THE EFFECT OF INSURANCE TELEMATICS AND FINANCIAL PENALTIES ON MARKET-WIDE MORAL HAZARD*

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ABSTRACT. Using a unique matched insurer-insuree panel dataset that contains rich information on 4,316,647 auto insurance contracts underwritten by *all* Italian insurers in the period 2013:Q3-2017 with associated claims and information on insurers' loading costs, I provide empirical evidence of *market-wide* moral hazard. I infer moral hazard by estimating the effect of (experience rating) financial penalties and of the so-called black box—telemonitoring devices transmitting data on driving habits to the insurer—on the frequency of accidents. I disentangle moral hazard from adverse selection and state dependence by exploiting the price variations across insurers and local markets, and the black box pricing experimentation by a major insurer. I find that (i) a 1 percentage point increase in financial penalties decreases the conditional accident probability by 9–47 basis points, and this effect varies across insurers, and (ii) a black box reduction of 44–80 basis points, with a declining moral hazard effect in the distance driven. I do not find a significant correlation between the presence of the black box and the frequency of accidents, implying that adopters are more risky drivers than non-adopters. This counterintuitive selection pattern can be rationalized by the reduction of claims liquidation time entailed by the black box within a model in which drivers only differ in ex-ante risk.

Keywords: Moral hazard, Adverse Selection, Insurance Telematics
JEL classification: D82, G22, G52

1. INTRODUCTION

Are automobile drivers less attentive when they know an accident is unlikely to increase their insurance premium? Existing evidence is mixed (Cohen and Siegelman, 2010), and previous work either only tests for—rather than measures—moral hazard, or is based on a

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company-specific sample of contracts. As observed by Salanie (2017), imperfectly competitive insurers typically attract different market segments. Thus, inference on market-wide moral hazard based on data from a single insurer might be biased.

There are two main mechanisms through which competition among insurers affects market-wide moral hazard. First, insurers could penalize accidents on driving records differently and/or attract different segments of the market; this heterogeneity in pricing strategies can arise in response to different cost structures. Second, insurers can choose to rely on "telemonitoring"' devices installed on the vehicle—the so-called black box—that record a host of "telematic" data, such as speed, distance, and types of roads driven. Empirical estimates of how effective the black box is in making drivers safer are almost absent.

In this article I measure moral hazard in the context of the Italian automobile insurance market. Exploiting a unique insurer-insuree dataset covering the entire Italian market, I address the following empirical questions: (a) How large is the elasticity of accidents to financial penalties accident *in the market*? (b) Does the *market-wide* moral hazard differ from the insurer-specific moral hazard because of sorting into insurers? (c) How much does the black box reduce the accident probability relative to the standard experience rating insurance contract? (d) Are policyholders who choose to be monitored by the black box inherently safer than non-adopters?

The Italian market provides a unique opportunity to answer these questions for several reasons. First, insurers rely on both the traditional experience rating (bonus-malus) incentive schemes and on the black box data to compute premiums. About 21 percent of contracts at the national level, and over 60 percent in some Southern provinces, include a black box clause. Second, the Italian black box contracts are dynamic in nature—premiums at year t depend on driving habits in year $t-1$—and the usage of the so-called crash data is also more advanced relative to other countries, such as the US. Third, the novel data I utilize in this article allow me to examine moral hazard at the market level, rather than confining the analysis to a single insurer.

The administrative data I describe represent a remarkable advancement relative to previously used datasets along several dimensions.[1] Notably, I have a representative and large—4,316,667 contracts and related claims from 2013 to 2017:Q3—matched insurer-insuree dataset, following policyholders after they change companies. Besides the traditional variables—number and severity of claims—information on nine additional clauses, including the presence of the black box, is available. The sample is representative of

[1]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.

the entire Italian market, and the data reflect striking geographical variations across local markets, which I rely on to disentangle moral hazard from adverse selection. The data also contain detailed information on the black box contracts underwritten by a large insurer (henceforth insurer A) and on individual driving habits by black box adopters covered by this insurer. Finally, this dataset is merged with information on loading costs—the administrative costs to manage contracts and liquidate claims—at the insurer-year level taken from the balance sheet data.

I start the analysis by providing striking visual evidence that drivers respond to the incentives of the bonus-malus system. I exploit 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 $t+2$. Moreover, accidents during the grace period of year t are likely to disappear from the driver's record if the driver switches to another company, due to a glitch in the system. As the hazard rate of accidents increases during the grace period, with a much more pronounced peak among the switchers, this research design is useful to demonstrate that penalties for accidents are salient; however, it is plagued by the endogenous nature of the switching decision.[2] I address this issue by relying on a mandatory divestiture that forced some policyholders to switch companies (the "exogenous switchers"), and I do find evidence of moral hazard. Again, much like the previous work, this evidence is not informative on the market-wide moral hazard because the sample of "exogenous switchers" might not be representative of the entire market. This preliminary analysis also reveals that (a) more severe accidents happen in the grace period, suggesting that ex-post moral hazard is not important, and (b) the black box reduces both the size of the damage and claim liquidation time.

One of the main contributions of this paper is to estimate the market elasticity of *transaction prices* to driving records and to the presence of the black box. I use the estimated effect of driving records on paid premiums to compute the penalty faced by a policyholder for an additional accident at a given driving record and insurer. This approach is robust to a number of frictions, such as the discounts given by sales agents, but it requires me to take into account the absence of some pricing variables. I address this problem by leveraging on the control function approach proposed by Bajari, Fruehwirth, Kim, and Timmins (2012) in the context of the hedonic house prices regression literature.
I find that a clean record implies, on average, a premium reduction of about 15 percentage points, and ranges across insurers from 13 to about 19 percentage points. On average, the presence of the black box reduces the (conditional) premium by about 10 percentage

[2]The salience of incentives in the auto insurance contract cannot be taken as given ex-ante; the presence of systematic mistakes generated by "mental gaps" has been extensively studied by the health insurance literature (Handel and Schwartzstein (2018) provide a summary of this work).

points, and this discount varies from 6 to 13 percentage points in the market.
How can these pricing differences across insurers be rationalized in a regulated market? The balance sheet data show that *loading costs are sizable* and there are substantial differences across insurers in the administrative costs of managing contracts (from 9 to 31 euros) and claims servicing costs (from 270 to 580 euros). Therefore, it is quite logical that, even in tightly regulated markets (such as the Italian market), insurers adopt different pricing strategies.[3]

In order to interpret the coefficients of interest in the accident probability equation I sketch a simple demand model in which consumers sort into insurers based on the penalty structures and premiums. I define moral hazard as the change in driving effort in response to variations in the marginal cost of an accident at the chosen insurer, and the market-wide moral hazard as a weighted average of the insurer-specific (average) moral hazard. I also illustrate a two-contract model in which low-risk types prefer the black box contract to the bonus-malus contract, in response to the customized pricing. I argue that this intuitive selection pattern does not necessarily take place if one takes into account that the crash data recorded by the black box reduce claims liquidation time, because this effect can compensate for the surcharge based on the customized black box pricing.

The main result is that a 1 percentage point increase in penalties generates a market-wide reduction of 9–47 basis points of the conditional accident probability, depending on the specification; moreover, I find evidence of strong and persistent *negative* state dependence. I also show that the elasticity of accidents to penalties varies across insurers and that inferences based on company-specific samples would lead one to *overestimate* moral hazard: having access to a representative sample of contracts is key to estimating behavioral responses at the market level.
With regard to the effect of the black box on the frequency of accidents, I find an accident probability reduction of 44–80 basis points, with a declining moral hazard effect in the distance driven. Therefore, customized pricing is effective in curbing moral hazard, but more so for low-distance drivers. To understand whether penalties change actual behavior or only increase ex-post moral hazard, I estimate the effect of bonus-malus penalties on adopters' driving habits. I find that a 1 percentage point increase in penalties translates into a 0.012 standard deviation decrease of the score used to measure driving habits, corroborating the hypothesis that the effect of penalties on accidents comes from more attentive driving. Moreover, conditional on pricing variables, black box adopters experience an accident probability similar to non-adopters. Given the size of the moral hazard effect,

[3]The evidence from the balance sheet data is also important because Chiappori, Jullien, Salanié, and Salanié (2006) have shown that checking for a positive correlation between the frequency of claims and coverage is not necessarily informative on the existence of asymmetric information in the presence of loading costs. My descriptive evidence implies not only that loading costs matter, but also, as conjectured by Fang and Wu (2018), that it matters which company one looks at.

consistently with the trade-off highlighted in the model, this implies that high-risk drivers adopt the black box.

From a methodological viewpoint, in contrast to previous work in which researchers could rely on a relatively small number of pricing variations, I rely on the time-variation of penalties within over 30 driving records charged by about 50 insurers and on repeated observations of the same policyholders to disentangle moral hazard from unobservable risk preferences. In this sense, I combine the approach of exogenous "rich" price variations proposed by Einav, Finkelstein, and Cullen (2010)—homogeneous groups of consumers face different financial penalties—with the panel data-approach based on exogenous time variations of penalties.[4] My strategy also allows me to control for state dependence–typically neglected, that is taken into account by controlling for past accidents and driving records in the accident equation.
To take into account the potential correlation of the black box with unobservable risk preferences in the accident equation, I rely on (i) local markets (provinces) segmentation in terms of judicial efficiency and civil suits caseloads related to car accidents—I construct a measure of claims liquidation efficiency using micro data on claims liquidation time—and on (ii) the black box (estimated) discounts across local markets adoption shifters; moreover, the black box pricing experimentation adopted by insurer A in the period considered generates exogenous (relative) price variation. The results from the effect of province-level shifters on the adoption choices are consistent with the idea that policyholders who live in provinces where reimbursements are slow are more likely to adopt the black box to speed up the liquidation process. I also argue that the combination of the historically staggered process through which the black box was adopted in Italy across local markets—the black box was only initially adopted in some Southern provinces—and the intra-regional heterogeneity—contiguous provinces can differ quite markedly in terms of cost/frequency of accidents—represents valuable exogenous price variations.

This paper is structured as follows. In section 2 I describe the institutional features of the Italian market and the structure of the black box contracts, and in section 3 and 4 I offer a detailed description of my data and related summary statistics, respectively. Section 5 contains the inference based on the grace period. In section 6 I estimate my hedonic price regressions through a control function approach, and I describe the identifying price variations and how I compute penalties from the estimated coefficients on the driving record indicators. In section 7 I describe a stylized theoretical framework I use to conceptualize the behavioral responses I estimate; this section also contains the central results of the paper with evidence on the effect of penalties, black box, and driving habits on

[4] As observed by Fang and Wu (2018): *"In empirical applications, the range of the exogenous price variations is often quite limited. For example, Einav, Finkelstein, and Cullen (2010) have a total of six price levels (or three price levels if one only considers those with somewhat large number of consumers)."*

the frequency of accidents. In this section I also illustrate my identification strategy. Concluding remarks are in section 8; sections 9 and 10 contain tables and figures, respectively. The online appendix contains several details on the data and robustness checks.

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 covering damage to third parties' health and property in accidents where one is *not-at-fault*. The Italian insurance market–overseen by IVASS, the Italian supervising authority– is large: in 2018, about 31 million *rc auto* contracts were underwritten and over 4 million claims were filed. The Italian system follows the common tort (or fault-based) system in which, by definition, accidents are the result of someone's negligence.[5] All individuals involved in an accident who experience physical damages, with the exception of the liable driver, are compensated by the company covering the liable vehicle. It is possible to purchase comprehensive insurance contracts that cover your property damage ("*Kasko*") and physical damage ("*polizza infortuni*") for accidents when you are at-fault; in practice, however, because of the high prices, the vast majority of contracts only feature the compulsory coverage.

Accidents are characterized by a percentage of fault $x \in [0, 100]$. Someone holds "major" responsibility (*"responsabilità principale"*) if $x \geq 51$: there exists "equal responsibility" (*"responsabilità paritaria"*) and "minor responsibility" (*"responsabilità minoritaria"*) if $x = 50$ and $x < 50$, respectively, in which case the policyholder is not liable and the malus does not apply. Indemnities are proportional to x.[6] In Italy, as in many other countries, a uniform experience rating system relates the history of accidents to a class of risk, the so-called bonus-malus (BM) class. There are 18 classes, and BM class 1 is the best; youngsters without a driving history are assigned to BM class 14. 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. In the case of an accident with major responsibility or if the sum of accidents with minor fault during the previous five years exceeds 51, the malus is applied and the BM class increases by two. If no accident occurs, the BM class decreases by one.[7] Table 2 reports the evolution of the BM class as a function of the accidents at-fault.

Almost all contracts last one year, consumers decide whether to renew the contract or

[5] A major difference between at-fault and no-fault systems is that in the latter, insurers cover the damage regardless of who is at-fault. At-fault systems are based on a principle of fairness, while not-at-fault systems minimize litigation costs.

[6] If a driver is involved in an accident with damage D and holds percentage of fault x, the indemnity is $D(1-x)$.

[7] About 80% of policyholders are in class 1; therefore, as in many other bonus-malus systems the BM class is "saturated" (see Lemarie (1995)).

change companies at the end of the year, and contracts are exclusive.

Observation period 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 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.

Glitch in the system 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 is such that accidents in the grace period disappear from the record if the insurer change companies, generating a shift in the incentives during the contractual year I exploit to check if drivers game the system.[8]

Contractual clauses.— There are three types of contracts: bonus-malus, deductible, and mixed bonus-malus/deductible. The vast majority of contracts are bonus-malus (96%) or mixed bonus-malus/deductible (3.7%). Both for historical reasons and because of a peculiar law only a negligible fraction of contracts feature a deductible. The law establishes a mandatory minimum of liability coverage (*"massimali"*): if the damage to third parties exceeds this limit the policyholder is responsible for any amount exceeding this limit. The liability limits are 1 million and 6 million euros for property and health damage to third parties, respectively.[9] Contracts feature a number of clauses that link the size of the indemnity and/or current/future premium to the occurrence of specified conditions. The data provide information on the most common clauses, including the liability limits (see the online appendix), and two omitted clauses indicators: insurers are asked to report whether the contract features clauses other than the ones explicitly reported that increase or decrease the premium. The increasing/decreasing clauses indicators act as *sufficient statistics* for the presence of missing clauses.

[8]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.
[9]In June 2017, the minimum liability coverage increased to 1,220,000 and 6,070,000 euros.

Premium.— RC auto contracts report various components of the price charged for coverage: the price for coverage (premium), taxes (the tax rate varies across provinces) and contribution to national health system (NHS).[10] The data contain information on each of these components as well as on the fees provided to agents, if any, at the contract level. The premium net of taxes, contribution to NHS, and fees–the "net premium"–is the sum of the price charged to cover risk–the so-called pure premium–as well as loading costs, fees, underwriting costs, and profit margin. The average premium reported on contracts underwritten in 2018 (=415 euros) is divided as follows: 79.6% is the net premium, 12.1% goes to taxes and 8.4% to the health system.

2.1. **Black box contracts.** Black box (BB) contracts are based on the information provided by a telematic device installed on the vehicle–the black box–about driving habits and the circumstances of accidents. The data recorded include kilometers driven, frequency and harshness of braking, speed, distance driven on the highway versus other types of roads, and distance driven during the day/night hours. This information is typically aggregated to form a "score" companies use to compute the premium charged the following year. The distinctive feature of most BB contracts is the dynamic link between the driving habits during year t and the premium at year $t+1$: the insurer commits to a price based on the previous year's observations.[11] I provide some historical background on the evolution of insurance telematics in section 7.4.

Black box contracts are traditionally divided into two types: Pay-As-You-Drive (PAYD) and Pay-How-You-Drive (PHYD). The typical PAYD contract guarantees a "flat" percentage discount on the base premium of the first-year adoption year. The (percentage) discount on the base premium for the subsequent years is computed using the aggregate distance driven, on the basis of a price per KM or of a pre-specified distance band discount. The PHYD contracts are structured analogously but use data about the policyholder's driving habits in year $t-1$ to compute the premium of year t. In practice, many BB contracts are a hybrid between PAYD and PHYD. Consumption contracts represent an extreme type of PAYD contract: a given amount of KM is covered by the premium charged at the beginning of the year, and if policyholders drive more than that, they are charged on a monthly/quarterly basis. Finally, the so-called "purely telematic" contracts—the black box acts as anti-theft device and calls for assistance in the case of accidents—guarantee a flat discount on the base premium, with no utilization of the telematic data.

[10]The discretionary tax rate is capped at 16% and the average tax rate in 2018 is 15.7%; 97 of 107 provinces apply the highest tax rate, and in only three provinces it is set at the minimum of 9%.

[11]In the US most of the monitoring programs are based on an observation period of six months to one year, after which a permanent discount is given to safe drivers. To the best of my knowledge in the US State Auto is starting to use crash data, whereas other companies such as Liberty Mutual and Allstate are trying to introduce crash management.

Crash data.— The black box also records data related to accidents–the so-called crash data–such as the intensity of the crash (measured in GB), the area of the vehicle impacted by the crash, and the location where the accident occurred. Once an accident occurs and a claim is filed, the non-liable driver is matched with a claims adjuster whose role is to determine the nature and severity of the damage to the policyholder's car. His assessment relies on the police report, the other driver's testimony, any witness accounts of the incident, a medical examiner's report, and the damage done to the insured car. Because the circumstances of a claim are often disputable, insurers often engage in costly nitpicking (see Bourgeon and Picard (2014)). Nitpicking involves time-consuming bargaining that affects the liquidation time and, ultimately, the size of the indemnities. This is where the crash data kick in: they provide real-time information about the circumstances of the accident, allowing drivers to obtain a fair indemnity in a relatively short time.[12]

3. Data

The main source of information of this study is represented by a micro data set known as IPER (*"Indagine sui Prezzi Effettivi RC Auto"*) , collected by IVASS. IPER consists of two parts: a "static" part and a panel. The static component consists of a sequence of cross-sections with information on two million contracts underwritten at each quarter, starting from Q4:2013. Contracts are not followed over time. Each cross-section represents about one-third of auto insurance contracts underwritten each quarter, and contracts are sampled through a proportional sampling scheme. The panel component is a representative matched insurer-insuree panel containing the "insurance histories" of a core representative sample of 990,010 policyholders identified by their social security number, who subscribe one or more auto insurance contracts in 2013.[13] Section B of the appendix contains details on the sampling procedure. The sample employed in this paper contains information on 4,782,309 contracts underwritten in the period 2013-Q3:2017 and related claims, generated by the individuals of the core sample. The two components have different purposes. Given its sample size, the static part is useful for computing aggregate statistics at the nation/province level that reflect the actual composition of the market.[14] For example, the static part is ideal for running regressions at the province/year/quarter level. The panel component is useful for ascertaining the causal effect of a pricing variable at the contract level on prices by the traditional fixed-effects estimators. From now on, I

[12]Recently, some insurance companies began providing real-time indemnification: based on photos of the car after the crash and information such as the brand and value of the vehicle, the size of the damage is determined without any other intervention. from a loss adjuster. As a result, the non-liable driver is indemnified within one day from the occurrence of an accident. The use of crash data for these purposes is also likely to increase in markets characterized by lower adoption rates relative to the Italian market. In the US, State Auto uses crash data; Liberty Mutual and Allstate are developing projects to use the crash data.

[13]Fleet, taxis, trucks, and vehicles insured for non-private usage are not sampled.

[14]The static component is used by IVASS to compute the average prices across provinces and to monitor the price trends.

focus on the panel part, and I report a variety of weighted–using the sampling weights–and unweighted statistics.

New features.— In addition to the representativeness of the sample, IPER is characterized by several novel features with respect to the data used insofar. First, policyholders are followed through changes of companies after the contract(s) expire; if someone in the core sample underwrites a contract to cover a newly purchased vehicle after 2013, the evolution of such a contract is traced out. Therefore, the unit of observation is the SSN, and each record corresponds to a contract, uniquely identified by a pair plate number-SSN. The structure of the data is therefore analogous to the well-known matched employer-employee panel dataset obtained from administrative data on labor force participation. In order to appreciate the richness of the dynamics in the data, figures 8 and 9 show two prototypical insurance histories.

INSERT FIGURES 8 and 9

The notes under the figures explain in detail some of the many possible situations in the data: switches from one company to another, periods in which the vehicle is not covered, or the same individual underwriting contracts with different companies to cover different vehicles. Traditionally, following policyholders through switches of companies is not considered an important feature of the data because auto insurance markets are typically tightly regulated. While the Italian market is no exception, I empirically document that company-specific samples are subject to dynamic selection; therefore, inference based on "fixed effect" approaches is subject to *non-random* attrition bias. Second, the data are *representative* because they cover 98 percent of the market and provide information on contracts underwritten by nearly 50 companies.

These aspects are in contrast with the data used insofar, which contain information on a single insurer and don't follow policyholders after they change companies. The limitations in the previous data are such that researchers cannot examine market-wide phenomena–their analysis is confined to specific segments of the market, see Salanie (2017)–unless the researcher can credibly argue that the pricing schemes are homogeneous across insurers due to the tightness of regulations, and drivers do not sort into companies.[15] These assumptions seem quite extreme in "modern" auto insurance markets, characterized by an

[15]To put these features into perspective, the seminal paper by Chiappori and Salaniè (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.

increasing adoption of insurance telematics and by a moderate degree of regulations.[16] I document how, despite the fact that IVASS has to approve of and supervises pricing rules enforced by insurers, Italian companies charge different prices to observationally similar consumers for analogous plans. One way to rationalize these differences has to do with the heterogeneity in the cost structures across insurers, which I also document. In this paper I leverage on the supply side heterogeneity for identification purposes.

The matched insurer-insuree data and the availability of *transaction* insurance prices and loading costs is such that the elasticities of insurance rates to pricing characteristics and contractual clauses can be estimated, whereas in the previous literature researchers employed the theoretical pricing rule–the tariff–adopted by the insurer at hand. I see this as an advantage rather than a caveat because in markets where sales agents have a relatively large discretion to apply discounts, looking at the theoretical relationship between tariffs and risk factors–age, vehicle characteristics, and so forth–might generate misleading results. I document substantial departures of transaction prices from tariffs: (a) only half of the variance of (transaction) prices can be explained by my rich set of pricing variables, and (b) about 70 percent can be explained within insurers who do not rely on sales agents for underwriting.

Missing pricing variables.— Because IPER was designed as a representative matched insurer-insuree panel dataset, gathering information on the full set of company-specific variables used for pricing was beyond the scope of the initial design. This design choice is the result of repeated interactions with sales agents and actuarialists from major insurance companies. Not only do pricing variables differ among insurers, but they also change frequently within insurers, in some case at a quarterly frequency, in response to variations in managerial practices and to aggregate market trends. Having access to the full set of pricing variables at each point in time appeared to be a daunting task, and we deliberately chose not to. Which pricing variables are missing, then? Provided that the indicators on the presence of clauses increasing/decreasing the premium acts as a sufficient statistic for unobservable clauses, I asked a few major companies (including company A) for the full set of variables used for pricing. Most of the missing variables regard vehicle characteristics–how many years a car has been possessed, whether the car is used or new, years during which the car has not been used, the presence of safety devices and socio-economic variables, such as type of occupation and zip code. Many of these variables are constant over time or evolve deterministically, so that ex-ante I expect standard-fixed

[16]The European commission establishes that insurers are free to set different prices conditional on the same set of observables, provided that they are "consistent" with the expected claim payout as computed from the historical data used by the company to set premiums.

estimates to have a moderate amount of bias.[17]

In sum, while my data are immune to the self-selection and non-random attrition–the limitation plaguing the data used in the previous work–an omitted (pricing) variable problem has to be addressed. Essentially, I need to estimate hedonic price regressions with missing attributes, a well-known problem in the literature. In contrast, if my data looked like those used in previous work, I would have to deal with a sample selection problem, which would require me to make substantive assumptions on the outside option.[18]

Some figures.— To give an idea about the sample representativeness, table 3 shows the number of companies in IPER–ranging from 42 to 49–and policyholders and contracts for each contractual year. The sample is large–4,782,311 records–both in absolute terms and relative to previously used datasets.[19]

INSERT TABLE 3

Two phenomena emerge. First, there is some attrition because the total number of contracts decreases over time (the drop from 975,937 to 702,206 contracts between 2016 and 2017 is because contracts underwritten in the last quarter of 2017 are not included in the sample). This decrease is due both to "natural" attrition–some policyholders don't renew the rc auto contract because of aging–and to the economic cycle.[20] Second, the number of contracts in each contract year is higher than the total number of subscribers, which is because a fraction of the core sample covers more than one vehicle.

INSERT TABLE 4

As can be inferred from table 4, between 10% and 13% have multiple contracts, the majority of whom subscribe two contracts. Interestingly, as can be inferred from table 5, more than 30% of multiple subscribers choose different companies.

INSERT TABLE 5

[17]For company A, the missing variables are fixed over time with the exception of socio-economic characteristics of the area of residence ("cella censuaria"), where the area is defined as a single municipality or a group of homogeneous municipalities with similar characteristics. Because internal migration in Italy is a limited phenomenon and driven by factors unrelated to auto insurance, it is reasonable to assume that unobservable factors affecting the prices of contracts underwritten by insurer A do not vary over time. In our sample, about 2% and 4.8% of policyholders changed province and municipality of residence at least once, respectively.

[18]This is the approach adopted by Israel (2004), who takes into account dynamic selection by assuming that, once policyholders change companies, they choose the same plan and expect to be charged a premium consistent with the prices of the plans at the current insurer.

[19]To give an idea, the seminal paper by Chiappori and Salaniè (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.

[20]In fact, during recessive periods such as the one covered by the panel, consumers choose not to insure vehicles and to adopt alternative means of transportations, i.e. there exists a *substitution effect*.

The availability of these new variations is because the individual, not the contract is the unit of observation. In this sense, the logic underlying IPER is more similar in spirit to the well-known longitudinal datasets on labor force participation, such as the PSID and the NLSY79/97, than to the previously used auto insurance datasets.

Claims.— No direct information on the claims that occurred each contractual year is available in IPER (other than the information on the driving record). To complement the data, IPER has been merged with another database–the Banca Data Sinistri (BDS)– containing the universe of claims. From the BDS, I have retrieved information on the date(s) of the accident(s) and the liquidation date(s) for the first three claims (in chronological order) at-fault and not-at-fault, if any, within each contractual year. Unfortunately, the claims not-at-fault are not available for 2013-2014. In addition, information on the indemnity received in accidents not-at-fault and/or corresponded to third parties in accidents at-fault has been obtained.
Table 6 shows the distribution of the number of claims in each contractual year.

INSERT TABLE 6

The probability of being responsible for one or more claims is about 5%, and it is extremely unlikely for more than two claims at-fault to occur in a given year.

3.1. **Black box data.** My data contain a variable on the presence of a black box clause taking the following values:

- 0: No telematic device is installed on the vehicle
- 1: A telematic device is installed on the vehicle, implying a reduction on the premium independent on the data recorded ("flat" discount)
- 2: A telematic device is installed on the vehicle, implying a reduction on the premium that depends on the driving styles/crash data and on the distance driven during the previous contractual year ("variable" discount)
- 3: A telematic device is installed on the vehicle, the premium paid upfront entails a maximum amount of yearly KM, and an additional balance is due during the year if the distance driven is higher than the maximum
- 4: A telematic device is installed on the vehicle, implying no reduction on the premium

Some data quality checks revealed that for several companies, some of the 1 and 2 codes were incorrectly imputed leading to measurement error.[21] Therefore, for companies other than insurer A, I collapsed the values 1-4 into 1, constructing a binary indicator for the presence of the black box. Given the structure of insurer A's black box contract, the black

[21]Due to mergers–the black box contracts of merged company were gradually converted into the type of black box contracts offered by the acquiring company–interpreting the values 1-4 in terms of the above description was problematic for the vast majority of companies.

box variable can take values of 0,1, and 2.

