016**	0.215***	0.019***
	(0.008)	(0.016)	(0.002)
2 acc on AR	-0.108***	0.170***	0.016***
	(0.022)	(0.036)	(0.004)
policyholder char.	Yes	Yes	Yes
car char.	Yes	Yes	Yes
city char.	Yes	Yes	Yes
clauses	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes
company FE	Yes	Yes	Yes
contr. year FE	Yes	Yes	Yes
province FE	Yes	Yes	Yes
R^2			0.053
N	2,736,518	745,615	2,736,518

Note: The dependent variable is a dummy taking value one if the policyholder switches at the end of the contractual year. Standard errors are reported in parentheses. Standard errors are clustered at the province level in (1). *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Source: IPER (contracts starting in 2013, 2014, 2015, 2016, and in the first quarter of 2017).