Driving habits.— The data were complemented with information on the driving habits of black box adopters covered by insurer A. Insurer A's black box contract is an hybrid PAYD/PHYD, meaning that the distance driven is weighted differently depending on the amount driven on highways versus urban roads, weekdays versus weekends, and day versus night, allowing the computation of an aggregate "score". Discounts on the base premium of year $t+1$ are based on the score recorded during year t by applying a band-specific discount on the base premium, while a "flat" discount is applied on the first adoption year premium. A lower band implies a lower distance driven and a higher discount. I will describe insurer A's black box contract in detail later on.

The data provide the realized score during a contractual year, the distance band the driver was assigned to, and the total number of bands adopted each year.[22] Given the structure of the contract, in theory, only a few sequences of the black box codes are conceivable. By this I mean that (a) a value of 1–flat discount–should not be observed for two consecutive years and (b) a value of 2 cannot be followed by a 1. In practice, sequence (a) can be observed within black box contracts underwritten by merged companies that did not base the premium on distance driven and within contracts in which the lack of sufficient data recorded during year $t-1$ induced the insurer/agent to provide another year of the flat discount on the premium of year t. Sequence (b) can be observed either because of a lack of sufficient telematic data or if, for some reason, the contract has been underwritten under new terms. Both (a) and (b) are not prevalent, and I keep these cases in the estimating sample.

BB pricing experimentation.— The first source of exogenous price variation comes from pricing *experimentation*. The period covered by the data was characterized by massive investments in know-how–machine learning algorithms–and technological infrastructure that allowed the largest companies (including insurer A) to more accurately process the large amount of telematic data.[23] As more "telematic" evidence became available, the potential to customize prices and extract rent from consumers became evident.
Insurer A has been a leader in insurance telematics in the Italian market and the black

[22]Information on the score/bands is available for 201,486 records of the 218,698 for whom, in principle, we would have expected to have this information (black box variable equals 2). In 12,177 cases, the recording time was not sufficient to associate the contract with a distance band; in 5,035 cases, the policyholder was covered by a black box contract underwritten by companies that were subsequently merged into insurer A and, again, no information on driving habits was recorded. When these situations occurred, insurer A agreed to give a small discount until the contract was gradually transformed into A's black box contract. For the 17,212 falling into one of these two situations, the score/distance band was set, conservatively, to a missing.
[23]This narrative was confirmed by insurer A when we asked about the reasons underlying the previously documented changes in the pricing strategy.

box contract in terms of a flat discount on the base premium the first year after adopting the black box and a "variable" discount on the premium in subsequent adoption years based on the distance driven the previous year.

Insurer A has been a leader in insurance telematics in the Italian market and the black box contract in terms of a flat discount on the base premium upon adopting the black box the first year and a "variable" discount on premium of subsequent adoption years based on the distance driven during the previous year.[24] The evolution of the flat discounts over time is as follows:

(1) from November 2012: 10%
(2) from March 2013: 20%
(3) from January 2015: 20%(15%) for new(old) customers
(4) from March 2016: 25% for new clients, 20% for old customers living in 5 southern regions and 15% for old customers in other regions
(5) from October 2016: 25% for new clients, 15% for old customers living in 5 southern regions and 10% for old customers in other regions

The rule mapping the score into a percentage discount evolved as follows:

(1) from November 2012: 5 distance bands with discounts from 3% to 30%
(2) from May 2015: 7 distance bands with discounts from 5% to 30%
(3) from March 2016: 10 distance bands with discounts from 5% to 30%

The increase over time of the number of distance bands reflects the greater ability of the insurer to price-discriminate consumers through the telematic data. Table 32 shows the proportion of contracts covered by the 5, 7, and 10 band regimes in the period under consideration. Only in 2015 and 2017 do two regimes (5-7 and 7-10) co-exist; only about 5,000 contracts in 2017 are covered by the 10-band regime.

3.2. **Balance sheet data.** The last source of information is represented by the balance sheet data (BSD) containing information on the insurers' loading costs, claims payout, and accident rate at the insurer-(calendar) year level.[25] The BSD pools together costs related to contracts covering motorcycles, boats, and cars, with cars accounting for 84% of the covered vehicles. By merging the BSD with IPER+BDS ("Banca dati sinistri") I obtain information at the insurer-year level on the loading costs for about 95% of the contracts in IPER.
The types of loading costs obtained from the BSD are as follows:

[24]The black box is installed for free and rented for about 66 euros a year, which is included in the premium; the black box entails the policyholder to additional services such as assistance in the case of an accident, pickup service if the car stops, and vehicle location in the case of theft. Moreover, through a smartphone policyholders can check the monthly distance driven and how it is divided among different types of roads.
[25]Recall that BDS stands for"Banca dati sinistri", whereas BDS refers to balance sheet data. Due to mergers, some companies did not transmit their balance sheet to IVASS. As a result, about 95% of the contracts cannot be associated with the BSD.

(1) liquidation and "direct" claim cost, henceforth labeled "*liquidation* costs" [26]
(2) acquisition costs: administrative costs to underwrite a new contract.
(3) sales agents' fees.
(4) administrative costs: loading costs to manage contracts.

To avoid confusion, I refer to (2)+(4) as to "*administrative* costs" because fees provided to sales agents are not considered administrative costs in the traditional sense. I generically refer to administrative and liquidation costs as "loading costs".

The BSD also provides information on the number of claims, their numbers, and the total number of contracts underwritten. Given the representativeness of the panel I can compute average–using sampling weights–loading costs per contract. The average claims payout can be computed in two ways: using the information on the BDS at the contract level or using the average payout at the insurer-year level in the balance sheet data.[27] Despite the fact that the balance sheet also covers motorcycles and boats, the average claims payout at the contract level using the BDS is not far from what I obtain using the BSD.

4. Descriptive Statistics

Premium and price dispersion.— Table 8 shows descriptive statistics of the distribution of the premium and its components. The average unweighted(weighted) premium equals 463(451) euros with a standard deviation of 213 euros. The net (weighted) premium equals 326 euros (=premium−fees(=32.35)−taxes(=55.46)−contr.to NHS(=37.58)). The density of the premium is shown in figure 11: the distribution exhibits a fat right tail and well approximated by a log-normal distribution. The statistics on price dispersion are also of extreme interest. The interquartile range and the coefficient of variation equal 230 euros and 0.46, respectively; the Gini index–a popular measure of price dispersion–equals 0.234. As explained by Borenstein and Rose (1994), this means that the average absolute difference in the premium between two random policyholders is about 43 percent of the average premium (twice the Gini coefficient). To put this number into perspective, the Gini coefficient obtained from the sample of prices of airline tickets used by Borenstein and Rose equals 0.1. The interested reader can consult table 10 to learn about the effect of different set of controls on the Gini index, following the method of Almas and Mogstad (2012).

A more traditional way to measure price dispersion is to look at the R^2 of an OLS hedonic

[26]These costs include the compensation to experts for evaluating a claim and the administrative cost of liquidating a claim.

[27]Computing payouts is complicated by the relatively long time necessary to finalize claims. One possibility offered by the BSD is to look retrospectively from a given year t to the cumulated sum of payout for the claims occurred in years $\tau < t$. According to this "roll-over" approach, the average payout of claims increases in the difference between t and τ. Alternatively, one can look at the payout of year t for claims that happened the same year. This is the approach I follow. Under the assumption that the approximation error is constant over time, the average payout is comparable across the years.

price regressions controlling for all the pricing variables available in IPER, loading costs, province and insurer fixed effects, I describe later the pricing variables and the loading cost and perform this exercise. The R^2 of my baseline specification equals 0.536. Therefore, the rich set of controls available only explain half of the variability of transaction prices. This evidence demonstrates that the price of Italian auto insurance contracts exhibits considerable *price dispersion*, consistent with the equilibrium characterized by Lester, Shourideh, Venkateswaran, and Zetlin-Jones (2019).

Table 7 presents weighted and unweighted means of the pricing variables available in IPER.[28] The average Italian policyholder is 52 years old, most contracts are underwritten by policyholders who are 45-60 years old (36%) and over 60 (31%) and by male drivers (60%). About 80% of policyholders are assigned to BM class 1, 10% to classes 2-3 and 4-10; 82% of contracts feature zero accidents at-fault on the AR.

The clauses with the highest penetration rate are the black box (13%), the expert/free driving clause (43% and 48%), and the protected bonus clause (22%). About 38% of the contracts feature a higher coverage than the minimum requirement of 6 million. As will be shown later, given the distribution of the indemnity corresponded to third parties, the actual probability of provoking a damage larger than 6 million is (almost) zero. These statistics are consistent with the idea that a substantial fraction of the market is pessimistic, meaning that the perceived loss distribution dominates the actual one. It is also interesting to observe that 43% of the contracts feature more than one installment: because not paying the entire amount upfront (in one installment) implies a surcharge, this statistic suggests that a large fraction of the market is subject to liquidity constraints. On average, contractual relationships last 3.47 years; the switching rate is relatively high in absolute terms (12%) and lower than what is found by Honka (2014), who estimates an average switching rate of 40% in the US auto insurance industry. The average insured car is 8.6 years old with a power of 66 KW.

Heterogeneity among insurers's pools.— In the interest of space, I comment on the observable differences across the pool of consumers covered by the various insurers in section A.1 of the online appendix. Because commenting on the descriptive statistics associated with nearly 50 companies would be impractical, I group insurers according to their market shares as follows: the top-5 players–labeled A-E, with no particular ordering, to preserve confidentiality–and the medium and small companies.[29] This grouping will also be used in my econometric analysis. Two main facts emerge: (a) there exists substantial variation in the frequency of accidents and size of the claims, and (b) the differential

[28]The small difference between weighted and unweighted means are indicative of the mild adjustments of the sampling procedure.
[29]Medium companies are the top 6-12 players and the small companies are the remaining companies.

adoption rates of clauses suggest the presence of self-selection into companies based on risk preferences.

Balance Sheet Data.— Panel A of table 9 presents means at the contract level of the net premium, of the different components of the loading costs, claims payouts, frequency of accidents, fees, and claims liquidation speed obtained by merging the balance sheets data with IPER. The net premium in the table is obtained using the balance sheet data and not the micro data on prices from IPER. Again, because the only source of variation is across insurers and years, these statistics are more influenced by the cost structure of companies with large market shares.

The average net premium(= premium − taxes − contr. to NHS) equals 377 euros (column (1)) that is not far from what I obtain using the micro data in IPER (from table 8, the net premium is about 368 euros).[30] Average fees on contracts from the BSD equal 40.8 euros, while the underwriting contract's costs (col.(8)) and pure administrative cost (col. (9)) amount to 18 euros and 20 euros, respectively. Therefore, the total average administrative cost per contract is about 38 euros, accounting for about 11% of the premium net of fees (=336 euros=(1)-(7)), roughly what I obtain using IPER to measure the premium net of fees (11.6%). The average liquidation cost–the expenses incurred to file the claims, evaluate the damage, and so on–is relatively high (330 euros) when compared to the size of the indemnity (2,208 euros in column (5)), while the "direct" liquidation costs are negligible. The average profit per contract (column (2))(=premium *net* of taxes−frequency of claims× (claims payout + liquidation cost)−administrative cost) equals 156 euros.

In panel B of table 9, I compare insurers' cost structures. The cost to liquidate claims (column (3)) among the top 5 players ranges from 270 euros (company A) to 580 euros (company C); the administrative cost to manage contracts (columns (9)) ranges from 9 euros (insurer D) to 31 euros (insurer E). The administrative costs to underwrite contracts vary from 6 euros (insurer C) to 24 (insurer B) euros. The underwriting costs depend on the distribution channel: companies underwriting contracts through phone/internet have a lower costs than companies using sales agents. Section A.2 in the online appendix, compares traditional and direct insurers.

The balance sheet data confirm substantial consumer heterogeneity across companies: the frequency of claims ranges between 5% and 6% (col. (6) of table 9), and the smallest and largest average indemnity equal 1,959 euros (insurer D) and 2,447 euros (insurer C), respectively (column (5)). The heterogeneity on the supply side coupled with the sorting pattern into companies generate different per-contract profits across insurers (column (2)

[30]Recall that the variables reported on the balance sheet data refer to contracts also covering motorcycles and trucks.

of table 9), ranging from 134 euros (small companies) to 178 euros (company B).

These statistics are new in the literature and demonstrate that insurers (a) optimize on different cost structures and (b) differ in terms of the riskiness of the covered pool.

Competition.— In the period from 2013-Q3:2017, 52 insurers underwrote at least one contract in my panel, and the number of insurers active in each contractual year varies due to mergers and acquisitions. As illustrated by figure 10, the Herfindahl-Hirschman Index (HHI)–the mostly widely used measure of market competitiveness–decreased about 200 points during the period covered by the data, from 1,250 to 1,050.[31] Such a reduction is considered large; according to the guidelines of the Department of Justice, a merger that increases HHI more than 200 points is likely to increase market power. At the same time, according to the Horizontal Merger Guidelines issued in 1997, a market with an HHI of less than 1,500 is considered to be a competitive marketplace. Therefore, the Italian auto insurance market does not stand out as problematic along this dimension.

Variations across local markets.— The Italian auto insurance market is characterized by a tremendous degree of variability across local markets, defined by provinces. Figure 12 shows the histogram of premiums, frequency of accidents?defined as proportion of contracts with one or more claims at-fault within a year and size of claims at-fault at the province level. INSERT FIGURE 12 The insurance prices across provinces range from 313 to 730 euros, the frequency of accidents from 3.47 to 7.76%, and the size of claims–the indemnity to third parties in accidents at-fault–from 1,483 to 4,318 euros. A more immediate visualization of the variability of the premium is shown in figure 13. The map shows that premiums are higher in the Southern provinces and that there is considerable variability across provinces of the same region. The differences in the premium are related to differences in the frequency and size of claims, as shown in the scatter plots in charts 14 and 15.

INSERT FIGURES 14 AND 15

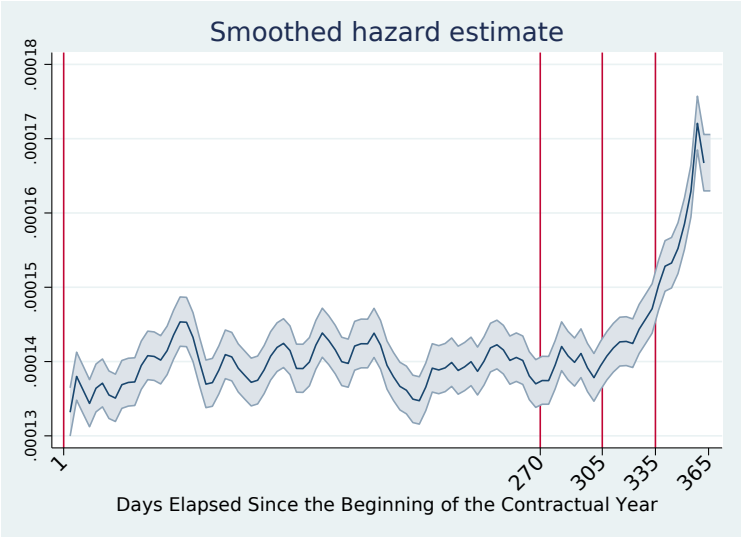
5. Grace Period

I start my analysis of moral hazard by providing visual evidence of behavioral responses to the jump in incentives before and after the grace period. Figure 1–showing the pattern of the hazard rate during the contractual year–provides clear evidence that incentives matter: the hazard rate increases 1.3-fold at the end of the year, a growth of about 30 percentage points. At first blush this phenomenon is striking, as one may wonder if the grace period financial incentives are salient. The abrupt shift of the hazard rate in the last month is unlikely to be generated by discounting–incentives within the contractual

[31]HHI is given by the sum of squared market shares and ranges between 0 and 10,000, the higher the index, the higher the degree of concentration.

year vary because the premium is paid on the first day of each contractual year–because such a mechanism should generate a decrease of the hazard rate as penalties in the grace period are inflicted sooner as the year approaches its end. Under the assumption that external time-effects, such as aggregate trends of the accident rate, are continuous along the contractual year, discontinuities of the hazard rate corresponding to the grace period can be interpreted as evidence of moral hazard. Because drivers can escape the penalty

FIGURE 1. Hazard Rate of Accidents During the Contractual Year

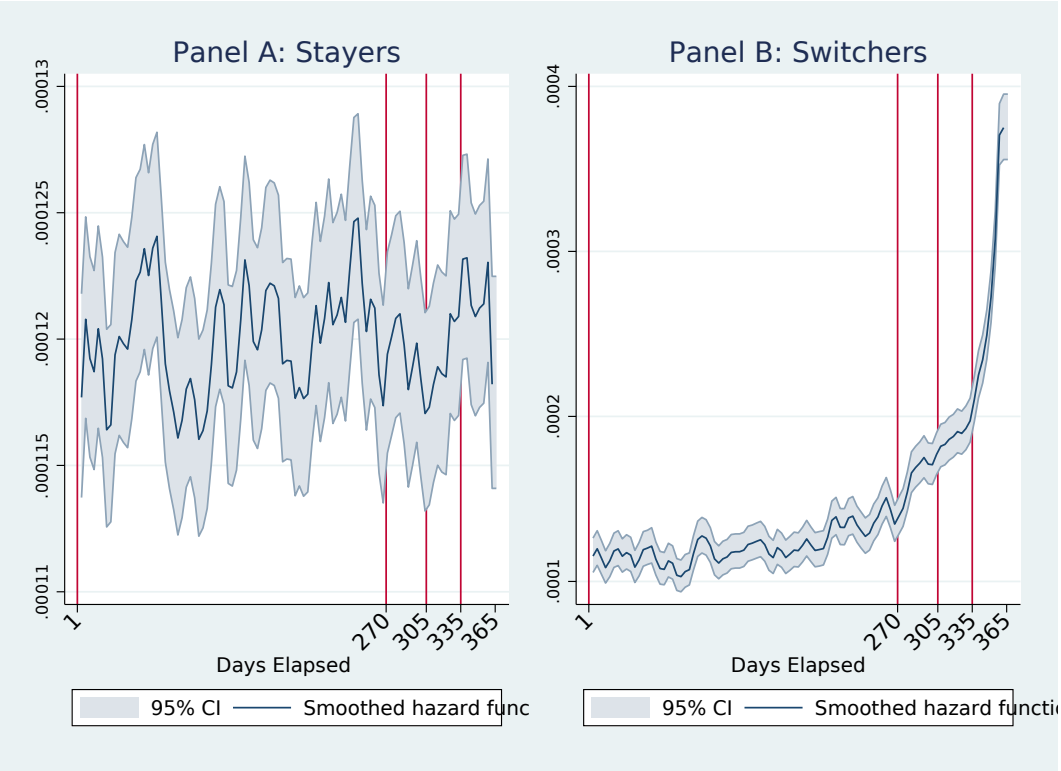


Note. The hazard rate is bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rate.
Sample: contracts covering years 2013-Q3:2017.

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. Panels A and B of figure 26 depict the hazard rate for stayers and for switchers, respectively. Interestingly, the grace period effect is far more pronounced among switchers–a 3.5-fold increase–while roughly constant within policyholders who do not change companies.

Based on the idea that in the absence of moral hazard, the hazard rate should be constant along the contractual year, one may be tempted to estimate the discontinuity of the hazard rate on the sample of switchers, where the grace period effect is more pronounced. This inferential procedure is unlikely to correctly identify the causal effect of moral hazard for two reasons. First, because the date on which the driver decided to change companies is not known, one concern is that the grace period effect within switchers is driven by self-insurance (see Elrich and Becker (1972)). In other words, perhaps 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 in the opposite direction: knowing that they can change companies, drivers are more careless. Second, as I document in section A.4 of

FIGURE 2. Hazard Rate within Switchers and Stayers



Note. This figure depicts the hazard rates of one ore more accidents, bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rates. Sample: contracts covering years 2013-Q3:2017.

the online appendix, policyholders with a poor driving record are more likely to change companies; it is then reasonable to believe that other unobservable traits–risk and risk aversion–determine this choice. In other words, the sample of switchers is a selected one. Reverse causality seems less of a concern because 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 then stay flat, as the accident probability only reflects the average risk in the market.[32]

Inspired by the instrumental variable strategy developed by Dafny, Duggan, and Ramanarayan (2012)–mergers/acquisitions create exogenous variation of concentration across markets–I exploit a mandatory divestiture to address selection and reverse causality. This event is such that that policyholders covered by the company acquired are somehow "forced" to switch. See section A.3 of the online appendix for the (conditional) event

[32]On the contrary, 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 panel B of figure 26.

history analysis through which I measure the jump after the grace period within the "exogenous" switchers. I find that a grace period effect exists in this sample: the growth rates of the third-to-last, second-to-last, and last months are 44 percentage points, 40 percentage points, and 26 percentage points, respectively, while the growth rate is negative in the first nine months (column (1) of panel B in table 28).

This analysis provides a useful start to demonstrate that moral hazard exists because the grace period design is robust to state dependence, as the grace period generates an "insurance event" (see Israel (2004) and Ceccarini (2007)). Unfortunately, as in the previous literature, this analysis is not necessarily informative of market-wide moral hazard because it focuses on policyholders affected by the divestiture. On the contrary, the grace period provides an opportunity to detect ex-post moral hazard in the entire market and, at the same time, to measure the effect of the black box on claims size and liquidation time.

5.1. **Ex-post moral hazard.** The implication of ex-post moral hazard is that accidents involving small damages are not filed–agents file a claim only if the size of the damage is larger than a given cut-off–because the involved parties engage in "street" agreements. Because the distribution of claims is left-truncated, the grace period shifts to the left the endogenous truncation point in the presence of ex-post moral hazard. A testable implication is that the size of claims drops in the grace period. Notice that a necessary assumption of this identification argument is that driving attentiveness affects the probability, but not the severity, of accidents. Recent evidence from the insurance telematics industry suggests that this is not the case, and insurers are developing systems, such as videos produced by smartphones, that prevent "distracted driving," i.e. driving while doing another activity such as talking on the phone or texting.[33] If this mechanism is at play but accidents and claims coincide (no ex-post moral hazard), the size of claims should increase in the grace period. If both ex-ante and ex-post are true, the size of claims unambiguously drops in the grace period.

I can test these predictions using claims from all insurers. Consider the following conditional mean model:

$$E[s_{ijkt}|\cdot] = \exp\left(\alpha g_{it} + \beta INJ_{it} + \beta bb_{it} + \gamma bb_{it} \times INJ_{it} + \delta bb_{it} \times g_{it} + \gamma g_{it} \times INJ_{it} + \beta_X \mathbf{X}_{it} + \iota_{jt} + \tau_{kt}\right) \quad (1)$$

where s_{ikt} measures the total indemnity received by the parties not at fault as a consequence of the first accident driver i covered by company j living in province k is liable for during contractual year t.[34] Modeling the conditional mean as an exponential function is appealing, given the skewness of the distribution of the indemnities and the large dispersion, and avoids the well-known bias induced by a log-linear specification (see Santos Silva

[33] ANIA, the Italian association of insurers, provided evidence that answering a phone call while driving increases the likelihood/severity of an accident as much as driving blindfolded for 110 KM at 90 KM per hour. A series of awareness campaigns have been produced on this topic.

[34] 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

and Tenreyro (2006)).

The indicator g_{it} takes value one if the first accident happened during the grace period, and zero otherwise. INJ_{it} is an indicator for the presence of bodily injuries–about 15 percent of claims involve bodily injury–$\mathbf{X}_{it}$ includes policyholder/car characteristics, contractual clauses, administrative and liquidation loading costs, and an indicator for whether the insurer is a direct one. This last set of variables captures the insurer's efficiency in liquidating claims. In particular, I control for my proxy of frauds ($SOARF_SINDEN$), the proportion of claims over which, in a given province and year, an auditing procedure started, and for area's characteristics.[35]

ι_{jt} and τ_{kt} are insurer-time and province-time fixed effects, respectively. I estimate the same regression on the sample of claims *not-at-fault* (NAF) associated with contracts underwritten in 2015-2017.

The results are reported in table 12. I find no effect on the indemnity associated to NAF claims (columns (1)-(2)) and significant and positive effect on the indemnities received by third parties not responsible for accidents that happened in the grace period of the non liable driver. The grace period effect equals 4.2 percentage points and 18.1 percentage points within all AF claims and AF claims filed by switchers, respectively. If anything, these results suggest that ex-post moral hazard is counteracted by damage inflation behavior and/or by the consequences of distracted driving. I also find that black box adopters generally file smaller claims with a reduction equal to 2.9 to 3.2 percentage points (column (1) and (2)). The negative effect of the black box primarily acts through the reduction of the effect of injuries (the interaction term $bb_{it} \times INJ_{it}$ is significant at the 95 percent level within NAF claims). However, because in unreported regression I found no direct effect of the black box on the probability of reporting an injury, it is likely that crash data act as a deterrence against personal damage inflation because severe personal injuries are incompatible with low GB crash events.[36]

Before I comment on the regression results, table 1 reports some statistics of the overall liquidation time within NAF claims; comparing the average indemnification time (almost four months) with the median (44 days), it emerges that considerable dispersion exists

[35] The variables proxying for an area's characteristics are: city and province of residence density of population–ratio between the number of people living in the city/province and the extension measure in squared KM–region dummies (21), macro-region dummies (5), and medium and big city dummies. Moreover ISTAT, the Italian Statistics Institute, assigns municipalities to one of four altimetric zones, capturing the elevation of the area, and to one of three categories capturing the geomorphologic features of the area. I construct dummies for each category and variable. Although most insurers do not price these variables, they are likely to be related to other pricing variables such as the incidence of frauds or the characteristics of the roads that determine premiums.

[36] 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.

TABLE 1. Statistics on the Liquidation Time

	P25	P50	P75	P90	Mean	St. Dev.	N
All Claims	22	44	123	309	118.9	219.49	154,749
No Bodily Injuries	20	38	85	214	90.88	195.25	133,989
With Bodily Injuries	113	216	404	695	304.69	274.37	19,909

NOTES: This table reports statistics on the distribution of the liquidation time, defined as the number of days between the filing and the closing date of claims not at fault occurred in the period 2015-Q3:2017.

in this data (the standard deviation equals 219 days). The average indemnification time more than triples in the presence of bodily injuries, due to the extra administrative time related to the legal and medical procedures. Overall, it takes a long time to obtain a reimbursement. Column (5) reports the results of the same regression specification as (12), but the dependent variable is the liquidation time (in days) within NAF claims. The presence of injuries, consistent with raw data, increase the time needed to liquidate the claim by about 100 percentage points, and, as one would expect, larger indemnities are associated with longer liquidation procedures. The black box has a direct positive effect (significant at the 95 percent level) but reduces liquidation time in the presence of personal injuries by 15.7 percentage points (significant at the 99 percent level), which is about 46 days at the mean, and the overall marginal effect is negative.

Sum-up of results.— There are three main takeaways. First, consumers understand, at least qualitatively, the bonus-malus financial incentives and react rationally. Second, ex-post moral hazard seems of second order. Third, the reduction of claims liquidation time entailed by the black box might generate counterintuitive *adverse selection* into this contract and push the black box in markets in which the liquidation process is inefficient. I will investigate the sign of selection into the black box contract later. I now turn to the effect of driving records and black box adoption on insurance rates.

6. HEDONIC PRICE REGRESSIONS

A central goal of this paper is to estimate hedonic price equations such as the following:

$$\log p_{ijkt} = \alpha^c \mathbf{c}_{jt} + \alpha^b bb_{it} + \alpha_0^b bb0_{it} + \alpha_1^b bb1_{it} + \sum_{j=1}^{J}\sum_{r=1}^{R-1} \alpha_{rj} R_{irt} + \gamma \mathbf{X}_{it} + \iota_{jt} + \zeta_{kt} + \tau_t + \xi_i + \xi_{it} \quad (2)$$

where p_{ijkt} denotes the price of the *rc auto* contract paid by insuree i living in province k to cover year t underwritten by company j; the dummy R_{irt} is an indicator taking value one if the policyholder is assigned to driving category j—defined as a combination of BM class and the number of accidents on record—at the beginning of year t; $bb0_{it}$ and $bb1_{it}$ are indicators for whether the black box is adopted for the first time ($bb0_{it} = 1$) or the premium is conditioned on the previous year's driving habits ($bb1_{it} = 1$) for contracts underwritten by A; and bb_{it} is an adoption dummy for policyholders covered by insurers

other than A.

In this notation, $\mathbf{c}_{jt}$ represents a vector containing the loading and liquidation costs associated with insurer j in year t. The vector of controls $\mathbf{X}_{it}$ contains individual and car characteristics, the number of installment fixed-effects, contractual clauses, the area's characteristics—described in footnote 35—tenure fixed-effects, and $SOARF_SINDEN$; ι_j and ζ_k denote insurer and province fixed effects that are time-varying because policyholders can switch companies and change their province of residence; τ_t signify time fixed-effects, containing the contract's starting month and year and month×year dummies. The previously discussed data limitations are such that the error term can be written as the sum of a time-constant unobserved component ξ_i—the car's brand—and a time-varying one—the car's value or marital status—denoted by ξ_{it}. To the extent that the dummy variables on the presence of clauses increasing/decreasing the premium allows me to control for omitted clauses, ξ_{it} can be thought of as a weighted average of the policyholder's and vehicle's attributes, such as the value of the car or the policyholder's occupation.

I focus on the elasticity of prices to the driving record (α_{rj}'s) and to the black box, the (α^b's). Driving records at time t are reasonably *predetermined* with respect to ξ_{it} because they depend on the previous year's driving record and on the number of accidents during year $t-1$; however, they are unlikely to be *strictly exogenous* because past realizations of the shocks ξ_{it}, by changing relative prices at each driving record, change the driving effort, and generate feedback effects of past shocks on R_{irt}. In contrast, the black box is fully endogenous to the innovations to the pricing variables because contractual clauses are likely to be decided conditional on ξ_{it}. These observations suggest that even though I can rely on panel data, the strict exogeneity assumption underlying the consistency of the traditional fixed effect estimators is likely to be violated.

Having spelled out the baseline specification, I write the hedonic price regression in a compact form as follows:

$$\log p_{it} = \mathcal{A}BB_{it} + \sum_{j=1}^{J}\sum_{r=1}^{R-1} \alpha_{rj} R_{irt} + \gamma_z \mathbf{Z}_{it} + \xi_i + \xi_{it} \tag{3}$$

where to ease notation, $\mathbf{Z}_{it} \equiv (\mathbf{X}_{it}, \iota_{jt}, \zeta_{kt}, \tau_t)$, $\mathcal{A} = (\alpha^b, \alpha_0^b, \alpha_1^b)$ and $BB_{it} = (bb_{it}, bb0_{it}, bb1_{it})$. To address the correlation between the endogenous variables and the time-varying error terms I leverage on the control function approach developed by Bajari, Fruehwirth, Kim, and Timmins (2012) (BFKT, henceforth). This approach rests on several assumptions. The first is that the unobservable pricing variables follow an AR(1):

$$\xi_{it} = \rho \xi_{i,t-1} + \eta_{it} \tag{4}$$

The second assumption is that, conditional on the information set at time $t-1$ ($\mathbf{I}_{i,t-1}$), the innovation to the unobservable pricing variables has zero mean

$$E[\eta_{it}|\mathbf{I}_{i,t-1}] = 0 \tag{5}$$

Assumption 5 implies that past prices are informative of the current unobserved pricing variable ξ_{it}; in other words, conditional on $\mathbf{I}_{i,t-1}$ policyholders forecast ξ_t to be $\rho\xi_{t-1}$. Substituting 5 into the main equation 3 I obtain:

$$\log p_{it} = \mathcal{A}BB_{it} + \sum_{j=1}^{J}\sum_{r=1}^{R-1}\alpha_{rj}R_{irt} + \gamma_z\mathbf{Z}_{it} - \rho\log p_{i,t-1} - \tag{6}$$
$$-\rho\sum_{j=1}^{J}\sum_{r=1}^{R-1}\alpha_{rj}R_{ir,t-1} - \rho\mathcal{A}BB_{i,t-1} - \rho\gamma Z_{i,t-1} + \eta_{it}$$

The control function method consists of two steps. For ease of exposition, assume that the driving record is binary; a driver either has a clean record or not. In the first step, the endogenous variables are projected on $\mathbf{I}_{i,t-1}$; I specify the following probit models:

$$R_{it} = 1 \Leftrightarrow \pi_0 R_{i,t-1} + \pi_1\mathbf{W}^R_{i,t-1} + v^r_{it} \geq 0 \tag{7}$$
$$bb_{it} = 1 \Leftrightarrow \mu_0 bb_{i,t-1} + \mu_1\mathbf{W}_{it-1} + \mu_2\mathbf{Z}_{it-1} + \mu_3 R_{i,t-1} + v^b_{it} \geq 0 \tag{8}$$
$$bb0_{it} = 1 \Leftrightarrow \nu_1\mathbf{W}_{it-1} + \nu_2\mathbf{Z}_{it-1} + \nu_3 R_{i,t-1} + v^{0b}_{it} \geq 0 \tag{9}$$
$$bb1_{it} = 1 \Leftrightarrow \lambda_1\mathbf{W}_{it-1} + \lambda_2\mathbf{Z}_{it-1} + \lambda_3 R_{i,t-1} + v^{1b}_{it} \geq 0 \tag{10}$$

where $\mathbf{W}_{i,t-1}$ and $\mathbf{W}^R_{i,t-1}$ is a vector containing additional predictors of the endogenous variables not included in the $Z_{i,t-1}$; I set $\mathbf{W}_{i,t-1} = (a_{i,t-1}, g_{i,t-1}, p_{i,t-1})$, so that the lagged premium proxies for $\xi_{i,t-1}$, and $\mathbf{W}^R_{i,t-1} = (a_{i,t-1}, g_{i,t-1})$.[37] Consistent with the timing of the events—the black box choice is made conditional on ξ_{it}—the shocks are related through a linear equation

$$\eta_{it} = \tau\mathbf{v}_{it} + \epsilon_{it} \tag{11}$$

Letting the information set $\mathbf{I}_{i,t-1} \equiv (\mathbf{W}_{i,t-1}, \mathbf{Z}_{i,t-1}, R_{ir,t-1}, bb_{i,t-1})$, the following orthogonality conditions are imposed

A1: $E[\epsilon_{it}|\mathbf{v}_{it}, \mathbf{I}_{i,t-1}] = 0$

where $\mathbf{v}_{it} = (v^r_{it}, v^b_{it}, v^{0b}_{it}, v^{1b}_{it})$. In words, conditional on the information set at $t-1$ and on the innovation to the observable endogenous variables, the innovations to the unobservable

[37]The conceptual interpretation of these relationships is different. Equation (7) approximates the law of motion of the driving record determined by the previous year's driving record, whether an accident has occurred ($a_{i,t-1}$), and, if so, whether it happened in the grace period ($g_{i,t-1}$). In contrast, equations (8)-(10) are reduced forms for the evolution of the adoption choices. In the case of insurers other than A—equation (8)—the degree of persistence of the adoption choices is captured by the coefficient μ_0. Within insurer A, I specify one equation for the probability of entering the black box contract—$bb0_{it} = 1$—and one for the probability of not exiting from the black box contract. Therefore, state dependence is implicitly taken into account by conditioning the sample on the previous year's adoption choice.

pricing variable have zero mean. At this point, an additional set of orthogonality conditions is postulated

A2: $E[v^r_{it}|R_{i,t-1}, \mathbf{W}_{i,t-1}] = 0$

and

A3: $E[v^b_{it}|bb_{i,t-1}, \mathbf{W}_{i,t-1}, \mathbf{Z}_{i,t-1}, R_{i,t-1}] = 0$

A4: $E[v^{0b}_{it}|\mathbf{W}_{i,t-1}, \mathbf{Z}_{i,t-1}, R_{i,t-1}] = 0$

A5: $E[v^{1b}_{it}|bb_{i,t-1}, \mathbf{W}_{i,t-1}, \mathbf{Z}_{i,t-1}, R_{i,t-1}] = 0$

Condition **A2** is quite natural: conditional on driving records and accidents that occurred in year $t-1$, variation in the driving records reflects unexpected idiosyncratic events, such as mistakes made by the insurer in updating the record. Conditions $\mathbf{A3}-\mathbf{A5}$ state that, conditional on current adoption choices—they reflect relevant information such as privately known risk preferences—future adoption choices are subject to unanticipated events, such as shocks to preferences, or changes in the pricing strategies.
Equation (6) can be rewritten as

$$\log p_{it} = \mathcal{A}BB_{it} + \sum_{j=1}^{J}\sum_{r=1}^{R-1}\alpha_{rj}R_{irt} + \gamma_z\mathbf{Z}_{it} - \rho\log p_{i,t-1} - \rho\sum_{j=1}^{J}\sum_{r=1}^{R-1}\alpha_{rj}R_{ir,t-1} - \\ -\rho\mathcal{A}BB_{it-1} - \rho\gamma Z_{i,t-1} + \xi_i + \mathbf{v}_{it} + \epsilon_{it} \tag{12}$$

Given $\mathbf{A1}-\mathbf{A5}$, a two-step estimation approach can be implemented. In the first step the fitted residuals $\mathbf{v}_{it}$ from regressions (7)-(10) are estimated. I take into account the discrete nature of the endogenous variables by retrieving the generalized residuals—see Gourieroux, Monfort, Renault, and Trognon (1987)—from a probit model if the dependent variable is dichotomous (black box) or by estimating a generalized linear model if the endogenous variable takes multiple values (driving record), in which case I retrieve the deviance residuals (see McCullagh and Nelder. (1989)). In the second step, the fitted residuals are used as additional regressors in the price equation (12); by applying a fixed effect transformation to eliminate ξ_i, under **A1**, consistent estimates of $(\alpha_{rj}, \mathcal{A})$ can be obtained.

Further identification arguments.— The matched insurer-insuree nature of the data and the size of the sample create several advantages with respect to the traditional datasets when estimating a hedonic price regression featuring unobservable heterogeneity; notably, it allows me to identify (and estimate) *company-specific* parameters, such as the insurer fixed effects ι_j's subsumed in $\mathbf{Z}_{it}$. The identification of these parameters is based on the information provided by those who change companies from one year to another.[38]

[38]The precision of the estimates of the insurer fixed effects depends on the company-specific switching rate and on the insurers' market share, each contributing to the company-specific switchers' cell sample size. The switching rate across companies varies from 4.8% to 20%. The size of the cells within the four smallest companies (of 50 companies) is in the order of a few dozens; the number of switchers rapidly increases to

Observe that, by controlling for the loading costs, I can interpret the price differentials across insurers—the fixed effects ι_j's—in terms of market power or perceived brand quality. If information from the balance sheet data was not available, loading costs would be pooled into the ι_j's. The identification of the pass-through parameters α^c associated with each insurer at each year appearing in the price equation (2) comes from the time-variation of the loading costs within companies and the (cross-sectional) variation across companies.

Preliminary results.— To compare the results from the various estimators, I summarized the driving record into a single indicator variable C_{it}, taking value one if the policyholder has a clean record, and zero otherwise. The estimated coefficients on the black box and clean record indicator by the OLS estimator and the standard fixed effect estimator (FE) are reported in columns (1) and (2) of table 13 (regression specification (3)). The estimates by the control function with contract fixed effects (CF-FE) are reported in column (3) (regression specification (12)).[39]
Relative to the OLS, both the FE and CF-FE estimator imply larger black box discounts and a lower reduction for having a clean record, an indication that unobservable heterogeneity exists. Because I know that within insurer A, only one missing variable is time-varying—this variable captures the average socioeconomic status of the zip code, which is likely to be rather constant over time due to limited mobility—it is reassuring that coefficients on $bb0$ and $bb1$ implied by the FE and CF-FE estimator—my preferred estimator—are not far away.
To give an idea of the magnitude of effects on prices, a driver with a clean record receives a discount of 15 percentage points on the premium (column (3) of table 13); black box adopters by insurers other than insurer A receive a discount of about 10 percentage points; first-time adopters covered by insurer A receive a discount of 15.3 percentage points, while the average reduction based on the previous year's driving habits recorded by the black box is 8.6 percentage points. Therefore, on average, insurer A's black box adopters are *backloaded*.

Column (4) of table 13 shows the results of a specification in which clean record and black box have been interacted with contractual year dummies. The time variation of the discount associated with a clean record appears moderate, while insurer A markedly increased the flat discount over time. Because such a pattern is absent in the other insurers, this evidence, coupled with the previously documented pricing experimentation put forth by A, indicates that this large insurer played a major role in pushing the black box take-up rate in the Italian market.

102, 259, and 318 records for the following (smaller) companies. Therefore, ι_j can be precisely estimated for the vast majority of companies.

[39]The residuals in $\mathbf{v}_{it}$ are the generalized residuals obtained from estimating four probit models, with the dependent variable being C_{it}, bb_{it}, $bb0_{it}$, and $bb1_{it}$.

To detect heterogeneity in the pricing schemes, I interacted clean record and black box indicators with company(group of companies) dummies. The estimates of the coefficients on these interacted variables are reported in column (5). The response of prices to a clean record varies from 13.1 to 18.7 percentage points, indicating that penalties vary across insurers. The discount on the black box across insurers other than A ranges from 6 to 12.9 percentage points; this heterogeneity also likely reflects differential services—such as assistance in the case of an accident—and other heterogeneous features of the black box contract.

Black Box discounts and penalties.— I now specify a more general hedonic price equation aimed at (i) demonstrating that the data display substantial geographical variations in the (conditional) black box discounts, and (ii) how, given estimates of the coefficients on the BM class and number of claims on record, I recover the penalties for an additional accident at each driving record/insurer from the estimates of the coefficients on the driving record indicators. As a preview of the steps ahead, the first objective is germane to constructing instruments for the black box adoption, which is itself instrumental to ascertaining its causal effect on the frequency of accidents. The heterogeneity in the penalties across insurers demonstrates that I can rely on an unusually rich set of variations to identify moral hazard. Letting A_t be an indicator taking value of one if the policyholder is covered by insurer A during year t, the augmented (with lagged controls, lagged premium, and generalized residuals) price equation is specified as follows:

$$\begin{aligned}\log p_{i,jkt} = \alpha^A_{0k} A_t bb0_{ikt} + \sum_{H\in\{5,7\}}\sum_{h=1}^{H} \alpha_{h-H} bb1_{it} A_{it} \mathbf{1}[h_{it}=h|H] + \alpha_k bb_{ikt} + \\ + \sum_{r=1}^{9} \beta^r_j \mathbf{1}[BM_{it}=r] + \sum_{h=1,2,\geq 3} \beta^h_j \mathbf{1}[n_{it}=h] + \\ + \gamma \mathbf{X}_{it} + \iota_{jt} + \zeta_{kt} + \tau_t + \beta^z \mathbf{Z}_{i,t-1} + \hat{\mathbf{v}}_{it} + \xi_i + \epsilon_{it}\end{aligned} \tag{13}$$

where k denotes the province and j the insurer; in this notation $\mathbf{1}[h_{it}=h|H]$ takes the value of one if the monitored driver is assigned to band h within the H-regime.[40] BM_{it} denotes the BM class the driver is assigned to and n_{it} the number of accidents on record at the beginning of year t; $\hat{\mathbf{v}}_{it}$ denotes the residuals from the first step of the control function estimator previously described, obtained by predicting the driving record and the black box.[41]

In this specification, the coefficients α^A_{0k} and α_{h-H}'s measure the (conditional) effect on the first adoption year in province k—the flat discount—and the discount for being assigned to

[40] Recall that H takes values 5, 7, and 10.

[41] Because the driving record takes multiple values, I estimate a generalized linear model with a Poisson family function and a binomial link function, and retrieve the deviance residuals (see McCullagh and Nelder. (1989)).

band h in the H regime relative to a non-adopter covered by insurer A, respectively; analogously, the coefficient α_k represents the average (across contracts and insurers) reduction on the base premium generated by the black box adoption for policyholders not covered by insurer A in province k. The parameter β_j^r measures the percentage difference in the premium within insurer j between BM class r and classes 10-18, the omitted category; β_j^h measures the penalty for having h accidents on record relative to a zero-accident record within company j.
The vector of lagged variables, analogously to specification (6), is defined as

$$\mathbf{Z}_{i,t-1} = (\log p_{i,jk,t-1}, \mathbf{X}_{i,t-1}, \iota_{j,t-1}, \zeta_{k,t-1}, \tau_{t-1})$$

As before, the generalized residuals from the first step $\hat{\mathbf{v}}_{it}$ are included in the control set.

Results.— Table 14 reports in columns (1)-(4) the estimates on the coefficients of the BM class and number of accidents on record by the FE estimator of specification (13). All these coefficients are significant at the 1 percent level, suggesting that, despite the fact that lagged values are in the control set, the sample size and the variations in the data allow me to precisely identify these parameters. Columns (1)-(3) show that within each insurer/group of insurers, the premium is increasing and convex in the BM class and in the number of accidents on record. Therefore, the nonlinear pricing in the Italian market allows one to implement the traditional strategy to infer moral hazard.
The numbers in the table can be used to *compute penalties* after the occurrence of an accident at each driving record. I define penalties as the difference between the premium of year $t+1$ if an accident occurs during year t and the premium of $t+1$ if no accident occurs. Given the low probability of having more than one accident, I assume that drivers place zero probability on this event.[42] An additional accident shows up on the public record holding at the beginning of year $t+1$ both through an increase of the BM class (by 2) and of the number of accidents on record (during the previous five years). Given the rules governing the bonus-malus system—if no accident occurs, the BM class decreases by one—the estimates of the coefficient on the BM class and on the number of accidents on record allow me to approximate the penalties at each driving record, defined as a combination of these two variables. The approximation arises because I assume that in the case of no accidents, the number of accidents on record at the beginning of year $t+1$—by law, only those that occurred during the previous five years are reported—remains unaltered. This imputation exaggerates penalties because if some of the accidents reported on the record at year t occurred during the first of the previous five years, the number of claims on record at $t+1$ decreases by one if no new accident occurs. As a result, my test is biased *against* the null hypothesis; the intuition is that not finding a behavioral response to penalties that are larger than the actual ones makes me reject more often than I should

[42]See Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2019) for a similar approach.

the hypothesis of moral hazard, i.e. the imputation increases the chances of a false negative.

A few examples will be useful to clarify how the numbers in table 14 can be used to compute the marginal cost of an additional accident (penalty). Consider the case of a policyholder covered by insurer A who is assigned to BM class 1 with no accidents on record (clean record). In the case of an accident, the discount (relative to BM class ≥ 10) decreases from 57 percentage points (coefficient on BM 1$\times$ A in table 14) to 44.1 percentage points (coefficient on BM 3$\times$A), implying an increase in the premium of 12.9 percentage points. The malus then has to be summed to the increase in the premium from having one accident on record relative to none (the status quo), which equals about 7 percent. The overall penalty corresponds to about a 20 percentage point premium increase. Analogously, someone covered by insurer C assigned to BM 4 with one accident on record faces a BM penalty given by the difference between the coefficients on BM 6 ($= -23.2$) and on BM 3($= 44.4$), a BM penalty of 21.2 percentage points; this is summed to the difference between the coefficients on two accidents and one accident on record, implying a premium increase of 10 percentage points. In this case, the premium increases by about 31 percent.[43]

Given that the omitted category is the BM classes ≥ 10, this method only allows me to compute penalties for BM classes 1-8: the malus for BM classes ≥ 10 cannot be computed because these BM classes are absorbed into the omitted category ($BM \geq 10$), while the penalty for those in BM class 9—the difference in the premium between BM class 11 and BM class 8—can only be imprecisely estimated because BM class 11 is also pooled into the omitted category. Analogously, the increase in the premium faced by drivers with three or more accidents cannot be estimated because this category is omitted. This drawback is minor; the vast majority of policyholders are assigned to classes 1-9 and have fewer than two accidents on record, allowing me to compute penalties for 99 percent of the driving

[43]An alternative procedure to quantify the increase in the premium after an accident would be to estimate the coefficients on driving record $\times$ accidents occurred at $t-1$. Suppose there are only two driving categories, a clean record ($C=1$) or not ($C=0$). Letting A be an indicator for the occurrence of an accident, as an example suppose that the conditional mean of the premium is

$$p = \left\{ \begin{array}{ll} \alpha, & \text{if } C=1 \text{ and } A=0 \\ \beta, & \text{for } C=1 \text{ and } A=1 \\ \gamma, & \text{for } C=0 \text{ and } A=0 \\ \delta, & \text{for } C=0 \text{ and } A=1 \end{array} \right\}$$

in this case

$$p = C(\alpha-\gamma) + C \times A(\beta-\alpha-\delta+\gamma) + \gamma + A(\delta-\gamma) \tag{14}$$

Therefore, the coefficient on the interaction term $C \times A$ equals $\beta-\alpha-(\delta-\gamma)$, which is the differential increase in the premium after an accident between $C=1$ and $C=0$. Estimating this type of regression is feasible, but the number of policyholders assigned to a driving category who experienced an accident tends to be generally low, and more so for higher BM classes. The size of these cells decreases even more when one conditions on insurer and contractual year. As a result, the coefficients on $C \times A$ are imprecisely estimated. For this reason I estimate the unconditional (on having an accident) effect of the driving record on prices and adopt the previously described computation procedure.

records.[44]

Table 15 reports the penalties for each insurer and combination BM class-number of accidents on record, computed as in the previous example. Conditional on a driving record, the effect of an additional accident is heterogeneous in the market; focusing on the top 5 players, within a given driving record, the difference between the highest and the lowest penalty is about 4 to 10 percentage points.
The main takeaway from this table is that, although the Italian auto insurance market is as "tightly" regulated as other markets, companies enjoy a relative large amount of discretion on how to penalize accidents; this phenomenon reflects the adoption of heterogeneous classification schemes—"internal merit" class ("classi di merito interne")—and the effect of sales agents' discounts on transaction prices.[45] This disparateness in the pricing schemes is not surprising in light of the previous evidence on the heterogeneity of cost structures. For instance, it is reasonable that insurers with larger claims liquidation costs face stronger incentives to prevent moral hazard by inflicting relatively larger financial penalties.[46]

Black Box price discrimination.— Column (4) of table 14 reports the estimates of the effect of distance bands used to discretize the score by insurer A. Within the 5-band regime it appears that those assigned to bands 1-3 enjoy a discount relative to non-adopters, while those in classes 4-5 face a surcharge. Interestingly, within the 7-band regime, only those assigned to the highest distance band are subject to a small surcharge of 1.3 percentage points. Therefore, the pricing experimentation implemented by insurer A led to higher price dispersion within the monitored drivers. At the same time, because renting the black box costs about 30 euros, some black box adopters would have saved money by choosing the standard contract. This puzzle can be explained by drivers' uncertainty about typical distance driven, lack of saliency of the band-based pricing, nudging on the flat discount, and switching (across contracts) costs.

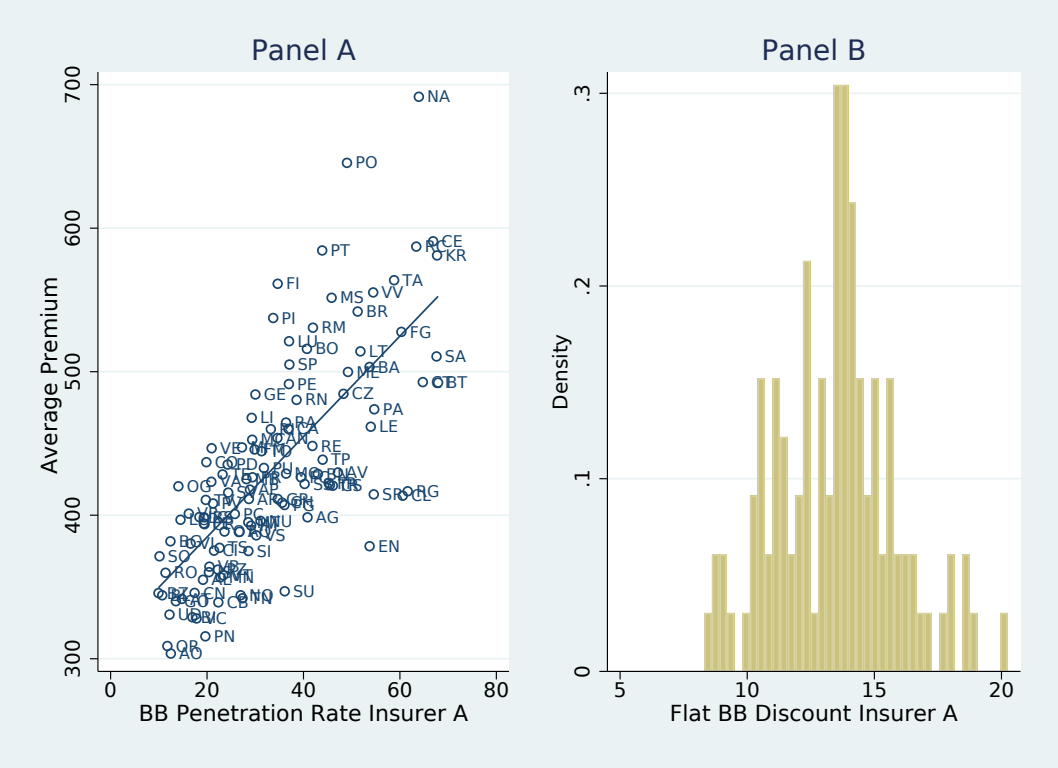
Black Box: geographical variations.— As illustrated by panel A of figure 3, there is a positive correlation between the premium and the black box penetration rate across provinces. One interpretation is that in Southern provinces, where the average auto insurance premium is among the highest in Europe and yet income is among the lowest, low-risk drivers obtain larger savings from the black box. This narrative is consistent

[44]In my sample 97.1 percent of policyholders are assigned to BM classes 1-9; of those, 76.7, 4.47, 4.73, 2.69, and 2.44 are assigned to classes 1, 2, 3, 4, and 5, respectively. Moreover, 99.81 percent of policyholders have fewer than three accidents on record, and the vast majority (86.26 percent) have no accidents on record.
[45]Jeziorskiy, Krasnokutskaya, and Ceccarini (2017) provide evidence of large discretionary discounts within the Portuguese auto insurance market.
[46]Understanding the equilibrium relationship between penalties and loading costs is an important avenue of future research (see Fang and Wu (2018)).

with the positive correlation between the number of installments and the premium across provinces, a further indication that contractual arrangements are shaped by the need to mitigate liquidity constraints.

To appreciate the degree of variation in the relative price of the black box, panel B of figure 3 depicts the histogram of the estimated flat discounts within insurer A at the province level, computed as $-\widehat{\alpha}^{A}_{0k} \times 100$. These coefficients are all significant at the 1 percent level and range from about 8 to 20 percentage points.

FIGURE 3. Black Box Variations across Provinces



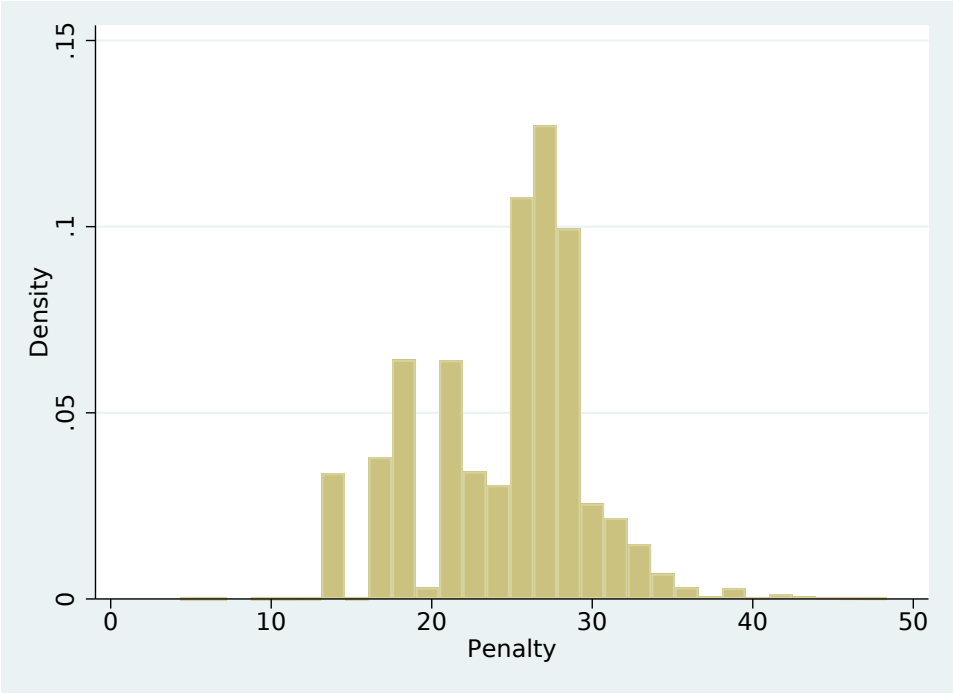
NOTES: The scatter plot in panel A shows the relationship between the percentage of contracts with a black box clause and the average premium within contracts underwritten by A across provinces. The histogram in panel B corresponds to the distribution of the estimated flat discounts, the α^{A}_{0k} in regression specification (13) multiplied by -100.

Saturated Specification.— The full set of variations to implement my identification strategy is obtained by allowing the effect of driving records to vary across time, and to let the flat discount on the black box charged by insurer A and other insurers to vary both across provinces and time. In other words, the set of coefficients $(\alpha^{A}_{0k}, \alpha_k, \beta^{r}_{j}, \beta^{h}_{j})$ in baseline regression specification (13) depend on the contractual year index t.[47] The purpose of this exercise is twofold: to (i) expand the support of financial penalties faced

[47]While one could allow the effect of $bb1_{it}$, BM_{it}, n_{it} to also vary across provinces and years, I regard this augmented specification as parsimonious relative to the purpose of having enough price variation while being consistent with the pricing strategies inferred from multiple conversations with major insurers.

by consumers and (ii) generate a large number of price variations that can act as an instrument for the decision to sort into the black box. The vast majority of the coefficients obtained from an estimating sample of 2,832,562 records are significant at the 1 percent level.[48] As it would be impractical to comment on such a large number of coefficients, figure 4 shows the histogram of penalties at the contract level obtained from the saturated specification. The average penalty in the market for having an accident corresponds to a premium increase of 20 percentage points.

FIGURE 4. Distribution of penalties at the contract level

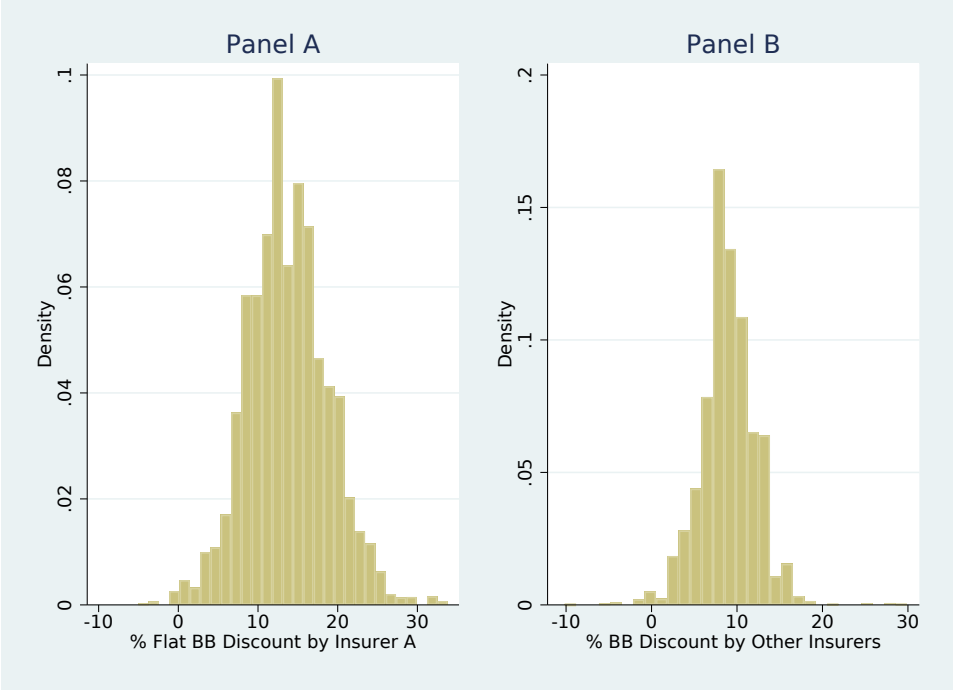


Note: This figure illustrates the distribution of penalties at the contract level associated with contracts covering 2014-Q3:2017. Penalties have been computed using the coefficients on the BM class and number of accidents on record interacted with the (7) insurer/group of insurers dummies and contractual year indicators in the baseline specification.

From figure 5, containing the histogram of (flat) black box discounts by insurer A (panel A) and other insurers (panel B) across provinces and contractual years, it can be observed that adopters covered by A face a larger geographical dispersion relative to those covered by other insurers. The results of the estimates convey the message that, conditional on

[48]The number of coefficients on the driving record indicators equals 336 (=(9 BM class indicators + 3 number of accidents on record indicators)× 4 periods × 7 group of insurers), out of which only 9 coefficients on the BM 9 are not significant at the 1 percent level. Because BM 9 is not used to compute penalties through the procedure previously described, this has no effect on the significance of penalties. Out of 440 coefficients(= 110 provinces × 4 time periods) on $bb0_k^A$, only 31, 24, and 19 are *not* significant at the 1, 5, and 10 percent levels, respectively. For what concerns the coefficients on bb_{ikt}, 82, 58, and 52 out of 440 are *not* significant at the 1, 5, and 10 percent levels, respectively.

FIGURE 5. Distribution of black box discounts at the contract level



Note: Panel A contains the histogram of the flat discount associated with contracts covering 2014-Q3:2017 underwritten by insurer A. The distribution is generated by the variation at the contract level of the estimates of $\widehat{\alpha}^{A}_{0kt} \times (-100)$) obtained from the saturated specification (specification (13) in which the black box flat discount α_{0k} also depends on t).
Panel B depicts an analogous histogram obtained from the variation of the discounts on the black box ($\widehat{\alpha}_{kt} \times (-100)$) within insurers other than A.

province-specific risk factors, rich price variations can be exploited to distinguish moral hazard from selection.

7. Moral Hazard

7.1. **Conceptual framework.** Consider a driver living for two periods with innate risk $\theta \in (\underline{\theta}, \overline{\theta})$ and utility function $u(w-p)$ increasing and concave in consumption, that is equal to wealth w minus the premium p. Risk is distributed in the population according to a distribution $F(\theta)$ with associated density $f(\theta)$. If an accident occurs, the policyholder is surcharged by the malus $\delta \geq 0$, and, to simplify the analysis, assume that no bonus is given if no accident occurs. Let a be an indicator taking the value of one in the case of an accident, and zero otherwise. For simplicity, only one accident can happen, the associated damage is equal to one, and there is full insurance. Let the market be served by two insurance companies A and B, charging a base premium p_j and a surcharge δ_j in the case of an accident, with $j \in \{A, B\}$; without loss of generality, let $p_A < p_B$ and $\delta_A > \delta_B$, and there exists a switching cost between insurers.[49] Let $\pi(e, \theta)$ denote the accident probability, which is decreasing in effort $e \in (0, 1)$ and increasing in risk θ. The second period value function reads

$$U_j(\theta) = u(W - p_j - a\delta_j) - c(0) \tag{15}$$

where $c(e)$ denotes the cost of exerting effort, increasing in e. The first period value function reads

$$V_j^1(a) \equiv \max_e \{u(W - p_j) - c(e) + \pi(e, \theta)[u(W - p_j - \delta_j) - u(W - p_j)]\}$$

Each type θ picks a first period optimal effort $e_j(\theta)$ when covered by insurer j and an insurer choice for both periods. In this model, given the heterogeneity of pricing strategies, there exists sorting of risk types into companies. Suppose that a driver of risk θ chooses $\text{A} \Leftrightarrow \theta < \theta^\star$. I define MH as the effort response to a marginal change of penalties at a given point δ_0

$$MH(\theta)\Big\|_{\delta_0} = \frac{\partial e(\theta)}{\partial \delta}\Big\|_{\delta_0} \tag{16}$$

The market-wide MH is the sum of the average insurer-specific moral hazard

$$AMH = \underbrace{\int_{\overline{\theta}}^{\theta^*} MH(\theta)\Big\|_{\delta_A} dF(\theta)}_{AMH_A} + \underbrace{\int_{\theta^*}^{\overline{\theta}} MH(\theta)\Big\|_{\delta_B} dF(\theta)}_{AMH_B} \tag{17}$$

Because of sorting, the distribution of risk within insurers is endogenous; in this example insurer A(B) attracts the low(high)-risk segment of the market. If the researcher has access to insurer-specific samples of contracts and claims, inference on AMH_A or AMH_B can be drawn by applying an identification strategy, perhaps based on panel data and

[49] If changing companies is costless, for every type θ the optimal choice would be to be covered by insurer A and then insurer B in the first and second periods, respectively. An alternative assumption to generate sorting is the presence of insurer-specific preferences shock.

non-linearities of the pricing schemes. However, if $\delta_A \neq \delta_B$—as previous evidence on heterogeneous penalties indicates—or if insurers differ in terms of other unobservables, these two parameters are different and inference on the market-wide moral hazard (AMH) cannot be drawn. In practice, having access to a non-representative (of the market) sample is unlikely to be an impediment to obtaining unbiased results from a simple test of moral hazard. However, it is possible that results on the *economic significance* of the moral hazard effect depends on the insurer-specific sample one uses for inference. For example, suppose that only data on insurer A are available and δ_A is small and/or it exhibits little variation. In this hypothetical scenario, one would most likely conclude that moral hazard is economically unimportant while still accepting the null of moral hazard from a statistical viewpoint.

Black box contracts.— Suppose now that consumers can choose between the standard bonus-malus (BM) and a black box (BB) contract. A BB contract offered by insurer j consists of first-year price p_1^j and second-year price $p_{2,j}^{BB}(e+\theta)$ increasing in the score $e+\theta$, observed by the insurer. In this set-up, the insurer cannot tell apart unmodifiable driving habits (θ) and the endogenous driving effort (e). In contrast, the standard bonus-malus (BM) contract specifies a fixed premium p^S. Let $e_j(\theta)$ and $e_j^{BB}(\theta)$ denote the first period effort when covered by insurer j under the standard BM and BB contract, respectively. Let Θ_j^{BB} denote the *endogenous* subset of risk types adopting the BB contract within insurer j. Moral hazard in this case is defined as the difference in driving effort under the black box and the standard contract, within black box adopters.

$$MH_j^{BB}(\theta) = e_j^{BB}(\theta) - e_j(\theta) \Rightarrow AMH_j^{BB} = \int_{\Theta_j^{BB}} MH(\theta)^{BB}$$

In general, $MH_j^{BB}(\theta)$ depends on insurer j because driving data are priced differently in the market, captured by indexing the second year black box pricing rule by j. Because policyholders only differ in terms of risk, it is easy to show that low θ's sort into the BB contract. This intuition does not go through if the value of the contract also depends on claims liquidation time x, which varies across contracts and is shorter if the black box is adopted. This feature can be modeled in terms of partial insurance: the policyholder is indemnified by a contract-dependent amount x with $1 > x^{bb} > x^s$. This feature introduces a trade-off: on the one hand, high-risk types are penalized by the black box customized pricing, but, because they are more prone to accidents, they can adopt the black box to reduce the expected loss.

Remark.— The behavioral assumption underlying my stylized model is that drivers optimize at year t based on the premium increase at year $t+1$; they respond to the *local* slope of the premium-driving record schedule, but not on the entire schedule. In other words, they are forward looking, but not too much. Three observations help to

rationalize this assumption. First, the existence of heuristics adopted by rational agents to approximate complex non-linear tax schemes has been studied in public finance (see Liebman and Zeckhauser (2004)), and empirical evidence based on experiments exists (see **?**); moreover, an increasingly influential literature in insurance shows that consumers often fail to optimize even on relatively simple insurance plans (see Bhargava, Loewenstein, and Sydnor (2017)). Second, if anything, not taking into account the effect of the entire penalty structure will bias my test *against* the null of moral hazard. Thus, evidence of behavioral responses to marginal penalties is unlikely to reflect a false positive. Third, in the context of heterogeneous penalty structures across insurers, a fully optimizing agent will condition his behavior on the entire set of premium-driving record schedules adopted by nearly 50 insurers. Because this is an implausibly large and complex information set, the researcher would have to impose some type of restriction anyways.

7.2. **Estimating moral hazard.** Consider the following linear probability model:

$$a_{it} = \sum_{r=1}^{9} \beta^r \mathbf{1}[BM_{it} = r] + \sum_{h=1,2,\geq 3} \beta^h \mathbf{1}[n_{it} = h] + \gamma \mathbf{X}_{it} + \iota_{jt} + \zeta_{kt} + \tau_t + \theta_i + \xi_{it} + u_{it} \quad (18)$$

where a_{it} takes value 100 if one or more accidents occur during year t, and 0 otherwise; θ_i represents time-constant risk preferences, and u_{it} is a zero mean idiosyncratic error term that is uncorrelated with the regressors; as in the previous notation, ξ_{it} measures unobservable pricing variables. In this specification β^r and β^h measure the (conditional) differential accident probability between two identical drivers assigned to BM class r and with h accidents on record, respectively, relative to the omitted categories (BM classes 10–18 and zero accidents on record).

The linear probability model is particularly appealing for two reasons. First, the coefficients can be interpreted directly in terms of marginal effects. Second, if one assumes that unobservable heterogeneity is time-invariant, the standard fixed-effect estimator allows me to identify the causal effect of the driving record and of the black box on accidents—the moral hazard effect—without imposing parametric assumptions on their correlation structure with unobservable heterogeneity.[50]

The traditional approach to infer moral hazard is to estimate equation (18) by fixed-effects, and to check whether the pattern of the β^r's and β^h's—the effect of the bonus-malus class and the number of accidents on record—is consistent with the nonlinearities 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. Thus, under the null of no moral hazard, these coefficients

[50]Binary dependent variable models such as the logit or probit model suffer from the incidental parameter problem. Fixed-effect logit models identify the marginal effect of the black box only using the (small and selected) sample of contracts who switch from the black box to the standard contract. Ketchamp, Lucarelli, and Powers (2015) also adopt a linear probability model with individual fixed effects to estimate the effect of inertia on the probability of switching companies.

should be zero; conversely, under moral hazard and given the estimates of the effect of driving records on premiums (table 15)—we expect the β^r's (β^h's) to be positive and decreasing (negative and increasing), reflecting the fact that penalties are increasing in the BM class and number of accidents on record. The identification argument is based on the fact that driving records are subject to exogenous time-variation driven by the shocks u_{it} and on repeated observations of the same policyholder, allowing the researcher 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. However, as noted by Ceccarini (2007) and Israel (2004), a driver might respond to an accident by driving more carefully or by giving up the car for a while, leading to *state dependence*.

Does state dependence matter?.— To examine the importance of state dependence, table 16 reports estimates of the driving record coefficients without controlling for the lagged outcome variable (column (1)), and controlling for one, two, and three lags of the outcome variable (columns (3)-(4)). Column (1) shows that the coefficients on the BM class and on the number of accidents on record display a pattern consistent with moral hazard. Once $a_{i,t-1}$ is included in the control set (column (2)), I obtain evidence of *negative* state dependence, and although I am still unable to reject moral hazard, the difference between the two adjacent β^h's and β^r's decreases in absolute value. The reduction of the moral hazard effect is further amplified when I control for $a_{i,t-2}$ (column (3)), whose coefficient is also significant at the 1 percent level. Finally, when I also control for $a_{i,t-3}$ (column (3)), the coefficients on the BM class are no longer consistent with moral hazard, while those on the number of accidents on record are; moreover, all the lagged outcome variables are significant with a decaying pattern.

The bottom line of this analysis is that the coefficients on the driving record also pick up some state dependence; as such, the traditional strategy can easily fail to disentangle state dependence from moral hazard if the persistent effect of past accidents is not taken into account.

7.3. **Main regression.** In order to separate out moral hazard from state dependence I adopt the following specification:

$$a_{it} = \underbrace{\alpha\widehat{\pi}_{ijrt} + \beta_0^A A_{it} bb0_{it} + \sum_{H\in\{5,7\}}\sum_{h=1}^{H} \beta_{h-H} bb1_{it} A_{it}\mathbf{1}[h_{it}=h|H] + \beta bb_{it} +}_{\text{moral hazard}} \tag{19}$$

$$\underbrace{\sum_{r=1}^{9}\beta^r\mathbf{1}[BM_{it}=r] + \sum_{h=1,2,\geq 3}\beta^h\mathbf{1}[n_{it}=h] + \alpha_1 a_{i,t-1} + \alpha_2 a_{i,t-2} +}_{\text{state dependence}}$$

$$+\underbrace{\gamma\mathbf{X}_{it} + \iota_{jt} + \zeta_{kt} + \tau_t + \theta_i + v_{it}^{\theta} + \xi_{it} + u_{it}}_{\text{observable and unobservable heterogeneity}}$$

where $\widehat{\pi}_{ijrt}$ denotes the penalty faced by policyholder i covered by insurer j and assigned to driving record r if an accident occurs during year t, as estimated by the CF-FE estimator within the saturated price regression. In this more general specification, v_{it}^{θ} is a serially uncorrelated error term capturing the unexpected realization of risk. Unlike u_{it}, v_{it}^{θ} is *known* to the policyholder *before* the effort decision is made; ξ_{it} represents unobservable pricing variables that are known to both the insurer and insuree but not to the econometrician.

In the presence of moral hazard, we expect α—an estimate of AMH in formula (17)—to be negative because higher financial penalties should induce more attentive driving; we also expect β_0^A and β_{h-H} to be negative if policyholders covered by A drive less or drive more carefully under the black box contract than when they are covered by a standard contract. Specifically, β_0^A can interpreted as the average first adoption year moral hazard effect, the change in behavior once effort (distance driven) becomes contractible. Analogously, β_{h-H} measures the endogenous reduction of the accident probability among drivers assigned to band h conditional on the H-bands regime. Because it was previously shown that the discount on the black box is decreasing in the band—column (4) of table 14—under moral hazard, β_{h-H} should not only be negative, but should also be decreasing in absolute value, mimicking the pattern of the band-specific price elasticities.

This specification allows me to disentangle moral hazard from state dependence because the latter is measured by lagged outcome variables and driving record indicators, while the former by the coefficients on penalties and black box indicators.
The identification of the moral hazard coefficients is threatened by two omitted variables: ξ_{it}—unobservable pricing variables—and the time-specific risk $\theta_i + v_{it}^{\theta}$. I address the first problem by controlling for $\widehat{\xi}_{it}$, the estimated residualized premium from the saturated price regression. I address the second problem by resorting to some assumptions that justify a

control function approach I now describe.[51]

Driving records endogeneity.— First, $\widehat{\pi}_{ijrt}$ is reasonably predetermined with respect to v_{it}^{θ} and ξ_{it} because it only reflects past realizations of risk, but it is not strictly exogenous.[52] My solution is to exploit the cross-sectional variation of penalties across insurers and the time variation within insurers, conditional on driving record and history of accidents. In other words, I compare behavioral responses to heterogeneous penalties (across companies and time) of observationally similar drivers assigned to the same driving record category with analogous histories of accidents.

The crucial assumption is that the premium-driving record schedules are exogenous to $v_{i,t}^{\theta}$, although they are allowed to be correlated with θ_i. A number of behavioral assumptions can be made to justify this restriction; (i) consumers receive information or they update their belief on penalties (the parameter δ in the model in section 7.1) after subscribing the contract, or (ii) penalties are not a salient feature of the contract and consumers sort into companies based on the base premium, additional services, or insurer-specific clauses.[53] An ancillary piece of evidence corroborates this hypothesis: $\widehat{\pi}_{ijrt}$ does not have an economically large impact on the switching probability from one company to another, estimated within a linear probability model with individual fixed effects and the full set of controls.[54].

7.4. **Black Box endogeneity.** The above assumption on the timing of the event is less realistic when applied to the black box adoption, as one would imagine that shocks such as changes in the distance driven because of a new job do affect the adoption choices. Other possible time-varying correlated unobservables are tastes for privacy, cost of effort, and income elasticity.

To mitigate this bias I rely on the following source of price variations that shift the adoption choice: (a) the previously documented variation of the black box discounts across provinces, (b) the time-variation of the (flat) discount and, within insurer A, of the number of bands used to discretize the score (insurer A used 5 to 10 bands), and (c) systematic differences in the (conditional) time to liquidate claims across provinces. Moreover, I argue that the historical process through which the black box was adopted coupled with the intra-regional heterogeneity provides valuable price variations.

[51] Strictly speaking, $\theta_i + v_{it}^{\theta}$ becomes at least partially observable to the econometrician within A's adopters and is measured by the score, posing a self-selection rather than an omitted variable problem. However, self-selection can be interpreted as an omitted variable problem (see Heckman (1979).

[52] In this situation, by first differencing (19) an OLS estimate of α is not consistent because $\widehat{\pi}_{ijrt} - \widehat{\pi}_{ijr,t-1}$ is correlated with $v_{it}^{\theta} - v_{i,t-1}^{\theta}$. $\widehat{\pi}_{ijrt}$ is correlated with $v_{i,t-1}^{\theta}$ via moral hazard and state dependence: past effort and accidents respond to $v_{i,t-1}^{\theta}$ and determine the current driving record, which, in turn, determines the penalties enforced by the current insurer.

[53] This assumption is also consistent with recent evidence on limited considerations sets, see Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2019) and Coughlin (2019).

[54] The coefficient is estimated at -0.001.

In the first step I instrument the first adoption choice and the (black box) retention probability by policyholders covered by insurer A, and the adoption choice by policyholders covered by other insurers. In practice, I estimate the following linear probability model on the sample of contracts underwritten by policyholders covered by A who did not choose the black box contract during the previous year (first adopters)

$$bb0_{ikt} = \alpha\pi_{iAt} + \nu N_t + \gamma T_{kt} + \delta\widehat{\alpha}^{A}_{0kt} + \beta_X X_{it} + \beta_Z \mathbf{Z}_{kt} + \zeta_{kt} + u_{it} \tag{20}$$

I estimate the same regression on the sample of adopters covered by insurer A with a black box contract during the previous year (old adopters). The adoption probability within other insurers is estimated through the same model but with $\widehat{\alpha}_{kt}$ instead of $\widehat{\alpha}^{A}_{0kt}$ and π_{ijt} instead of π_{iAt}, without controlling for the number of bands (N_t), on company-specific samples. The vector $\mathbf{Z}_{kt}$ contains area characteristics, and I also control for the province-year fixed-effects (ζ_{kt}). I also control for T_{kt}, a measure of local market efficiency that I will describe next. I retrieve the residuals of these linear models and use them as additional controls in the baseline accident equation (19).[55] I prefer the control function to the instrumental variable approach because in some specifications I control for quadratic and cubic terms of penalties to flexibly capture the effect of incentives.

The first requirement for the black box province-specific discounts to be valid shifters is that, conditional on $(\mathbf{Z}_{kt}, \zeta_{kt})$, u_{it} is idiosyncratic. I feel relatively confident about this orthogonality condition because many variables—see footnote 35—are included in $\mathbf{Z}_{kt}$; moreover, as a robustness check I also included the unemployment rate and the realized average claim cost at the province-year level.

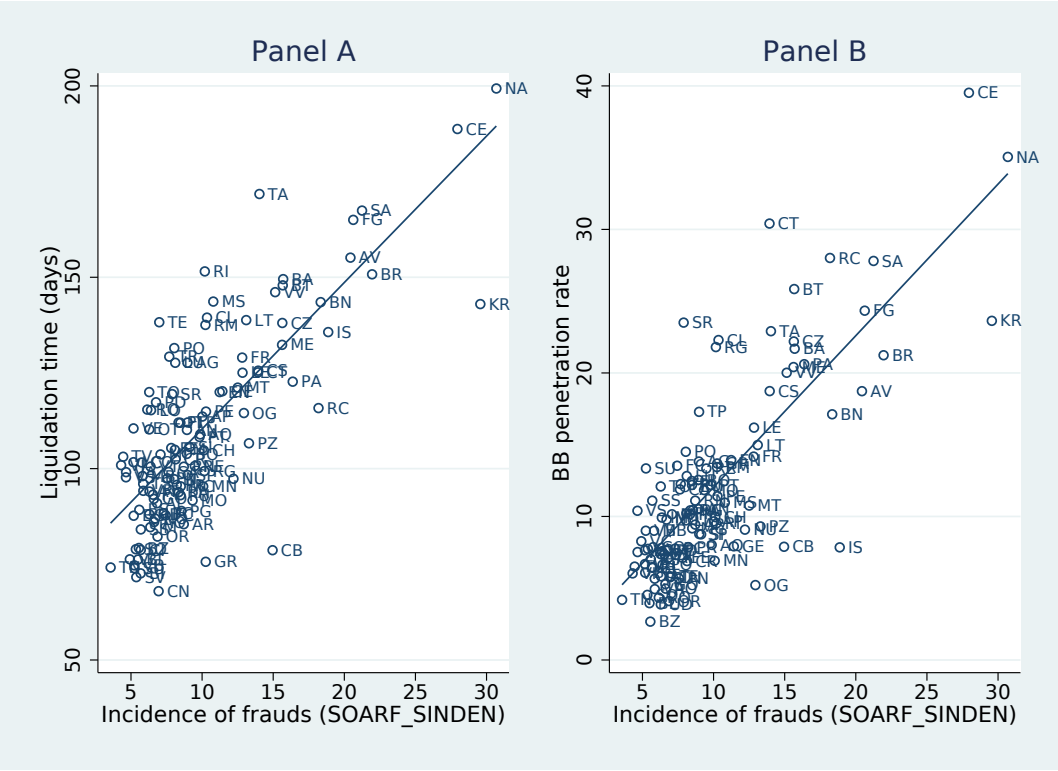
Claims liquidation time.— In light of the evidence on the effect of the black box on claims liquidation time illustrated in section 5.1, exogenous geographical variations in the factors affecting liquidation time unrelated to the adoption choice are potentially valid instruments. One such variation has to do with the fact that in tort systems, such as the Italian bonus-malus system, accidents often generate a legal dispute regarding who is to blame. In such disputes, the crash data can be used to ascertain individual liabilities and speed up the dispute resolution. Table 17 shows the distribution of auto insurance claims subject to a legal dispute (*"cause civili" di I grado*) in 2017, across Italian regions. The first striking fact is that 36 percent and 14 percent of disputes take place in the regions of Campania and Lazio, respectively. More in detail, the provinces of Napoli (in Campania) and Rome (in Lazio) account for 24.5 percent and 14.1 percent of the total (column (1) of table 17).[56] The second stylized fact has to do with the differential degree of *efficiency*

[55] After extensive experimentation, I adopted a linear model rather than a logit or a probit for convenience because non-linear models face convergence problems with a large number of fixed-effects. Linear models are increasingly popular to model probabilities with a large number of covariates, see Chatla and Shmueli (2013).

[56] These disparities in the amount of litigation generated by insurance claims are not justified by the number of accidents, but rather by the prevalence of fraud.

of the local judicial system, as measured by the difference between the number of cases settled and those started in 2017 (column (4) in table 17). These data indicate systematic geographical variations in (i) the likelihood that an auto insurance claim will be followed by a legal dispute and (ii) how long it takes to settle auto insurance disputes across markets. These differences are reasonably due to the incidence of fraud and to the efficiency of the local judicial system in resolving auto insurance claims. As shown in figure 6, there is a clear and positive correlation between the mean liquidation time and my proxy for the incidence of fraud $SOARF_SINDEN$ (panel A) and between the black box adoption rate across provinces and the incidence of fraud (panel B). Consistent with the pervasive differences in the level of social capital in Italy documented by Guiso, Sapienza, and Zingales (2004), the proportion of claims under investigation for possible fraud ranges from 5 to 30 percentage points, and the Southern provinces are characterized by a high incidence of fraud. This background evidence justifies the construction of a measure of

FIGURE 6. Liquidation Time



Note: Panels A and B represent the correlation between $SOARF_SINDEN$ and the average liquidation time (in days) and the black box penetration rate across provinces, respectively.

province-specific liquidation efficiency obtained from the following regression:

$$E[t_{ijkt}|\cdot] = \exp\left(\alpha s_{it} + \beta INJ_{it} + \gamma bb_{it} \times INJ_{it} + \delta bb_{it} \times s_{it} + \beta_X \mathbf{X}_{it} + \sigma SOARF_SINDEN_{kt} + \iota_{jt} + \tau_{kt}\right) (2$$

where t_{ikt} is the number of days between the filing and closing date within not-at-fault claims in claim i liquidated by insurer j in province k; s_{it} is the indemnified amount; INJ_{it} is an indicator for the presence of bodily injuries; $\mathbf{X}_{it}$ includes policyholder/car characteristics, contractual clauses, administrative and liquidation loading costs, and an indicator for whether the insurer is a direct one; and ι_{jt} and τ_{kt} are insurer-time and province-time fixed effects, respectively. Loading costs and insurer dummies capture the insurer's efficiency in liquidating claims, while controlling for the indemnified amount and presence of injuries allows me to compare liquidation times within homogeneous claims across markets. The fixed-effects τ_{kt} absorb all legal/administrative factors that vary systematically across markets.

I estimate a Poisson regression on the sample of claims not at fault associated with contracts underwritten in 2015-2017, as data on closing dates of the claims are not available for 2013-2014.[57] As for the measure of financial backwardness employed by Guiso, Pistaferri, and Schivardi (2013), I retrieve the estimated fixed-effects $\widehat{\tau}_{kt}$ for each province and year and center this measure on its minimum value $T_{kt} = \widehat{\tau}_{kt} - \min(\widehat{\tau}_{kt})$, that I use in the first stage equation (20). Interestingly, when I do not control in regression (21) for $SOARF_SINDEN$, the relationship at the province-level between T_{kt} and black box penetration rates is positive, as intuition suggests (panel B of figure 7). However, the opposite is true when I control for the incidence of fraud (panel A of figure 7), suggesting a first-order effect in determining judicial inefficiencies in settling auto insurance claims.

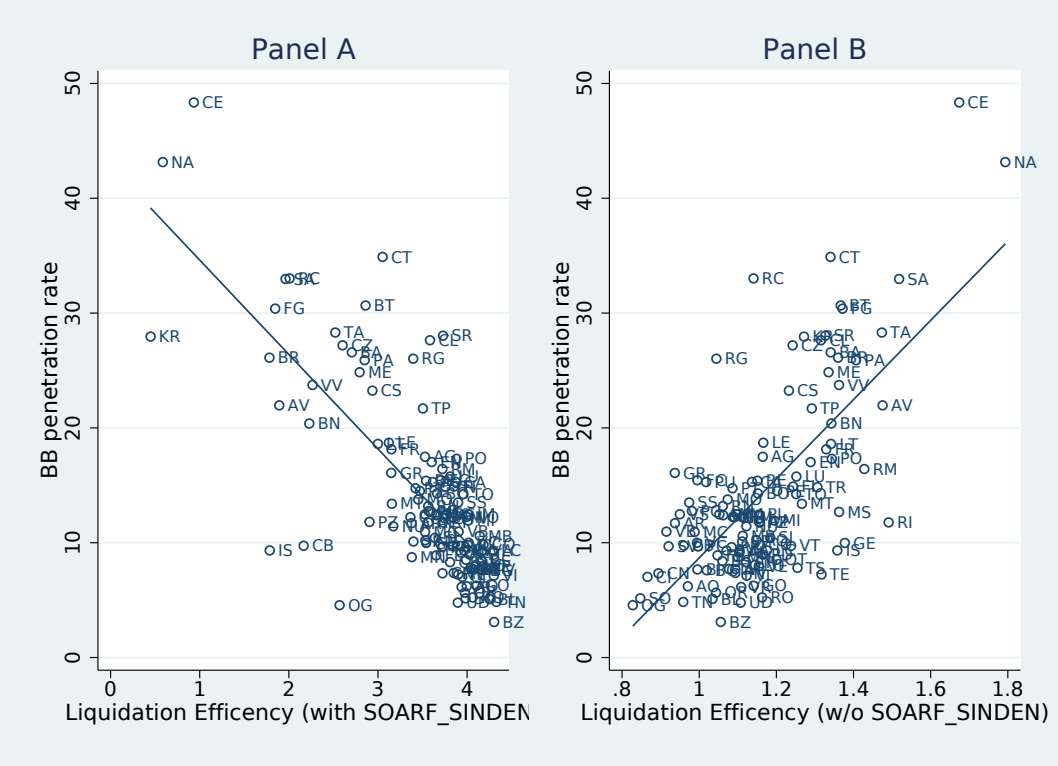
I now illustrate my final source of variation, stemming from the timing of the black box diffusion across Italian provinces. I argue that this historical process is reasonably unrelated to variation in risk factors and that heterogeneity between adjacent provinces further generates quasi-experimental variations.

Black box diffusion process: background.— Insurance telematics in Italy started in the early 2000s as a way to prevent insurance fraud—mostly concentrated in the Southern provinces—by using crash data.[58] Since then, the penetration rate experienced a three-fold increase, from 6 to nearly 18 percentage points.[59] Figure 16 illustrates this trend over the period Q4:2013-Q2:2018.

Insert Figure 16

[57]Modeling the conditional mean as an exponential function is appealing, given the skewness of the distribution of the discounts, and the non-negligible presence of contracts with zero discounts, and because it avoids the well-known bias induced by a log-linear specification (see Santos Silva and Tenreyro (2006)).
[58]Originally, policyholders received a flat discount after installing the device; after a decade, the original anti-fraud device evolved into the usage-based-insurance (UBI) products as the traditional actuarial approach evolved to allow premiums to depend on the highly predictive telematic data.
[59]These statistics indicate that the penetration rate within the Italian market is a multiple of other comparable markets; for instance, the penetration rate within the US market is around 5 percent.

FIGURE 7. Liquidation Efficiency and Black Box Penetration



Note: This scatter shows the correlation between my measure of liquidation efficiency (T_{kt}) and the black box penetration rates across Italian provinces.

The historically early diffusion in the Southern provinces translates into considerable geographical variation; as shown in figure 17, the percentage of contracts entailing a black box clause varies from 2.7 to 40 percent and is higher in Southern provinces.

Insert Figure 17

Importantly, the diffusion process started in the provinces of Caserta and Napoli, where the black box was encouraged by insurers to prevent and detect fraud; the growth rates were faster in other Southern provinces—located in Sicily and Puglia—and the black box *gradually* conquered the Northern provinces. These dynamics are represented in figures 18, 19, and 20

Insert Figures 18, 19, and 20

Insurer A's price experimentation and aggressive strategy to push the black box played a major role in boosting the black box across markets. The *staggered* adoption rate combined with the high degree of *intra-regional heterogeneity*—provinces in the same region can differ markedly in accident rates and size of claims—generates identifying *quasi-experimental* time variations. As an example, the provinces of Benevento and Avellino in the region of Campania are characterized by a frequency/cost of claims and incidence of fraud that are comparable to some provinces in the North. Nevertheless, the black box adoption rates

grew faster because of the proximity to the provinces of Caserta and Napoli. The idea is that, as evidence of black box profitability cumulated, sales agents underwriting contracts in areas covering adjacent provinces with different adoption rates felt more confident in pushing the black box in those areas where this type of contracts were less popular.[60]

In sum, although I cannot rely on a research design based on true random exposure to the black box as Gentzkow and Shapiro (2008) and Durante, Pinotti, and Tesei (2019) do in the context of TV viewership, the dynamics of black box diffusion indicate that local prices reflect a sequence of exogenous supply shocks. I now illustrate the results from the first stage.

First stage.— To easily learn about the quantitative importance of my shifter on the black box demand, I estimated linear probability models, with the dependent variable taking the value of 100 if the black box is adopted. The coefficients of interest are reported in panel A of table 19.
Column (1) of table 19 reports the OLS estimates of the effect of my instruments on the first adoption choice probability by insurer A's policyholders. The flat discount at the province-year level (estimated by the CF-FE estimator within the saturated specification) is significant at the 5 percent level and implies that a 12 basis point increase in the flat discount expands the adoption rate by about 1 percentage point (column (1)). My measure of liquidation efficiency is also significant at the 1 percent level with a positive sign, as intuition suggests. Retention probability (column (2)) is not affected by local efficiency, suggesting a certain degree of inertia. Furthermore, both the first adoption and the retention probability are impacted by the number of bands adopted by insurer A to discretize the score. These price shifters are also significantly associated with the adoption/retention probability by other insurers—columns (2)-(7)—but the sign is counterintuitive, probably because $\widehat{\alpha}_{kt}$ is a weighted average across insurers (other than A) and therefore does not truly measure the black box price faced by the policyholder covered by a specific insurer; therefore, the coefficient on the liquidation efficiency picks up some of the difference between $\widehat{\alpha}_{kt}$ and the "real" coefficient. Nevertheless, it is reassuring that a statistically significant association exists.

Drivers of black box demand.— The first stage also gives me the opportunity to further investigate the mechanism leading to the black box adoption: the black box could act as a signal of honesty from the insuree to the insurer, improving trust in insurance and the quality of the overall contractual relationship (see Gennaioli, La Porta, Lopez de Silanes, and Shleifer (2020)), or perhaps honest drivers primarily adopt the black box to speed up the liquidation procedure, which is typically slow in high fraud provinces.

[60]Sales agents' compensation is increasing in to the so-called loss ratio—the ratio between total premiums cashed and claims payout. This interpretation is consistent with the raw data on sales agents' discounts.

One way to test whether the first channel is at play is to check whether $SOARF_SINDEN$ has a positive effect on demand for the black box. Testing causality is problematic because $SOARF_SINDEN$ might pick up correlated unobservables. This concern seems valid because the associated coefficient is significant, but the sign changes across insurers (panel B of table 19). To examine the causal effect of local incidence of fraud on black box demand, as in Guiso, Sapienza, and Zingales (2004), I leveraged on the information in the sample of movers. The idea is that if someone moves to another province, their propensity to sort into the black box should respond to the new province's level of fraudulence.[61] Keeping in mind that moving is not exogenous to risk and is not random across provinces, I estimated a linear probability model of the black box indicator on lagged black box, lagged $SOARF_SINDEN$, lagged province dummies and the usual controls, including contemporaneous $SOARF_SINDEN$ and province/year dummies. The lagged variables help control for the correlation between aggregate fraud and individual preferences. I found no statistically significant effect. Moreover, when I do (not) control for $SOARF_SINDEN$ in regression (21), there exists a counterintuitive positive(negative) correlation between T_{kt} and the black box adoption rate, as shown in panel A(B) of figure 7.

This evidence suggests that the black box primarily acts as a technological remedy to the overload of legal disputes generated by the lack of social capital, allowing for faster reimbursement of claims through the crash data.

Correlates of adoption.— The association between the black box and other relevant observables, such as driving record, penalties, number of installments, and age, are reported in panel B of table 19. A positive(negative) correlation with the number of accidents(penalties) exists. Again, while a causal interpretation to these coefficients cannot be given, these findings broadly indicate non-trivial selection patterns. The negative correlation with the number of installments and the magnitude of the effects of two/three installments relative to one installment—the entire premium is paid up front—is also very interesting. It turns out that the many policyholders choosing two or more installments—about 44 percent of the market—who are willing to pay an overall higher premium to delay payments—paying the premium up front or choosing two installments reduces the premium by about 19 and 7 percentage points relative to three installments, according to the saturated regression—are also *less* likely to adopt (and stay in) the black box contract.

[61] Internal migration in Italy is a rather limited phenomenon—in my sample, only 2.2 percent of the units of observations move at least once in the period 2013-Q3:2017—and is primarily due to job-related motives, i.e. young individuals moving from the Southern to the Northern regions. Table 24 reports the means of several observable characteristics of the sample of movers and stayers. The two samples are generally balanced, although movers are 7.5 years younger and hold a slightly higher bonus-malus class. The estimates from a linear probability model in which the dependent variable takes the value of one if the policyholder moves indicates a significant but weak association between the moving decision and observable characteristics. Column (6) of table 24 reports the percentage change of the moving probability relative to the sample mean after a one standard deviation increase of each covariate.

These results generally suggest that that liquidity constraints play an important role in shaping contractual arrangements.[62]

Main Results.– The estimates of the coefficients of interest are reported in table 20.[63] In all five specifications, the coefficient on penalties is negative but only significant when individual fixed effects are taken into account (columns (4)-(6)). In the specifications reported in columns (4) and (5) a 1 percentage point increase in penalties reduces the conditional accident probability about 47 basis points. In order to account for non-linear effects I controlled for quadratic and cubic terms and I also tried different ways to take state dependence into account. In particular, in specifications in columns (2)–(3) and (5)–(6) I also include dummies for year $t-1$ accidents not-at-fault, the indemnity associated with the first not-at-fault claim, and the presence of injuries. In specification (3) and (5) I do not control for a_{t-2} and include year $t-1$ driving record indicators. The results—reported in table 21—indicate a smaller effect of penalties on the conditional accident probability, ranging from -0.35 to -0.09 basis points, suggesting that driving efforts are non-linear in marginal premium increases.
Given that the (unconditional) mean accident probability is about 5 percent, the estimates obtained including non-linear effects imply that a one percent penalty increase leads to a reduction of 1.8–6.9 percentage points of the mean accident probability, an economically large effect.

As I explained in the introduction, estimates of the response to accidents to penalties are absent within the auto insurance literature; in contrast, a range of moral hazard effects, defined as the responsiveness of demand for healthcare to the out-of-pocket price charged to the consumer (see Einav and Finkelstein (2018)) has been estimated in the health insurance literature.[64] This approach is more common in the public finance literature in which researchers typically estimate sufficient statistics such as labor supply responses to tax rates, and in the health insurance literature.

The second result is evidence of strong *negative* state dependence: both one and two lags of the outcome variable are significant with a negative sign; experiencing an accident

[62] Ericson and Sydnor (2018) examine the role of liquidity constraints to measure the efficiency of insurance contracts in a dynamic setting.
[63] Recall that penalties are computed using the CF-FE estimates associated with the driving record indicators within the saturated price regressions, in which the effect of the black box and of driving records on the premium is allowed to vary at the province-time and at province-company level.ained by adding as controls the lagged premium, lagged covariates, and generalized residuals from the first step. The set of penalties obtained this way takes 673 distinct values.
[64] As noted by Einav and Finkelstein (2018), the phenomenon traditionally studied in the health care literature has to do with ex-post moral hazard, rather than ex-ante moral hazard, or with hidden state rather than with an hidden action asymmetric information problem. Assuming that no ex-post moral hazard is at play, the parameters $(\alpha, \beta_0^A, \beta_{h-H})$ measure a genuine ex-ante moral hazard effect.

in year $t-1(t-2)$ decreases year-t accident probability by 47(28) percentage points (column (5)) of table 20).

7.5. **The effect of the black box.** A precursory step of the analysis of the black box moral hazard effect regards whether there is adverse, advantageous, or no selection; by adverse selection I mean that high-risk drivers sort into the black box contract.[65] The well-known positive correlation test by Chiappori and Salanièe (2000)—the econometrician looks at the conditional correlation between accidents and black box adoption—elucidates on the selection patterns. If negative, it could be that the moral hazard effect offsets adverse selection or that both moral hazard and advantageous selection co-exist. Nevertheless, quantifying the moral hazard effect allows one to infer the sorting patterns by netting out the estimated moral hazard effect from the (conditional) correlation. For example, if the black box causal (negative) effect exceeds in absolute value the (negative) correlation between accidents and the black box, this means that adopters are more risky drivers than non-adopters.

By pooling together the moral hazard and selection effects, the coefficients on the black box dummies estimated by OLS (column (1) of table 20) represent an estimate of the conditional correlation. In this specification I only construct two black box indicators for insurer A and the other insurers; that is, the first adoption and the distance bands for adopters covered by A are pooled into a single indicator. The black box coefficients are negative but not statistically significant. The zero correlation is unlikely to be driven by (a) the absence of some of the pricing variables in the control set because I control for the residualized premium from the saturated price equation, or (b) misspecification, as I obtain the same result from a probit model or by estimating a bivariate probit as proposed by Chiappori and Salanièe (2000). How can this result be rationalized? An interesting pattern emerges from the OLS estimates of the baseline specification (19) in which I now distinguish between first adoption and distance-band the policyholder is assigned to from the second adoption year onward. While the correlation within adopters from other insurers remains unaltered, the coefficient on first adopter by A (β_0^A) is significant at the 95 percent level and estimated at -0.24. Moreover, the coefficients on the distance bands are significant and reveal an interesting pattern: within the 5-bands(7-bands) regime, adopters assigned to bands 4 and 5(5-7) are *more* likely to have an accident relative to non-adopters. Instead, the likelihood of an accident within drivers assigned to low distance bands is *lower* with respect to non-adopters. The *non-monotonicity* of accident

[65]This definition of advantageous/adverse selection is different than the one traditionally adopted, according to which an insurance contract is adversely selected if the marginal and average cost curves are downward sloping in the relative price, see Einav, Finkelstein, and Cullen (2010). However, because the black box contract is inherently dynamic and the standard model is static, the traditional definition inadequately captures how the average cost of the black box contract varies with its (relative) price.

occurrence in the score explains why no relationship was found when I also collapsed for insurer A the black box adoption into a binary indicator (column (1)). In the absence of a moral hazard effect, this pattern would imply that no self-selection into the black box takes place. Column (3) reports OLS estimates obtained by controlling for the residuals of the first step—the adoption choice equations. The black box coefficient within all insurers and the flat discount by insurer A remain insignificant and the non-monotonicity in the score remains, indicating that some of the OLS effect is causal.

Individual (contract) fixed-effects are taken into account without and controlling for residuals from the first step in columns (4) and (5) of table 20, respectively. I obtain large and significant moral hazard effects: first adopters experience a reduction of almost 80 basis points in the conditional accident probability, a ten-fold increase relative to the specification without contract fixed effects. Moreover, the accident probability decreases in the score with a pattern similar to the OLS estimates but with larger coefficients in absolute value. This means that, because within drivers assigned to bands 4-5(6-7) in the 5(7) bands regime there is no moral hazard, the average reduction of accidents caused by the black box comes from low-distance drivers.
The black box contract also induces some more-attentive driving within those covered by insurers other than A, with a reduction of 44 to 51 basis points.

In column (6) I report the results of a specification in which penalties are interacted with the black box indicators. The coefficients on the interaction terms are negative and significant at the 99 percent level, indicating that black box and bonus-malus financial incentives act as complements in stimulating safe driving.

Taken collectively, these sets of results—no correlation between the presence of the black box and the frequency of accidents, and the significant moral hazard effects—indicate that (i) *on average*, the moral hazard effect is offset by the *adverse* selection into the black box contract, i.e low-risk drivers choose the standard contract, and (ii) the moral hazard effect is heterogeneous within monitored drivers.
Adverse selection into the black box seems counterintuitive because common sense suggests that low-risk drivers sort into the black box contract, the empirical result in Jin and Vasserman (2019) obtained using data on a single US insurer. I discuss potential mechanisms through which (my notion of) adverse selection can arise.

Pathways of selection.— In a frictionless model, the presence of *multiple dimensions* of private information can be advocated (see Finkelstein and McGarry (2006) and Cohen and Einav (2007)). For example, if agents differ in driving habits and preferences for privacy and if these two dimensions are *negatively* correlated, adopters can, in principle, be

characterized by *higher* ex-ante risk than policyholders who choose the standard contract (see Jin and Vasserman (2019)).

The relative complexity of the dynamic distance-based pricing naturally leads one to think about *behavioral biases* involving mental gaps and optimization errors (see Handel and Schwartzstein (2018)). Among the possible biases, (i) agents might use the flat discount as a reference point, i.e. they do not take into account that for some drivers, premiums in the second adoption year (and onward) will increase relative to the first adoption year and will cost more than a no-black box contract, (ii) systematic underestimation of the risk related to their driving habits, and (iii) inertia in contractual choices. In any of these situations, the insurer can exploit switching/deinstallation costs to attract consumers to the black box contract by offering a flat discount, and subsequently use the telematic data to more accurately price them based on distance driven while curbing the moral hazard problem. Indeed, the fact that high-distance black box adopters obtain a negligible discount or even a surcharge (column (4) of table 14), and yet a substantial fraction of these policyholders do not exploit the lack of commitment by sorting into the black box to enjoy the flat discount and then switch back to the standard contract, cannot easily be rationalized in the absence of behavioral biases and/or inertia.

Finally, the mechanism sketched in the black box model section 7.1 provides a novel explanation without having to resort to multidimensional heterogeneity. In short, marginal drivers face a trade-off: higher customized insurance from the second year onward (relative to a standard BM contract) versus a first-year discount coupled with reduced liquidation time and smaller damages, *conditional* on having an accident. This is a new insight because the few insurance models of customized insurance pricing abstract from the benefit of the crash data once the harmful event has taken place.

Ex-post moral hazard.— To ascertain whether the effect of the black box on the frequency of accidents stems from changes in driving habits or is merely a manifestation of ex-post moral hazard, I estimated the following regression on the sample of first adopters:

$$s_{it} = \alpha\widehat{\pi}_{ijt} + \beta\mathbf{X}_{it} + \gamma\mathbf{Z_{kt}} + \hat{\xi}_{it} + \tau_t + \epsilon_{it} \tag{22}$$

where s_{it} is the standardized score computed by insurer A after observing the policyholder's driving habits during an entire year. To account for self-selection into the black box I use the fitted residuals from (20)—the selection equation in the Heckman selection model—as additional controls in (22).[66] Focusing on first adopters has the advantage of not having to deal with dynamic selection due to non-random exit from the black box contract. Also, I control for the residualized premium $\hat{\xi}_{it}$, obtained from the saturated price regression.

[66]This procedure is similar to the Heckman two-step estimator in which the Mill's ratio from the selection equation is added as an additional control in the main equation. Again, because of the large number of fixed-effects, adopting a probit model for the selection equation is impractical.

The results are reported in columns (1) and (2) of table 22. I find that a 1 percentage point increase in penalties translates into a 0.012 standard deviation decrease of the score, and this effect is significant at the 95 percent level (column (1)). Therefore, "true" driving habits respond to financial penalties.
Because in the EU it is forbidden to price on gender, I detect the presence of differential responses between male and female drivers by interacting penalties with a dummy for whether the policyholder is male, and I find no differential effect (column (2)). Therefore, current regulation does not introduce distortions along this dimension.[67]

I interpret the results from the selection model and the negative effect of the black box on the size of damage as indicative of the second-order importance of ex-post moral hazard.

7.6. **Does sorting into companies matter?** One natural question is as follows: in a hypothetical scenario in which researchers only have access to insurer-specific samples, what is the effect of self-selection into companies on my estimates of moral hazard? To answer this question, I act as if the researcher could use the correct incentives to infer moral hazard—the penalties I recover in the first step—but could only access the company-specific samples. I proceed as follows: first I estimate a modified version of the accident probability equation (19) on the full sample by the usual CF-FE estimator to account for the endogenous nature of the black box:

$$a_{ijt} = \sum_{j=1}^{7} \alpha_j \widehat{\pi}_{ijrt} + \sum_{j=1}^{7} \beta_j bb_{ijt} + \tag{23}$$
$$\sum_{r=1}^{9} \beta^r \mathbf{1}[BM_{it} = r] + \sum_{h=1,2,\geq 3} \beta^h \mathbf{1}[n_{it} = h] + \alpha_1 a_{i,t-1} + \alpha_2 a_{i,t-2} +$$
$$+\gamma \mathbf{X}_{it} + \iota_{jt} + \zeta_{kt} + \tau_t + \theta_i + \widehat{v}^{\theta}_{it} + \widehat{\xi}_{it} + u_{it}$$

The coefficients of interest are the insurer-specific responses to penalties and black box—the α_j's and the β_j's, with $j = 1, \ldots, 7$, indexing the top-5 players, the medium ($j = 6$), and small companies ($j = 7$)—whose estimates are not affected by dynamic selection because I follow policyholders after they change companies. I obtain a crude assessment of the effect of data limitation/sorting into companies by comparing these coefficients to the ones I obtain by estimating the same regression by the FE estimator on company-specific samples. Notice that because I still control for $\widehat{v}^{\theta}_{it}$ and the residualized premium $\widehat{\xi}_{it}$, I am artificially helping a hypothetical researcher who only has access to the insurer-specific

[67] In columns (3)-(4) I report the results obtained by estimating the score regression (22) by the fixed-effect estimator, without accounting for self-selection. The effect of penalties on driving habits is insignificant. Taken at face value, this result indicates that dynamic selection is at play. At the same time, it is possible that this approach does not fully account for selection.

sample of contracts.

The results of this exercise are reported in table 23. In panel A I compare the response of accidents to penalties and in panel B the black box moral hazard effect. A few interesting facts emerge. First, all the insurer-specific coefficients on penalties obtained by estimating (23) on the full sample are significant at the 1 percent level and range from -0.2 to -0.9—recall that the average coefficient across companies is intermediate and estimated at -0.471 (column (5) in table 20)—suggesting that sorting into companies and the different penalty structures do have an effect on the magnitude of the behavioral responses. The estimates obtained by using the company-specific samples are severely downward biased and range from -3.309 to -2.189. Therefore, data limitations would not lead one to incorrectly reject moral hazard, but rather to *overestimate* its magnitude (see section A.4 of the online appendix). This result is also consistent with the fact that poor drivers switch companies more often: because low-risk types are over-represented over time in insurer-specific samples and penalties are negatively correlated with risk, the estimated effects of penalties on accidents are inflated because drivers are not followed when they leave the company.

To learn about the impact of sample selection on the black box coefficients, it is instructive to focus on company A, indexed by $j = 1$, because it is large and the structure of the black box contract is well understood. Notice that this coefficient pools together the behavioral responses of first and old adopters (across the different distance bands). The coefficient obtained using the full sample is estimated at -1.814, while the one using the insurer-specific sample at -2.063. Again, data limitations would most likely lead one to exaggerate the black box moral hazard effect. By inspecting the discrepancies of the estimated moral hazard effect across the different insurers—in some cases, using the company-specific sample, the effect is not significant—it further becomes evident how data limitations can bias inference.

8. Conclusions

As explained by Salanie (2017), the empirical literature on auto insurance has suffered from severe data limitations, impeding the empirical analysis of asymmetric information at the market level. In this article I presented a matched insurer-insuree panel dataset covering the entire Italian automobile insurance market—the outcome of a multi-year data collection effort—that can fill this gap. I believe these data can help us push the frontier of insurance economics by allowing researchers to quantify market-wide phenomena. In this article I pursued one such exercise by exploiting variations across local markets and insurers as well as pricing experimentation to quantify moral hazard. Estimates of novel parameters–the response of accidents to financial penalties and to the presence of the black

box–indicate that the market-wide moral hazard is large.

I conclude by arguing that this work sets the stage for a promising and policy-relevant research agenda. The data used in this article are also well suited to addressing other important issues such as the quantitative importance of 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. The availability of information on loading costs allows one to analyze how the heterogeneity of cost structures shapes market equilibria. Finally, the data on driving habits and the black box contracts are almost ideal to investigate empirically the equilibrium properties of the so-called third-generation insurance models, such as the ones developed by Brunnermeier, Lamba, and Segura-Rodriguez (2020) and Abrardi, Colombo, and Tedeschi (2020), in which asymmetric information can endogenously be removed by monitoring driving behavior through the black box.

9. Tables

TABLE 2. Bonus-Malus Class at Year $t+1$ as a Function of the Number of Accidents at Year t.

	Number of Accidents at Fault in Year t				
	0	1	2	3	≥ 4
	BM Class Year $t+1$				
BM Class Year t					
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 3. Insurers, Contracts, and Policyholders

Contractual Year	No. Insurers	No. Contracts	No. Policyholders
2013	47	1,111,311	989,602
2014	49	1,013,110	886,501
2015	48	979,354	848,558
2016	42	975,937	838,409
2017 (Q1:Q3)	40	702,206	623,078
Total	52	4,782,311	1,001,396

Notes. This table reports the number of insurers, contracts, and policyholders subscribing a contract during each contractual year in IPER. Contracts underwritten in Q4:2017 are not included in the sample, which is why the number of contracts dramatically drops in 2017.

TABLE 4. Multiple Subscribers

	Contractual Year				
	2013	2014	2015	2016	2017
No. of subscribers associated with one contract	878,477	771,431	730,079	714,549	550,445
	88.73	87.02	86.04	85.23	88.34
No. subscribers associated with two contracts	102,674	105,114	107,876	112,150	67,050
	10.37	11.86	12.71	13.38	10.76
No. of subscribers associated with two contracts	8,859	9,931	10,604	11,710	5,583
of $>$ two contracts subscribers	0.89	1.12	1.25	1.4.	0.9

Notes. This table reports the number distribution of the number of contracts underwritten by the same insuree during each contractual year.

TABLE 5. Multiple Insurers Among Multiple Subscribers

	Contractual Year				
	2013	2014	2015	2016.	2017
choosing the same insurer	68.91	66.75	66.28	65.52	66.51
choosing different insurers	34,672	38,248	39,950	42,702	24,324
Total multiple insurers	111,533	115,045	118,480	123,860	72,633

Notes. This table reports the proportion of multiple subscribers underwriting contracts with the same(different) companies.

TABLE 6. Frequency of Claims

	Contractual Year				
	2013	2014	2015	2016	2017
	Claims at Fault				
No. contracts with 0 claims	1,054,324	961,526	929,004	926,363	667,638
% of contracts with 0 claims	94.87	94.87	94.86	94.92	95.08
No. contracts with 1 claim	53,342	48,809	45,408	44,380	30,919
% of contracts with 1 claim	4.80	4.82	4.64	4.55	4.40
No. contracts with 2 claims	3,151	2,812	4,317	4,597	3,245
% of contracts with 2 claims	0.28	0.28	0.44	0.47	0.46
No. contracts with claims ≥ 3	495	353	625	597	404
% of contracts with claims ≥ 3	0.04	0.03	0.06	0.06	0.06
	Claims Not at Fault				
No. contracts with 0 claims			924,750	922,842	665,695
% of contracts with 0 claims			94.42	94.56	94.80
No. contracts with 1 claim			51,652	50,355	34,625
% of contracts with 1 claim			5.27	5.16	4.93
No. contracts with 2 claims			2,801	2,587	1,765
% of contracts with 2 claims			0.29	0.27	0.25
No. contracts with claims ≥ 3			151	153	121
% of contracts with claims ≥ 3			0.06	0.06	0.06

Notes. This table reports the distribution of the number of claims at fault during each contractual year obtained by merging IPER with the BDS. The merge with the BDS was implemented in September 2019. Because of the time needed for claims to be filed and finalized, the number of claims associated with contracts underwritten in 2016 is likely to be slightly underestimated.

TABLE 7. Summary Statistics of Covariates at the Market Level from IPER

	Variable	Weighted mean[a]	Mean[b]	Std.dev.	Min	Max
Clauses	Inspection	0.00	0.00	0.02	0	1
	Repairing	0.136	0.13	0.34	0	1
	Increasing	0.352	0.35	0.48	0	1
	Decreasing other	0.044	0.04	0.20	0	1
	Corporate Agreement	0.189	0.19	0.39	0	1
	Black box	0.130	0.13	0.33	0	1
	Exclusive driving	0.042	0.04	0.21	0	1
	Expert driving	0.431	0.43	0.50	0	1
	Free driving	0.480	0.48	0.50	0	1
	Other driving	0.047	0.05	0.21	0	1
	Protected bonus	0.218	0.21	0.41	0	1
	Min. liability coverage	0.618	0.62	0.48	0	1
	Liability Coverage[e]	13.816	13.86	21.31	6	139
	Deductible[c]	402.830	418.38	2346.96	0.49	51,600
Type of contract	Bonus-malus	0.962	0.962	0.19	0	1
	Deductible	0.002	0.002	0.04	0	1
	Mixed(bonus-malus+deductible)	0.037	0.036	0.19	0	1
No. installments		1.442	1.45	0.52	1	4
	1	0.568	0.56	0.50	0	1
	2	0.426	0.43	0.50	0	1
	>2	0.007	0.01	0.08	0	1
Demographics: Age		52.067	48.573	14.71	18	100
	18-24	0.015	0.025	0.16	0	1
	25-34	0.107	0.166	0.37	0	1
	35-44	0.204	0.242	0.43	0	1
	45-60	0.361	0.338	0.47	0	1
	>60	0.314	0.230	0.42	0	1
Gender	Male	0.590	0.578	0.49	0	1
Driving record:	BM class	1.883	2.002	2.370	1	18
	BM 1	0.784	0.766	0.423	0	1
	BM 2-3	0.090	0.092	0.289	0	1
	BM 4-10	0.108	0.120	0.325	0	1
	BM 11-18	0.017	0.020	0.142	0	1
	No. acc. on record	0.158	0.156	0.417	0	60
	0	0.824	0.822	0.383	0	1
	1	0.118	0.116	0.320	0	1
	2	0.014	0.013	0.115	0	1
	>2	0.044	0.049	0.216	0	1
Tenure	Days since first contract	1257.46	1193.206	1267.56	0	16,802
	Proportion of switchers	0.120	0.127	0.333	0	1
Car's characteristics	Power[d]	66.472	66.732	26.842	0	541
	Years since registry	8.663	8.438	4.887	0	19
	Cubic cilinder	14.020	14.031	4.180	0	82
Power supply	Diesel	0.427	0.438	0.496	0	1
	Petrol	0.463	0.520	0.500	0	1
	Hybrid	0.002	0.002	0.045	0	1
	GPL	0.032	0.033	0.178	0	1
	Other	0.000	0.000	0.007	0	1
Macro-Region of Residence	North	0.486	0.492	0.500	0	1
	Center	0.207	0.208	0.406	0	1
	South	0.203	0.199	0.399	0	1
	Islands	0.105	0.101	0.301	0	1

NOTES: This table reports statistics on the contracts underwritten in the period 2013-Q3:2017.
a] Sampling weights have been used.
b] Sampling weights not been used.
c] Euros.
d] Power of the vehicle in KW.
e] Million Euros.

TABLE 8. Statistics of Premium and Its Components—IPER

	Premium	Discount	Fee	Taxes	Contribution to NHS
Unweighted Mean	463.28	95.48	33.04	56.84	38.58
Std. Dev.	213.04	121.02	22.19	26.99	17.75
Weighted Mean	451.37	94.43	32.35	55.46	37.58
P5	224.13	0.000	0.000	25.83	18.71
P25	321.04	1.000	20.48	39	26.740
Median	416.63	61.95	30.98	51.17	34.70
P75	550.42	136.95	43.82	68.07	45.83
P95	861.70	314.12	71.74	107.09	71.75
P75-P25	229.38	135.95	23.34	29.07	19.09
Gini index	0.234	0.59	0.36	0.24	0.23
CV	0.46	1.268	0.67	0.45	0.46
Skewness	2.02	1.18	1.95	3.34	2.03
Kurtosis	11.68	7.55	11.33	30.55	11.71
Min	0.02	0.000	0.000	0.01	0.01
Max	4513.08	5148.38	388.84	570.84	374.62

Notes. This table reports statistics on the premium and its components as reported on contracts underwritten in the period 2013-Q3:2017.

TABLE 9. Means of Variables from the Balance Sheet Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A–Market									
	Net Premium	Profit	Liquidation cost	Direct Claim cost	Claims Payout	Acc. Freq.	Fees	Underwriting Cost	Admin. Cost	Speed
Mean	376.99	156.36	330.55	0.90	2,208.89	0.06	40.80	18.19	19.56	0.79
St. dev	0.02	0.02	0 .06	0.00	0.11	0.00	0	0.01	0.00	0
	4,581,388	4,581,388	4,581,388	4,581,388	4,581,388	4,581,388	4,581,388	4,581,388	4,581,388	2,588,436
	Panel B—Insurers									
	Net Premium	Profit	Liquidation cost	Direct Claim cost	Claims Payout	Acc. Freq.	Fees	Underwriting Cost	Admin. Cost	Speed
A	397.97	169.98	270.74	0.58	2,274.75	0.06	51.75	16.89	18.09	0.81
B	403.59	178.21	452.87	0.78	2,155.82	0.05	50.17	23.67	17.28	0.81
C	377.56	146.42	579.69	0.50	2,447.32	0.06	40.92	5.50	17.04	0.75
D	334.66	145.57	236.20	1.39	1,959.50	0.06	36.90	13.86	9.02	0.80
E	362.66	163.83	273.40	0.38	2,086.37	0.05	38.20	15.54	30.68	0.78
Medium Companies	369.15	151.35	278.97	1.08	2,112.17	0.06	30.64	21.65	19.50	0.79
Small Companies	354.31	134.75	281.24	1.47	2,235.45	0.06	33.06	21.95	25.07	0.79

Notes. This table reports means and standard deviations of the loading costs across contracts obtained by matching each record in IPER to the year-specific balance sheet data of the company underwriting the contract. All the means except the accident frequency and speed—columns(6) and (7)—are expressed in euros.
Sampling weights have been used. The statistics in Panel A are obtained using contracts underwritten by all insurers. In Panel B the same statistics are obtained for the top-5 players and the set of medium/small companies.
The only source of variation is across companies and years (2013-2017). The net premium in column (1) is obtained by subtracting taxes and contribution to the health system to the premium corresponded.
The profit per contract in column (2) is computed as: net (of taxes) premium−fees (7) −frequency of claims ((9))× (claims payout ((5))+ claims liquidation cost (= (3) + (4))-administrative costs(=undewriting cost (8)+admin. cost (9)).
In column (10) the mean claim liquidation speed–the proportion of claims occurred in year t liquidated in the same year–is reported.

TABLE 10. Premium–Gini Index

	Adj. Gini=0.231		Adj. Gini =0.218		Adj. Gini =0.22		Adj. Gini =0.193		Adj. Gini =0.186	
	Adj. Var.	Controls	Adj. Var.	Controls	Adj. Var.	Controls	Adj. Var.	Controls	Adj. Var.	Controls
Age	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Driving record	NO	NO	YES	NO	YES	NO	YES	NO	YES	NO
Clauses/No. Installments	NO	YES	NO	YES	YES	NO	YES	NO	YES	NO
Car's charact.	NO	YES	NO	YES	NO	YES	NO	NO	NO	YES
Tenure	NO	YES	NO	YES	NO	YES	NO	NO	NO	YES
Province FE	NO	YES	NO	YES	NO	YES	YES	NO	YES	NO
Company FE	NO	YES	NO	YES	NO	YES	NO	YES	YES	NO
Gender/size of the city	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

NOTES. This table reports the adjusted Gini Index proposed by Almas and Mogstad (2012).

TABLE 11. Number of Distance-Bands Regimes

Number of Bands	2013	2014	2015	2016	2017
5	100	100	59.34	0	0
7	0	0	40.66	100	88.01
10	0	0	0	0	11.99
Number of Contracts	20,149	27,768	44,221	59,073	49,992

NOTES. This table reports the proportion of contracts assigned to each number of bands-regime at each contractual year, conditional on having been monitored the previous year. In 2013(2014) all policyholders monitored in 2012(2013) are assigned to one of five distance bands. Discounts for contracts starting before(after) September of 2015 are based on a five(seven)-distance band regime.

TABLE 12. Ex-Post Moral Hazard

	(1) NAF Claims		(2) NAF Claims (Switchers)		(3) AF Claims		(4) AF Claims (Switchers)		(5) Liq. Days	
grace	0.01	[0.010]	0.009	[0.041]	0.042***	[0.013]	0.181***	[0.060]		
black box	-0.029**	[0.012]	-0.025	[0.052]	-0.032**	[0.013]	-0.046	[0.044]	0.039**	[0.017]
injury	1.220***	[0.018]	1.161***	[0.047]	1.029***	[0.018]	0.966***	[0.038]	1.076***	[0.037]
grace×black box	-0.029	[0.022]	0.042	[0.091]	0	[0.025]	0	[0.065]		
grace×injury	0.003	[0.017]	-0.034	[0.072]	0.008	[0.020]	-0.091	[0.091]		
black box × injury	-0.048***	[0.017]	-0.089	[0.077]	0.015	[0.022]	0.041	[0.061]	-0.157***	[0.038]
direct insurer	0.077*	[0.044]	0.27	[0.175]	0.029	[0.076]	-0.101	[0.168]	-0.065	[0.053]
SOARF SINDEN	5.155***	[0.214]	24.739***	[1.791]	1.952***	[0.270]	-10.958***	[1.789]	17.431***	[0.418]
policyholder char.	Yes		Yes		Yes		Yes		Yes	
car char.	Yes		Yes		Yes		Yes		Yes	
driving record FE	Yes		Yes		Yes		Yes		Yes	
clauses	Yes		Yes		Yes		Yes		Yes	
loading costs	Yes		Yes		Yes		Yes		Yes	
tenure FE	Yes		Yes		Yes		Yes		Yes	
no. installments FE	Yes		Yes		Yes		Yes		Yes	
insurer FE	Yes		Yes		Yes		Yes		Yes	
province × year FE	Yes		Yes		Yes		Yes		Yes	
R^2										
N	131,227		8,121		109,780		6,704		127,624	

NOTES. This table reports the effect of the grace period and of the black box on the size of the indemnities estimated within a Poisson model. The dependent variable in columns (1)–(2) is the indemnity corresponding to the first accident not-at-fault associated with contracts underwritten in 2013–Q3:2017. The dependent variable in columns (3)–(4) is the indemnity corresponding to third parties for the first accident at-fault associated with contracts underwritten in 2015–Q3:2017. Indemnities have been trimmed using the 99 percentile.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively. Standard errors are reported in parenthesis and clustered at the province level in the OLS regressions.

TABLE 13. The Effect of Clean Record and Black Box on the Premium

	(1) OLS		(2) FE		(3) CF-FE		(4) CF-FE		(5) CF-FE	
BB all insurers	-0.046***	[0.007]	-0.100***	[0.001]	-0.098***	[0.002]				
$bb_0 \times A$	-0.082***	[0.008]	-0.138***	[0.001]	-0.153***	[0.001]			-0.155***	[0.001]
$bb_1 \times A$	-0.047***	[0.007]	-0.093***	[0.001]	-0.086***	[0.001]	-0.064***	[0.001]	-0.088***	[0.001]
clean record	-0.262***	[0.005]	-0.112***	[0.001]	-0.153***	[0.001]				
clean record×2014							-0.141***	[0.001]		
clean record×2015							-0.145***	[0.001]		
clean record×2016							-0.148***	[0.001]		
clean record×2017							-0.158***	[0.001]		
bb other companies×2014							-0.108***	[0.002]		
bb other companies×2015							-0.113***	[0.002]		
bb other companies×2016							-0.098***	[0.002]		
bb other companies×2017							-0.106***	[0.002]		
bb_0×2014							-0.112***	[0.002]		
bb_0×2015							-0.159***	[0.002]		
bb_0×2016							-0.202***	[0.002]		
bb_0×2017							-0.163***	[0.002]		
clean record×A									-0.157***	[0.001]
clean record×B									-0.131***	[0.001]
clean record×C									-0.162***	[0.002]
clean record×D									-0.168***	[0.002]
clean record×E									-0.187***	[0.002]
clean record×MEDIUM									-0.144***	[0.001]
clean record×SMALL									-0.155***	[0.001]
BB×B									-0.129***	[0.002]
BB×C									-0.103***	[0.002]
BB×E									-0.060***	[0.006]
BB×MEDIUM									-0.104***	[0.002]
BB×SMALL									-0.068***	[0.003]
policyholder char.	Yes		Yes		Yes		Yes		Yes	
clauses	Yes		Yes		Yes		Yes		Yes	
tenure FE	Yes		Yes		Yes		Yes		Yes	
loading cost	Yes		Yes		Yes		Yes		Yes	
measure of fraud incidence	Yes		Yes		Yes		Yes		Yes	
car char.	Yes		Yes		Yes		Yes		Yes	
area char.	Yes		Yes		Yes		Yes		Yes	
insurer FE	Yes		Yes		Yes		Yes		Yes	
province FE	Yes		Yes		Yes		Yes		Yes	
lagged controls	No		No		Yes		Yes		Yes	
lagged premium	No		No		Yes		Yes		Yes	
general. residuals clean record	No		No		Yes		Yes		Yes	
general. residuals BB	No		No		Yes		Yes		Yes	
R^2	0.525		0.430		0.456		0.460		0.458	
N	4,553,471		4,553,471		2,972,345		2,972,345		2,972,345	

NOTES: This table reports the effect of a clean driving record and of the black box on the log of the premium (the dependent variable).
Columns (1) and (2) report the estimates obtained by the OLS and FE estimator applied to specification (3).
Columns (3)-(5) report the estimates from the CF-FE estimator (specification (12) is estimated by the FE estimator). In these regressions I also control for the residuals from the first step equations, the generalized residuals from the four probit models.
The estimating sample in (1) and (2) is represented by contracts underwritten by all insurers in the period 2013-Q3:2017, while the estimating samples in columns (3)-(5) by contracts underwritten in the period 2014-Q3:2017.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses, and clustered at the province level in (1).

TABLE 14. The Effect of Driving Records on the Premium Across Insurers

	(1)		(2)		(3)		(4)		
Insurer	1 Accident on AR		2 Accidents on AR		$\geq$ 2 Accidents on AR		Driving Band		
A	0.070***	[0.001]	0.189***	[0.002]	0.284***	[0.006]	1 of 5	-0.116***	[0.002]
B	0.080***	[0.001]	0.146***	[0.003]	0.220***	[0.009]	2 of 5	-0.078***	[0.003]
C	0.071***	[0.002]	0.171***	[0.004]	0.216***	[0.011]	3 of 5	-0.003**	[0.002]
D	0.027***	[0.002]	0.079***	[0.004]	0.169***	[0.012]	4 of 5	0.016***	[0.002]
E	0.132***	[0.002]	0.337***	[0.006]	0.380***	[0.021]	5 of 5	0.047***	[0.003]
MEDIUM	0.074***	[0.001]	0.166***	[0.002]	0.241***	[0.005]	1 of 7	-0.134***	[0.002]
SMALL	0.091***	[0.001]	0.178***	[0.003]	0.228***	[0.007]	2 of 7	-0.100***	[0.002]
							3 of 7	-0.066***	[0.002]
	BM 1		BM 2		BM 3		4 of 7	-0.038***	[0.001]
A	-0.570***	[0.004]	-0.477***	[0.004]	-0.441***	[0.004]	5 of 7	-0.027***	[0.002]
B	-0.569***	[0.005]	-0.519***	[0.005]	-0.415***	[0.005]	6 of 7	-0.017***	[0.002]
C	-0.614***	[0.005]	-0.559***	[0.006]	-0.444***	[0.005]	7 of 7	0.013***	[0.003]
D	-0.680***	[0.006]	-0.567***	[0.007]	-0.446***	[0.006]			
E	-0.630***	[0.008]	-0.550***	[0.009]	-0.505***	[0.008]			
MEDIUM	-0.560***	[0.004]	-0.497***	[0.004]	-0.379***	[0.004]			
SMALL	-0.614***	[0.005]	-0.548***	[0.005]	-0.456***	[0.004]			
	BM 4		BM 5		BM 6				
A	-0.352***	[0.004]	-0.302***	[0.004]	-0.230***	[0.004]			
B	-0.385***	[0.005]	-0.338***	[0.005]	-0.262***	[0.005]			
C	-0.389***	[0.006]	-0.320***	[0.006]	-0.232***	[0.006]			
D	-0.414***	[0.007]	-0.326***	[0.007]	-0.226***	[0.007]			
E	-0.416***	[0.009]	-0.348***	[0.009]	-0.284***	[0.009]			
MEDIUM	-0.352***	[0.004]	-0.302***	[0.004]	-0.213***	[0.004]			
SMALL	-0.406***	[0.005]	-0.345***	[0.005]	-0.258***	[0.005]			
	BM 7		BM 8		BM 9				
A	-0.169***	[0.004]	-0.133***	[0.004]	-0.050***	[0.003]			
B	-0.215***	[0.006]	-0.167***	[0.006]	-0.077***	[0.004]			
C	-0.207***	[0.006]	-0.147***	[0.007]	-0.053***	[0.004]			
D	-0.182***	[0.008]	-0.121***	[0.008]	-0.041***	[0.006]			
E	-0.224***	[0.010]	-0.188***	[0.010]	-0.104***	[0.008]			
MEDIUM	-0.174***	[0.004]	-0.144***	[0.004]	-0.052***	[0.002]			
SMALL	-0.197***	[0.005]	-0.164***	[0.005]	-0.072***	[0.004]			

NOTES: This table reports the coefficients on the BM class and number of accidents on record interacted with insurer dummies, as from regression specification (13). The estimates are obtained the CF-FE estimator described in the main text. The set of controls is listed at the bottom of table 13 (column (3)). *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

TABLE 15. Penalties Across Insurers

Insurer	BM	No. Acc AR	Penalty	BM	No. Acc AR	Penalty	BM	No. Acc AR	Penalty	BM	No. Acc AR	Penalty
A	1	0	19.85	2	0	28.74	3	0	24.42	7	0	24.88
B	1	0	23.48	2	0	26.38	3	0	26.06	7	0	26.53
C	1	0	24.09	2	0	29.60	3	0	31.03	7	0	25.11
D	1	0	26.10	2	0	29.26	3	0	26.75	7	0	21.24
E	1	0	25.65	2	0	34.56	3	0	33.32	7	0	31.14
MEDIUM	1	0	25.47	2	0	28.14	3	0	26.95	7	0	23.50
SMALL	1	0	24.86	2	0	29.82	3	0	29.44	7	0	27.62
A	1	1	24.82	2	1	33.71	3	1	29.39	7	1	29.84
B	1	1	22.15	2	1	25.05	3	1	24.73	7	1	25.20
C	1	1	26.94	2	1	32.45	3	1	33.89	7	1	27.97
D	1	1	28.58	2	1	31.75	3	1	29.23	7	1	23.73
E	1	1	32.99	2	1	41.89	3	1	40.65	7	1	38.47
MEDIUM	1	1	27.22	2	1	29.89	3	1	28.69	7	1	25.25
SMALL	1	1	24.49	2	1	29.45	3	1	29.07	7	1	27.25
A	1	2	22.39	2	2	31.28	3	2	26.95	7	2	27.41
B	1	2	22.85	2	2	25.75	3	2	25.43	7	2	25.91
C	1	2	21.42	2	2	26.93	3	2	28.37	7	2	22.45
D	1	2	32.42	2	2	35.59	3	2	33.07	7	2	27.57
E	1	2	16.82	2	2	25.73	3	2	24.49	7	2	22.31
MEDIUM	1	2	25.54	2	2	28.21	3	2	27.01	7	2	23.57
SMALL	1	2	20.81	2	2	25.77	3	2	25.39	7	2	23.58
A	4	0	28.15	5	0	25.34	6	0	23.89	8	0	23.84
B	4	0	23.22	5	0	25.05	6	0	25.14	8	0	29.47
C	4	0	28.30	5	0	25.33	6	0	24.42	8	0	27.82
D	4	0	24.64	5	0	25.94	6	0	23.24	8	0	20.88
E	4	0	35.26	5	0	32.36	6	0	29.19	8	0	35.57
MEDIUM	4	0	24.07	5	0	25.25	6	0	23.27	8	0	24.83
SMALL	4	0	28.86	5	0	29.94	6	0	27.16	8	0	28.82
A	4	1	33.11	5	1	30.30	6	1	28.86	8	1	28.80
B	4	1	21.89	5	1	23.72	6	1	23.81	8	1	28.14
C	4	1	31.15	5	1	28.19	6	1	27.28	8	1	30.67
D	4	1	27.13	5	1	28.42	6	1	25.72	8	1	23.37
E	4	1	42.59	5	1	39.70	6	1	36.53	8	1	42.90
MEDIUM	4	1	25.81	5	1	27.00	6	1	25.01	8	1	26.58
SMALL	4	1	28.49	5	1	29.57	6	1	26.80	8	1	28.45
A	4	2	30.68	5	2	27.87	6	2	26.42	8	2	26.37
B	4	2	22.59	5	2	24.43	6	2	24.51	8	2	28.84
C	4	2	25.63	5	2	22.66	6	2	21.76	8	2	25.15
D	4	2	30.97	5	2	32.26	6	2	29.56	8	2	27.21
E	4	2	26.43	5	2	23.54	6	2	20.37	8	2	26.74
MEDIUM	4	2	24.13	5	2	25.32	6	2	23.33	8	2	24.90
SMALL	4	2	24.81	5	2	25.89	6	2	23.12	8	2	24.77

NOTES: This table reports the penalties–percentage increase of the premium after the occurrence of an accident–across insurers at each driving record. Penalties are estimated using the coefficients reported in table 14 through the method described in the main text.

TABLE 16. State Dependence and Moral Hazard

	(1)		(2)		(3)		(4)	
BM 1	20.146***	[0.213]	15.165***	[0.319]	5.791***	[0.507]	-0.023	[0.940]
BM 2	13.353***	[0.210]	6.867***	[0.313]	3.800***	[0.496]	0.303	[0.920]
BM 3	10.092***	[0.204]	9.847***	[0.304]	6.303***	[0.482]	1.854**	[0.897]
BM 4	8.984***	[0.198]	6.353***	[0.295]	3.409***	[0.466]	0.799	[0.869]
BM 5	7.033***	[0.192]	5.020***	[0.284]	2.942***	[0.449]	0.701	[0.832]
BM 6	5.483***	[0.184]	4.322***	[0.271]	2.478***	[0.424]	1.100	[0.779]
BM 7	4.215***	[0.174]	2.967***	[0.254]	1.764***	[0.391]	1.079	[0.712]
BM 8	2.928***	[0.163]	2.224***	[0.231]	1.544***	[0.346]	1.634***	[0.620]
BM 9	1.671***	[0.151]	1.340***	[0.204]	1.163***	[0.287]	0.618	[0.473]
1 acc AR	-17.032***	[0.063]	-17.814***	[0.084]	-16.099***	[0.116]	-12.868***	[0.195]
2 acc AR	-26.050***	[0.150]	-30.582***	[0.201]	-27.833***	[0.276]	-23.593***	[0.460]
acc AR >2	-3.749***	[0.074]	-39.297***	[0.458]	-35.532***	[0.639]	-30.277***	[1.077]
a_{t-1}			-0.274***	[0.001]	-0.468***	[0.001]	-0.722***	[0.002]
a_{t-2}					-0.274***	[0.001]	-0.472***	[0.002]
a_{t-3}							-0.233***	[0.002]
policyholder char.	Yes		Yes		Yes		Yes	
clauses	Yes		Yes		Yes		Yes	
tenure FE	Yes		Yes		Yes		Yes	
fraud indicator	Yes		Yes		Yes		Yes	
car char.	Yes		Yes		Yes		Yes	
area char.	Yes		Yes		Yes		Yes	
province FE	Yes		Yes		Yes		Yes	
insurer FE	Yes		Yes		Yes		Yes	
Contr. Year FE	Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes	
Residualized Premium	Yes		Yes		Yes		Yes	
R^2	0.055		0.133		0.242		0.376	
N	4,553,418		3,047,052		1,895,653		1,052,350	

NOTES: This table reports fixed effect estimates of the effect of driving records on the frequency of accidents. The dependent variable takes value 100 if one ore more accidents occur during year t and zero otherwise.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

TABLE 17. Number of Civil Suits Related to Auto Insurance Claims

Region	(1) No. of Unsettled Claims	(2) No. of New Claims	(3) No. Settled Claims	(4) New − Settled Claims
Piemonte	6,864	4,199	4,126	73
Torino	3,928	2,544	2,481	63
Valle d'Aosta	311	134	142	-8
Liguria	4,248	2,567	2,320	247
Lombardia	15,117	8,818	8,444	374
Milano	8,179	4,982	4,840	142
Trentino A.A.	947	518	442	76
Veneto	8,391	3,872	4,386	-514
Friuli V. Giulia	2,089	1,081	1,157	-76
Emilia Romagna	9,606	4,983	5,446	-463
Marche	3,288	1,717	1,831	-114
Toscana	9,527	4,795	5,109	-314
Umbria	3,077	1,557	1,572	-15
Lazio	32,884	16,073	17,135	-1,062
Roma	23,016	11,562	12,336	-774
Campania	84,168	51,284	49,585	1,699
Napoli	56,020	32,531	31,824	707
Salerno	9,014	6,157	5,888	269
Caserta	12,255	8,219	7,841	378
Abruzzo	3,869	2,150	2,146	4
Molise	2,226	1,511	1,209	302
Puglia	15,949	8,974	10,231	-1,257
Basilicata	2,316	1,512	1,442	70
Calabria	10,985	4,419	5,004	-585
Sicilia	14,104	7,520	7,635	-115
Palermo	2,555	1,513	1,383	130
Sardegna	2,570	1,052	1,147	-95
Italy	232,536	128,736	130,509	-1,773

NOTES: This table reports the number of rc auto civil suits in the Italian regions in 2017.
SOURCE: This table is taken from the IVASS bulletin available at:
https://www.ivass.it/pubblicazioni-e-statistiche/statistiche/bollettino-statistico/2019/n4/Bollettino_contenzioso_r.c.auto_natanti_2010_2017.pdf

TABLE 18. The Effect of the Black Box on Liquidation Time

	(1) Liquidation Time		(2) Indemnity		(3) Presence of Injuries	
black box	0.047**	[0.021]	-0.010	[0.010]	-0.022	[0.015]
black box×indemnity	-0.000	[0.000]	-0.000	[0.000]		
indemnity	0.000***	[0.000]	0.000***	[0.000]		
injury	1.081***	[0.037]	0.265***	[0.014]		
black box×injury	-0.148***	[0.049]	0.002	[0.016]		
direct	-0.152	[0.114]	0.142***	[0.037]	0.248*	[0.144]
policyholder char.	Yes		Yes		Yes	
driving record FE	Yes		Yes		Yes	
loading costs	Yes		Yes		Yes	
tenure FE	Yes		Yes		Yes	
insurer FE	Yes		Yes		Yes	
no. installments FE	Yes		Yes		Yes	
residualized premium	Yes		Yes		Yes	
province×year FE	Yes		Yes		Yes	
R^2						
N	96,818		99,584		110,033	

NOTES: This table reports the coefficient from Poisson model, in which the dependent variable is the liquidation time–column (1)–and the indemnity (column (2)). In column (3) coefficients from a probit model, in which the dependent variable takes value of one if an injury is present, are reported.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses and clustered at the province level.

TABLE 19. The Effect of Price Shifters on the Black Box Demand

	(1) New Adopters A	(2) Old Adopters A	(3) B	(4) C	(5) E	(6) Medium	(7) Small
				Panel A			
flat discount A	0.127***						
	(0.024)						
BB discount other insurers			-0.698***	0.455***	0.014	-0.193***	0.251***
			(0.022)	(0.045)	(0.023)	(0.046)	(0.016)
liquidation efficiency	2.312***	-0.826	17.834***	-0.585*	-0.113	-3.231	-11.224***
	(0.496)	(2.361)	(1.033)	(0.317)	(1.005)	(2.482)	(0.783)
7 BANDS	-11.513***	50.473***					
	(1.287)	(2.138)					
10 BANDS	-12.272***	55.923***					
	(4.634)	(2.450)					
				Panel B			
SOARF_SINDEN	69.098***	76.445	497.110***	-127.232***	-1.210	-172.954***	-270.097***
	(4.698)	(48.494)	(28.590)	(12.604)	(24.485)	(58.805)	(20.567)
Penalty	-0.181***	0.067	0.189***	-0.043	-0.016	0.102**	0.021
	(0.035)	(0.042)	(0.038)	(0.028)	(0.012)	(0.047)	(0.027)
a_{t-1}	1.800***	-0.313	0.694***	1.477***	0.143	0.530*	0.524***
	(0.470)	(0.306)	(0.155)	(0.511)	(0.148)	(0.291)	(0.176)
age 18-25	6.270***	1.772**	1.247**	2.659***	0.043	0.654*	0.755***
	(0.756)	(0.729)	(0.548)	(0.385)	(0.173)	(0.350)	(0.184)
age 25-34	2.287***	0.018	0.573***	1.295***	0.091**	0.949***	0.133**
	(0.270)	(0.277)	(0.166)	(0.197)	(0.043)	(0.136)	(0.066)
age 35-44	0.306*	0.187	-0.070	0.291**	-0.057	0.509***	-0.140***
	(0.159)	(0.270)	(0.067)	(0.132)	(0.055)	(0.094)	(0.052)
age 45-60	0.718***	0.181	0.084	0.488***	0.069**	0.276***	-0.070
	(0.153)	(0.213)	(0.105)	(0.118)	(0.031)	(0.091)	(0.047)
three install.	-2.483***	-3.241***	-1.478***	-3.594***	-0.626***	-6.281***	-0.138
	(0.629)	(1.168)	(0.375)	(1.008)	(0.199)	(1.128)	(0.126)
two install.	-1.303***	0.310*	-1.165***	-1.266***	0.022	-0.298*	-0.212***
	(0.142)	(0.159)	(0.120)	(0.189)	(0.044)	(0.163)	(0.062)
one acc on AR	2.662***	1.387***	1.807***	0.600***	0.774***	0.015	0.471***
	(0.261)	(0.367)	(0.207)	(0.199)	(0.179)	(0.123)	(0.081)
two acc on AR	5.819***	3.483***	3.689***	2.016***	-0.287	1.091***	1.481***
	(0.545)	(0.623)	(0.587)	(0.462)	(0.206)	(0.251)	(0.526)
BM 1	8.073***	-0.424	-5.143***	-0.548**	0.105	-0.553	-0.931
	(1.478)	(0.380)	(1.094)	(0.249)	(0.380)	(1.944)	(0.928)
BM 2-3	10.763***	-1.002***	-5.020***	0.047	0.303	-0.313	-0.854
	(1.671)	(0.292)	(1.183)	(0.268)	(0.471)	(1.998)	(0.984)
BM 4-10	12.459***	0.000	-4.692***	0.000	0.334	0.490	-0.563
	(1.704)	–	(1.236)	–	(0.484)	(1.865)	(0.984)
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes	Yes
tenure FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
area char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
insurer FE	No	No	Yes	Yes	Yes	Yes	Yes
province × contr. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.314	0.496	0.044	0.105	0.048	0.116	0.413
N	342,782	150,304	247,029	196,052	112,090	513,672	373,366

NOTES: This table reports OLS estimates on the effect of discounts on the demand for black box. In column (1) and (2) the dependent variable takes value 100 if a policyholder covered by A adopts the black box at year t ($bb0_t = 1$), conditional on not adopting the black box, and zero otherwise. In column (3) the dependent variables takes the value of 100 if a policyholder adopts the black box during year t, conditional on adopting the black box and having being covered by A at year $t-1$, and zero otherwise. The estimating sample is restricted to contracts underwritten by A over the period 2014-Q3:2017.
In column (4) and (5) the dependent variable takes the value of 100 if policyholders covered by a top-5 insurer and medium/small insurers adopt the black box during year t, and zero otherwise. Contracts underwritten by insurers not offering the black box are not included in the estimating sample *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses and clustered at the province level.

TABLE 20. The Effect of Financial Incentives on the Frequency of Accidents

	(1) OLS	(2) OLS	(3) OLS-CF	(4) FE	(5) FE-CF	(6) FE-CF
Penalty (percentage points)	-0.012	-0.013	-0.013	-0.471***	-0.471***	-0.436***
	[0.008]	[0.008]	[0.008]	[0.011]	[0.011]	[0.012]
First BB year insurer A		-0.245**	-0.078	-0.798***	-0.832***	
		[0.105]	[0.121]	[0.174]	[0.188]	
BB other insurer	-0.101	-0.100	0.034	-0.441***	-0.509**	4.581***
	[0.114]	[0.115]	[0.122]	[0.148]	[0.205]	[0.918]
BB× insurer A	-0.08					0.972*
	[0.076]					[0.585]
BB insurer A×Penalty.						-0.117***
						[0.023]
BB other insurers×Penalty						-0.203***
						[0.032]
BAND 1 out of 5		-1.749***	-1.680***	-1.612***	-1.643***	
		[0.344]	[0.344]	[0.501]	[0.505]	
BAND 2 out of 5		-1.124**	-1.049**	-1.306**	-1.340**	
		[0.503]	[0.499]	[0.623]	[0.627]	
BAND 3 out of 5		-0.863***	-0.791***	-1.220***	-1.254***	
		[0.235]	[0.240]	[0.344]	[0.351]	
BAND 4 out of 5		1.009***	1.091***	0.049	0.014	
		[0.250]	[0.251]	[0.330]	[0.338]	
BAND 5 out of 5		1.414***	1.500***	-0.120	-0.157	
		[0.443]	[0.448]	[0.560]	[0.565]	
BAND 1 out of 7		-1.317***	-1.269***	-2.261***	-2.281***	
		[0.166]	[0.164]	[0.345]	[0.347]	
BAND 2 out of 7		-0.641***	-0.591**	-1.881***	-1.901***	
		[0.231]	[0.231]	[0.374]	[0.376]	
BAND 3 out of 7		-0.674***	-0.623***	-2.164***	-2.184***	
		[0.156]	[0.153]	[0.293]	[0.296]	
BAND 4 out of 7		0.092	0.146	-1.461***	-1.482***	
		[0.130]	[0.133]	[0.238]	[0.242]	
BAND 5 out of 7		0.580**	0.635***	-1.584***	-1.605***	
		[0.236]	[0.239]	[0.293]	[0.296]	
BAND 6 out of 7		1.350***	1.406***	-0.702	-0.723*	
		[0.314]	[0.318]	[0.428]	[0.430]	
BAND 7 out of 7		1.976***	2.033***	-0.600	-0.622	
		[0.314]	[0.318]	[0.501]	[0.503]	
a_{t-1}	3.029***	3.020***	3.019***	-47.531***	-47.531***	-47.527***
	[0.268]	[0.267]	[0.267]	[0.105]	[0.105]	[0.105]
a_{t-2}	1.994***	1.987***	1.988***	-27.832***	-27.832***	-27.829***
	[0.220]	[0.219]	[0.219]	[0.107]	[0.107]	[0.107]
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes
driving record FE	Yes	Yes	Yes	Yes	Yes	Yes
no. install. FE	Yes	Yes	Yes	Yes	Yes	Yes
tenure FE	Yes	Yes	Yes	Yes	Yes	Yes
proxy of fraud's incidence	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes
area char.	Yes	Yes	Yes	Yes	Yes	Yes
gen. residuals BB	No	No	Yes		Yes	Yes
residualized premium	Yes	Yes	Yes	Yes	Yes	Yes
insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
province×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.007	0.007	0.007	0.243	0.243	0.243
N	1,798,068	1,798,068	1,798,068	1,798,068	1,798,068	1,798,068

NOTES: This table reports the effect of penalties and black box on the frequency accidents. The dependent variable takes value of 100 if one or more accidents at fault occur within a year, and zero otherwise.
In columns (2)-(5) estimates of regression specification (19) obtained by the OLS, OLS-CF, FE, and FE-CF estimator are reported, respectively. In column (1) OLS estimates obtained by controlling for a single black box dummy are reported. In column (6) the black box indicator is interacted with penalties.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses and clustered at the province level in the OLS regressions.

TABLE 21. The Effect of Financial Incentives on the Frequency of Accidents—Non-Linear Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Penalty (marginal effect)	-0.347***	-0.264***	-0.095***	-0.362***	-0.249***	-0.089***
	[0.014]	[0.022]	[0.022]	[0.014]	[0.022]	[0.022]
Penalty	Yes	Yes	Yes	Yes	Yes	Yes
Penalty^2	Yes	Yes	Yes	Yes	Yes	Yes
Penalty^3	No	No	No	Yes	Yes	Yes
a_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
a_{t-2}	Yes	Yes	No	Yes	Yes	No
a_{t-1}^{NF}	Yes	Yes	No	Yes	Yes	No
indemnity$_{t-1}$	No	Yes	Yes	No	Yes	Yes
injury$_{t-1}$	No	Yes	Yes	No	Yes	Yes
driving record FE	Yes	Yes	Yes	Yes	Yes	Yes
driving record$_{t-1}$ FE	No	No	Yes	No	No	Yes
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes
no. install. FE	Yes	Yes	Yes	Yes	Yes	Yes
tenure FE	Yes	Yes	Yes	Yes	Yes	Yes
proxy of fraud's incidence	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes
area char.	Yes	Yes	Yes	Yes	Yes	Yes
gen. residuals BB	No	No	Yes		Yes	Yes
residualized premium	Yes	Yes	Yes	Yes	Yes	Yes
insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
province×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,798,068	1,091,118	1,233,290	1,798,068	1,091,118	1,233,290

NOTES: This table reports the marginal effect of penalties on the frequency accidents. The dependent variable takes value of 100 if one or more accidents at fault occur within a year, and zero otherwise. The estimates are obtained by the CF-FE estimator including quadratic and cubic terms. The linear specification corresponds to column (5) in table 20.

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

TABLE 22. The Effect of Financial Incentives on Distance Driven

	(1) OLS		(2) OLS		(3) FE		(4) FE	
Penalty	-0.012**	[0.006]	-0.013**	[0.006]	0.002*	[0.001]	0.001	[0.001]
man×Penalty			0.001	[0.002]				
residuals from selection equation	0.056***	[0.019]	0.056***	[0.019]				
policyholder char.	Yes		Yes		Yes		Yes	
clauses	Yes		Yes		Yes		Yes	
driving record FE	Yes		Yes		Yes		Yes	
previous year FE	Yes		Yes		Yes		Yes	
no. install. FE	Yes		Yes		Yes		Yes	
tenure FE	Yes		Yes		Yes		Yes	
residualized premium	Yes		Yes		Yes		Yes	
contr. year FE	Yes		Yes		Yes		Yes	
month FE	Yes		Yes		Yes		Yes	
proxy of fraud	Yes		Yes		Yes		Yes	
area char.	Yes		Yes		Yes		Yes	
R^2	0.207		0.207		0.022		0.029	
N	16,187		16,187		107,758		62,689	

NOTES: In columns (1) and (2) OLS estimates of the effect of penalties on the score from regression specification (22) are reported. Self-selection into the black box contract is taken into account by controlling for the residuals from the adoption equation (20). The estimating sample is restricted to first adopters covered by insurer A.
In columns (3) and (4) fixed effect estimates are reported. The estimating sample is represented by all black box contracts associated with a score.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses and clustered at the province level in parenthesis.

TABLE 23. The Effect of Self-Selection on Moral Hazard Estimates

	(1) (A)	(2) (B)	(3) (C)	(4) (D)	(5) (E)	(6) (Medium)	(7) (Small)
	Panel A: The Effect of Penalties on Accidents						
Penalty from full sample	-0.467***	-0.911***	-0.667***	-0.607***	-0.218***	-0.333***	-0.911***
	[0.016]	[0.042]	[0.020]	[0.048]	[0.023]	[0.022]	[0.034]
Penalty from insurer-specific sample	-3.309***	-1.545***	-1.661***	-0.927***	-0.065	-2.189***	-2.176***
	[0.054]	[0.070]	[0.037]	[0.102]	[0.078]	[0.094]	[0.070]
	Panel B: The effect of Black Box on Accidents						
BB from full sample	-1.814***	-1.655***	-0.399		-3.083***	-0.976***	-0.959*
	[0.204]	[0.345]	[0.338]		[1.046]	[0.264]	[0.550]
BB from insurer-specific sample	-2.063***	-1.874***	-0.512		0.142	-0.991*	-1.068
	[0.339]	[0.620]	[0.549]		[4.482]	[0.588]	[0.967]
policyholder char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes	Yes	Yes	Yes
tenure FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
proxy of fraud's incidence	Yes	Yes	Yes	Yes	Yes	Yes	Yes
car char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
area char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
insurer FE	Yes	No	No	No	No	No	No
a_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
a_{t-2}	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTES: In each column of this table the effect of penalties and black box on the frequency of accidents at the company-level is reported. In the first row of panels A and B, the company-specific coefficients from regression specification (23) are reported. In the second row of panel A and B the coefficients obtained using company-specific samples are reported. These coefficients are obtained by the CF-FE estimator. *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses and clustered at the province level in parentheses.

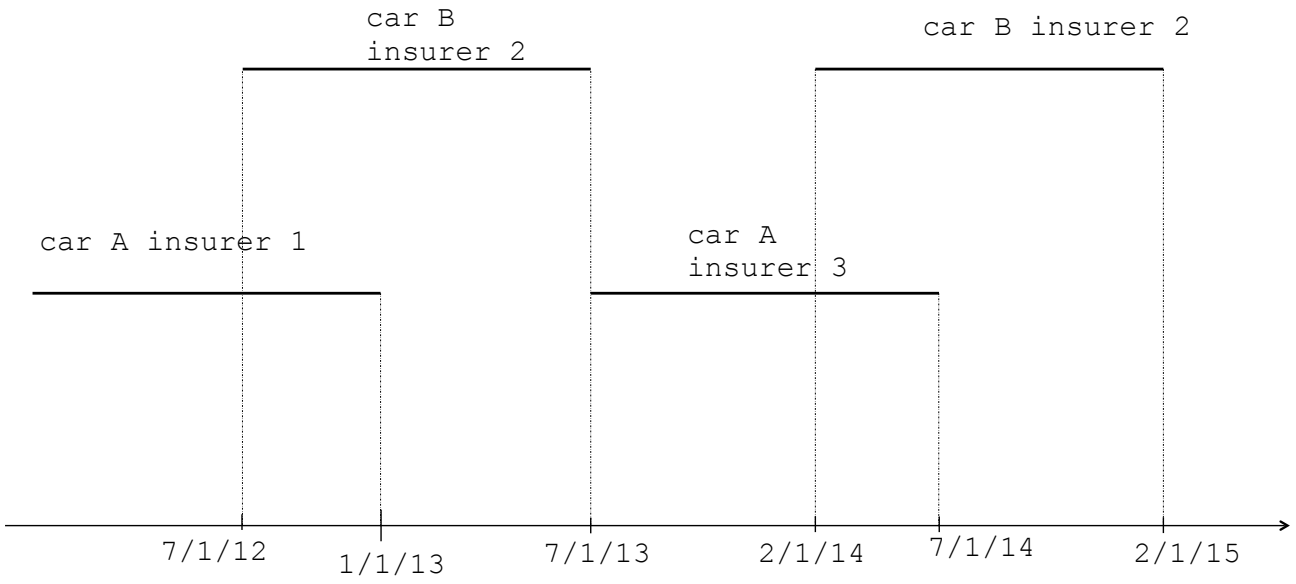
TABLE 24. Relationship Between Observables and Moving Decision

	(1) Stayers	(2) Movers	(3) Difference	(4) OLS	(5) P-value	(6) Marginal Effects
age	48.74	41.22	7.52	-0.001	0.00	1.05
man	0.58	0.58	0.00	0.002	0.00	0.91
medium city	0.18	0.19	0.00	0	0.00	1
big city	0.13	0.13	0.00	0.001	0.00	0.95
bm class	1.99	2.36	-0.37	0.001	0.00	0.95
no. acc on AR	0.16	0.15	0.01	-0.001	0.00	1.05
tenure (years)	3.28	2.59	0.70	-0.001	0.00	1.05
car age	8.45	8.00	0.45	0	0.00	1
cubic cilinder	14.03	14.16	-0.14	0	0.00	1
power (KW)	66.71	67.82	-1.12	0	0.00	1
diesel	0.44	0.50	-0.06	-0.001	0.00	1.05
petrol	0.52	0.45	0.07	-0.005	0.00	1.23
north	0.49	0.48	0.02	0.002	0.00	0.91
center	0.21	0.18	0.03	0	0.00	1
south	0.20	0.18	0.02			
islands	0.10	0.17	-0.07	0.018	0.00	0.18

Notes. This table shows means of the covariates between policyholders who do not change province of residence–column (1)–and those who move at least once–column (2)–within the period 2013-Q3:2017. The difference between column (1) and (2) is displayed in column (3).
The coefficients of an OLS regression and the p-values are shown in columns (4) and (5), respectively. The dependent variable takes value one if the policyholder moved at least once and zero otherwise. Each covariate has been standardized. The marginal effects relative to the sample mean (= 2.2%) are reported in column (6).

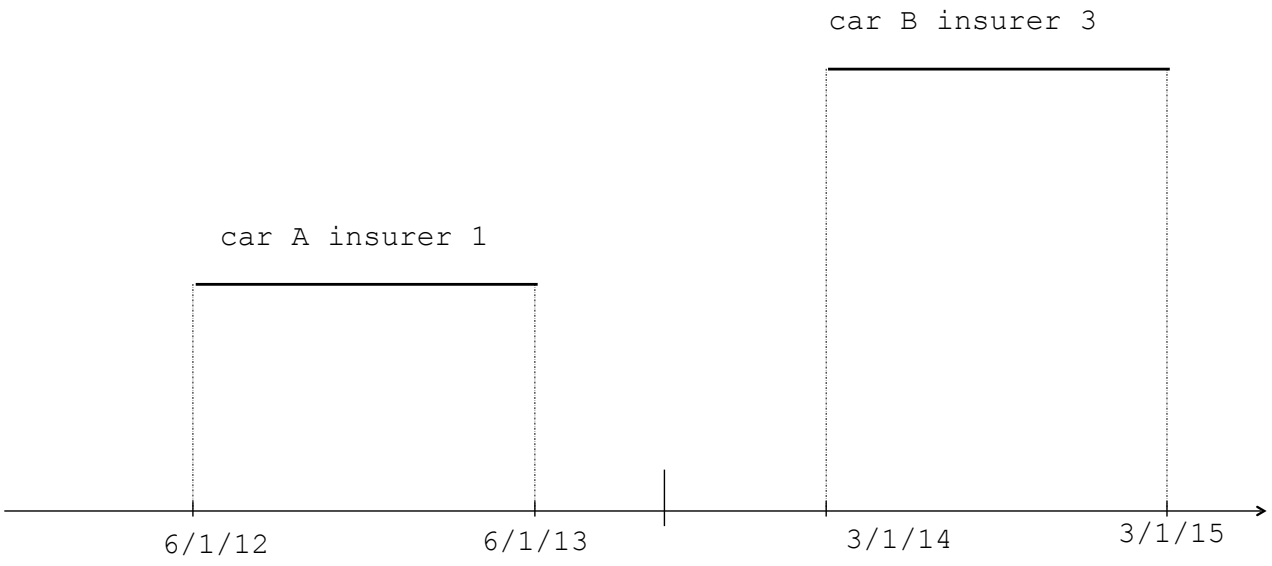
10. Figures

Figure 8. Example of Insurance Histories–I



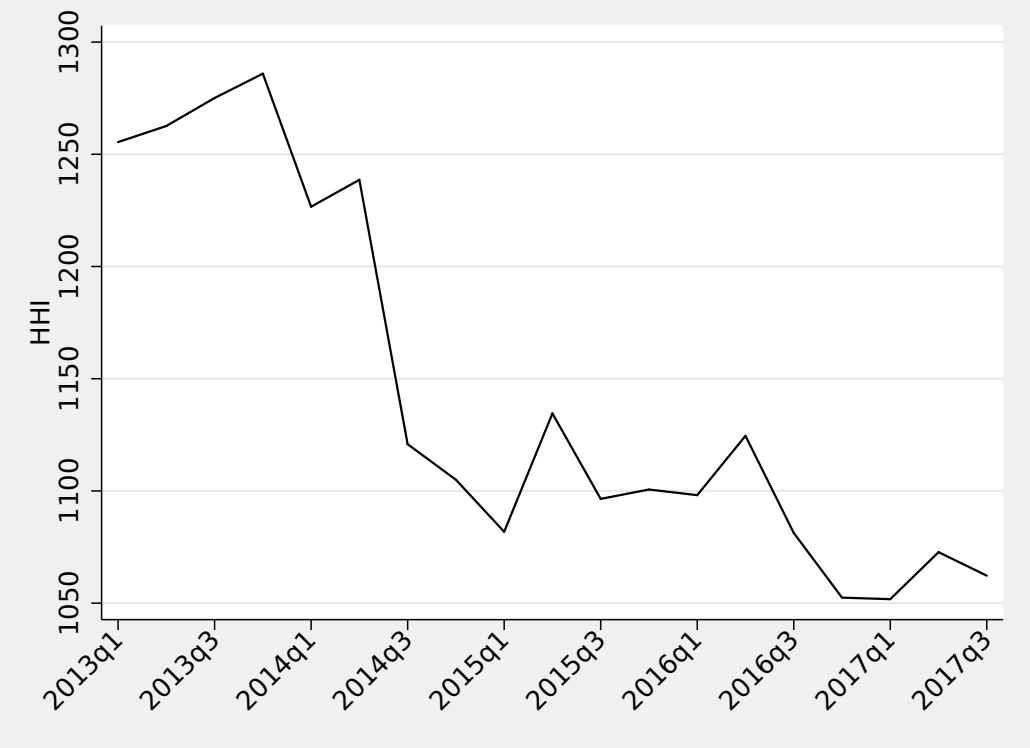
Note: In this chart a hypothetical insurance history is depicted. A policyholder covers two cars (A and B). The contract covering A spans the periods 1/1/2012-1/1/2013 and 7/1/2013-7/1/2014, i.e. the car is not covered in the period 2/1/2013-31/6/2013. Moreover, the policyholder switches from insurer 1 to 3 after the first of the two contractual years. Car B is covered in the contractual years 7/1/2012-7/1/2013 and 2/1/2014-2/1/2015 by insurer 2.

FIGURE 9. Example of Insurance Histories–II



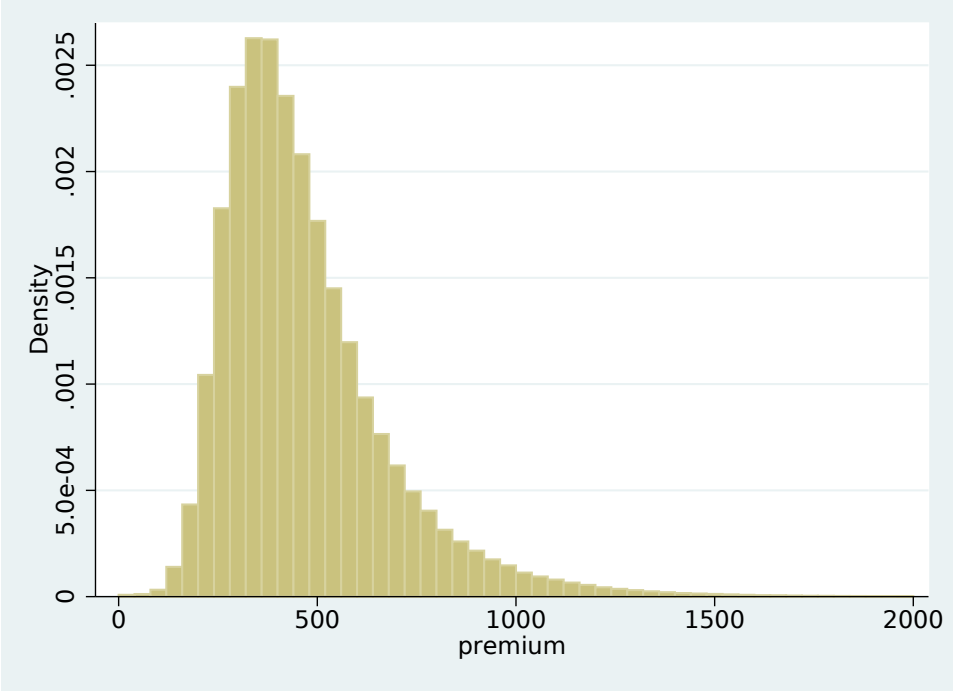
Note: In this chart a hypothetical insurance history is depicted. A policyholder covers two cars (A and B). The contract covering A spans the periods 6/1/2012-6/1/2013 and is underwritten by company 1; after the end of the first contractual year, the contract is not renewed. A second car B is purchased in 2014 and covered over the period 3/1/2014-3/1/2015 by company 3.

FIGURE 10. Time Trend of HHI Concentration Index



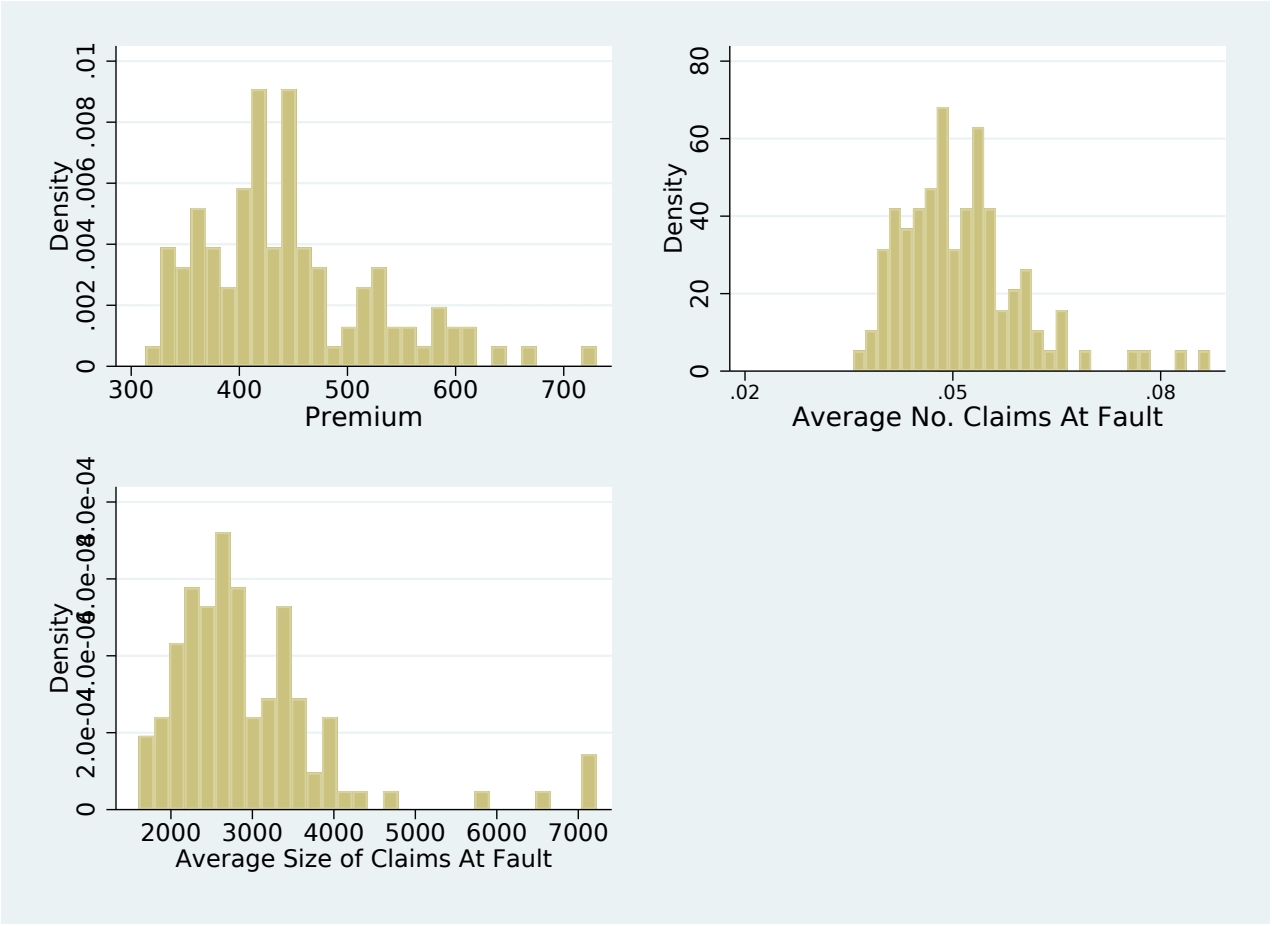
NOTES. This chart illustrates the time trend of the HHI concentration index.

FIGURE 11. Distribution of the Premium



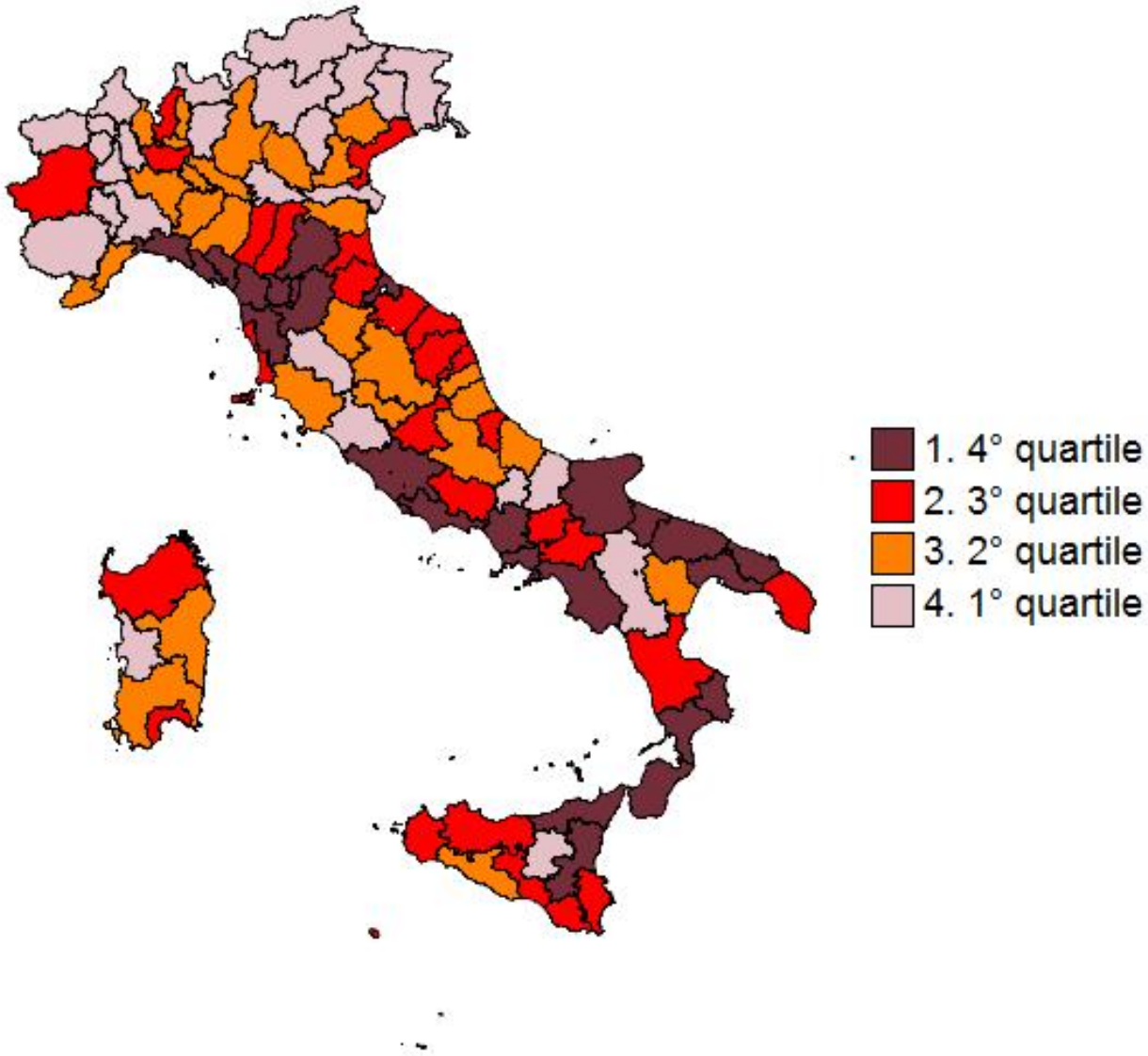
Note: The left panel contains the density of the indemnity trimmed using the 99^{th} percentile. The right panel contains the density of the logarithm of the indemnity.

FIGURE 12. Distribution of Premiums, Frequency, and Size of Claims Across Provinces



Note: This graph depicts the histogram of premiums, size and frequency of claims across provinces. The average premium is computed using IPER and the indemnities by merging the BDS with IPER. Contracts/claims from the third quarter of 2016 onward are excluded in the sample used to compute the frequency and size of claims to minimize the incompleteness of the claiming histories.

FIGURE 13. Map of Premiums Across Provinces



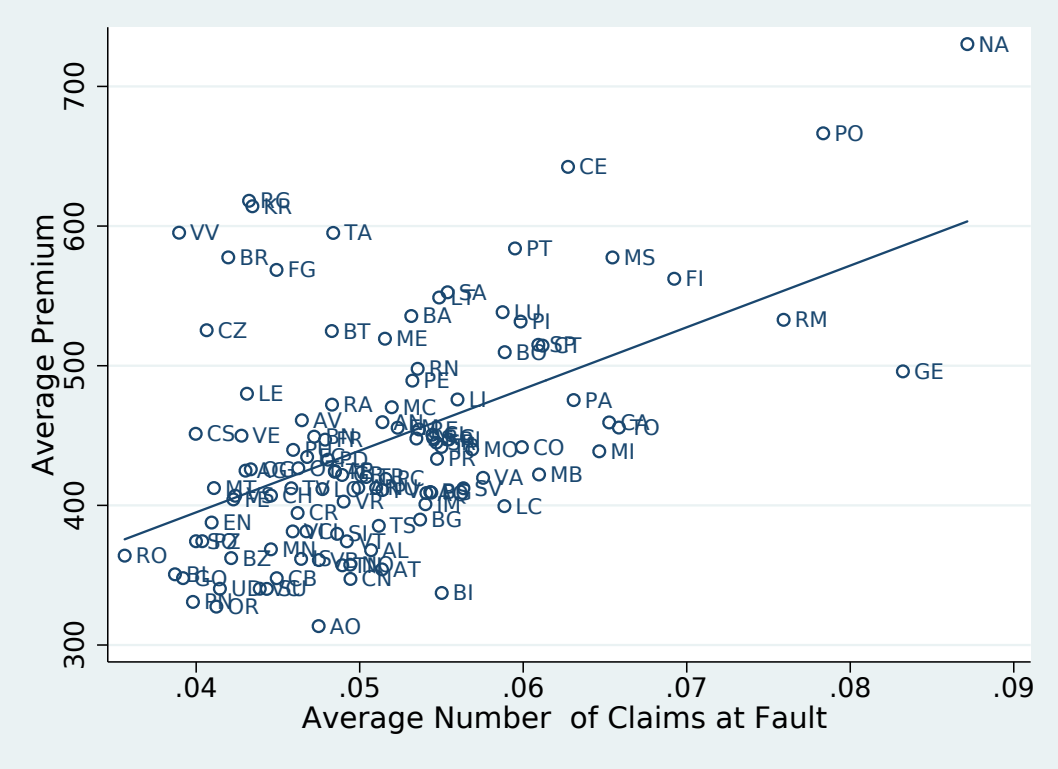
Note: This map shows the distribution of the premium across provinces in the period 2013-Q4:2017, discretized using the quartiles.

FIGURE 14. Relationship Between Premiums and Size of Claims Across Provinces



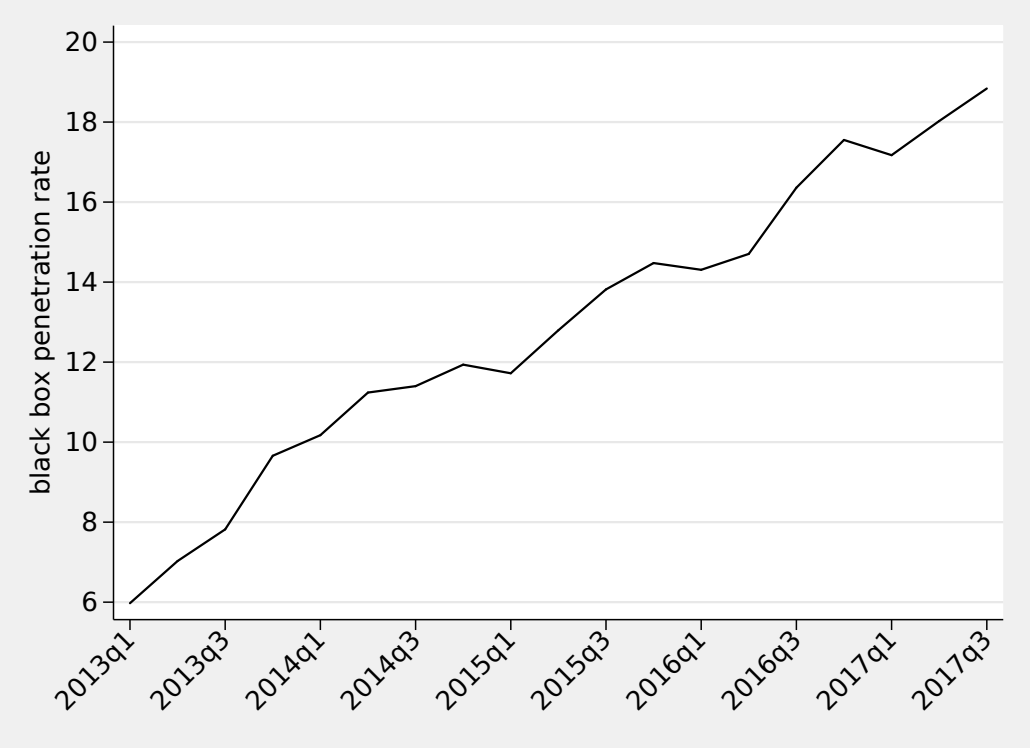
Note: This scatter plots the correlation between premium and indemnity across provinces. The average premium is computed using IPER and the indemnities by merging the BDS with IPER. Contracts/claims from the third quarter of 2016 onward are excluded to minimize the incompleteness of the claiming histories.

FIGURE 15. Relationship Between Premiums and Frequency of Claims Across Provinces



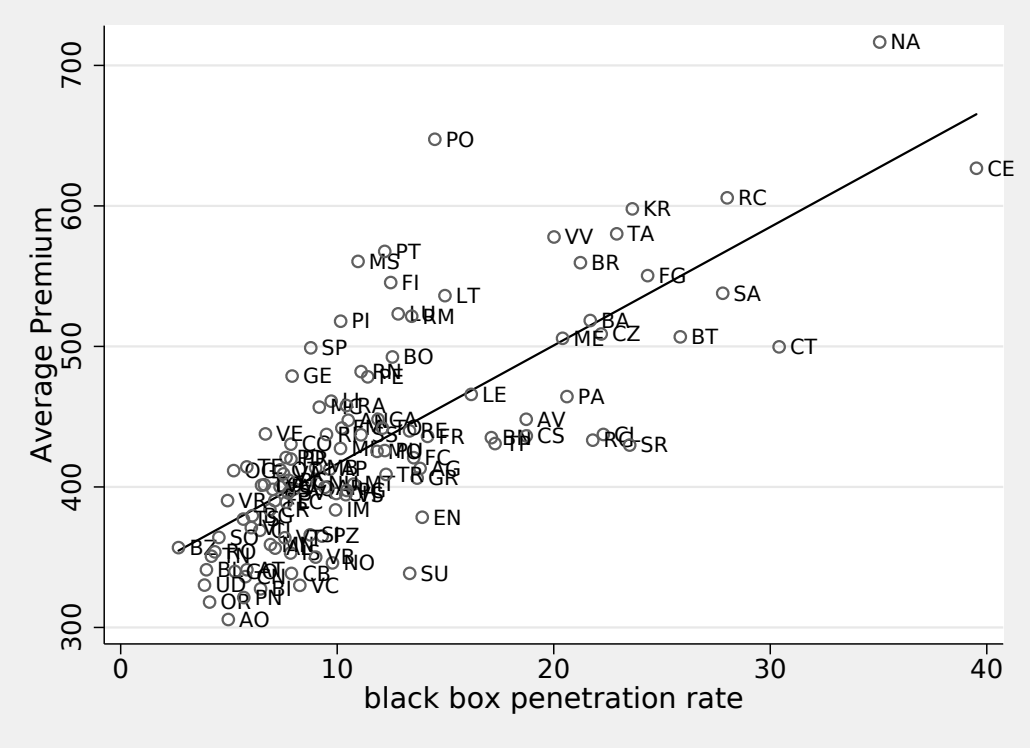
Note: This scatter plots the correlation between premium and the frequency of claims across provinces. The average premium is computed using IPER and the indemnities by merging the BDS with IPER. Contracts/claims from the third quarter of 2016 onward are excluded to minimize the incompleteness of the claiming histories.

FIGURE 16. Black Box Penetration Rate



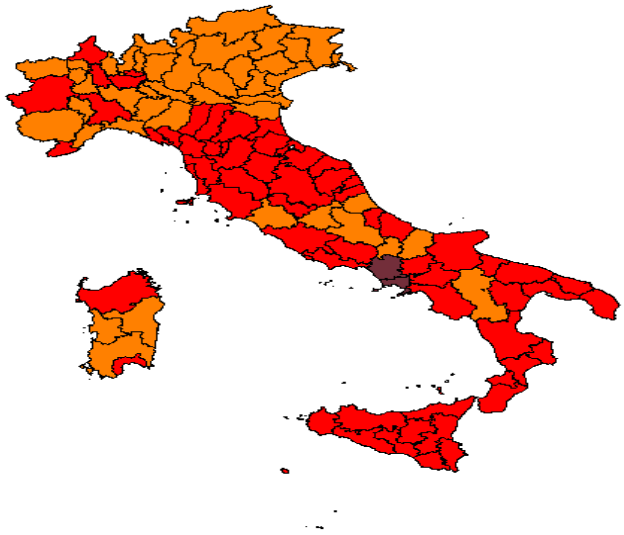
Note: This figure illustrates the black box penetration rate, defined as the fraction of contracts underwritten in a quarter featuring a black box penetration rate.

FIGURE 17. Black Box Penetration Rate and Premiums Across Provinces



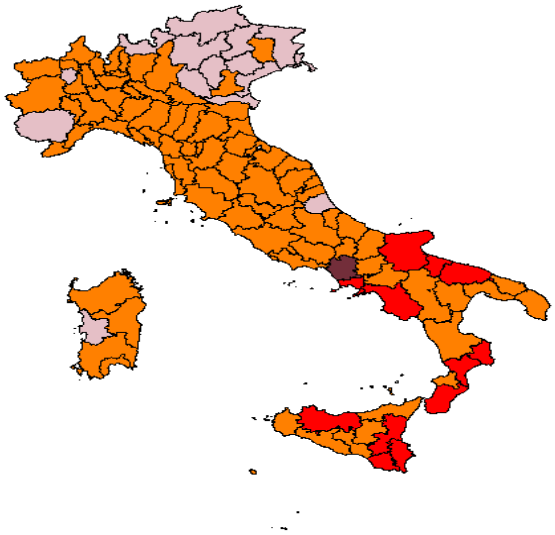
Note: This figure illustrates the black box penetration rate, defined as the fraction of contracts underwritten in a quarter featuring a black box penetration rate.

FIGURE 18. Black Box Penetration Rates in Q4:2014



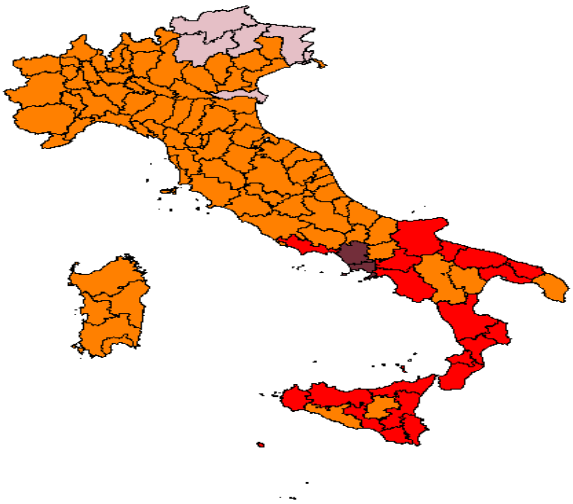
NOTES: This figure depicts the penetration rate across Italian Provinces in Q4:2014. There are four categories: 0–10% (grey), 10–30% (orange), 30–50% (red), $\geq$ 50% (brown).

FIGURE 19. Black Box Penetration Rates in Q4:2016



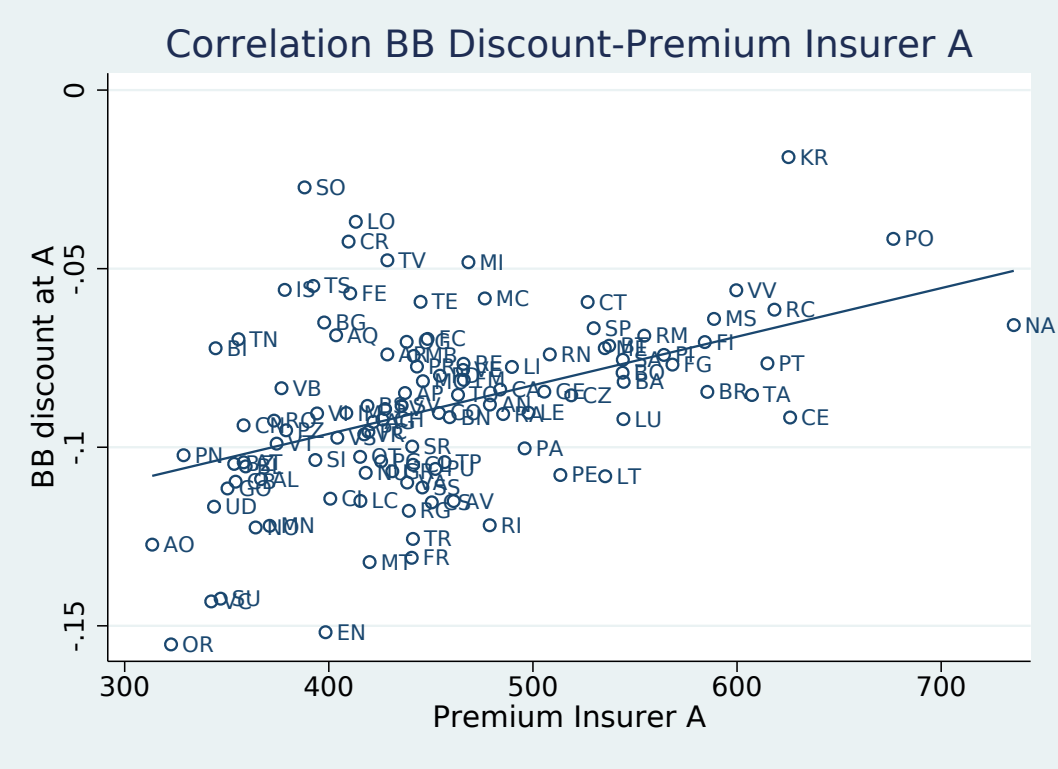
NOTES: This figure depicts the penetration rate across Italian Provinces in Q4:2014. There are four categories: 0–10% (grey), 10–30% (orange), 30–50% (red), $\geq$ 50% (brown).

FIGURE 20. Black Box Penetration Rates in Q4:2018



NOTES: This figure depicts the penetration rate across Italian Provinces in Q4:2014. There are four categories: 0–10% (grey), 10–30% (orange), 30–50% (red), $\geq$ 50% (brown).

FIGURE 21. Variation in the Black Box Discounts Across Provinces



NOTES: This figure shows the correlation between the estimated discounts on the black box by insurer and the average premium paid by A's insurees across provinces. These discounts are obtained by estimating by the CF-FE estimator a restricted specification of equation (13) in which the coefficients on the black box are assumed to be constant over time.

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Appendix A. Online Appendix

This online appendix is structured as follows: section A.1 contains summary statistics on observable heterogeneity in the pool of drivers covered by the top five insurers and the medium and small insurers; section A.2 shows the observable differences between insurers underwriting contracts through sales agents and those who do so online/by phone. In section A.3 I present the event history analysis based on the grace period and the identification strategy relying on the divestiture. I also discuss three confounders of the grace period research design: misreporting/fraud, learning, and seasonality effects. In section A.4 I estimate switching models and I show that policyholders with poor driving records change companies more frequently. Section B contains details on the procedure adopted to sample the core sample. In section C I describe the variables reported in the contracts I use in my econometric analysis. Sections C.1 and C.2 contain additional tables and figures, respectively.

A.1. **Pricing variables across insurers.** Table 26 shows the means of the pricing variables across groups of companies.

INSERT TABLE 26

The premium shows ample variation within the top 5 players: it ranges between 384 and 501 euros, while the average premium in the medium and small companies is 474 euros and 448 euros, respectively. The set of clauses adopted also shows substantial variability across insurers; for example, the expert driving clause ranges between 23.5% and 82.4%, and the black box between 0% (company E does not offer this clause) and 31.8%; the proportion of policyholders choosing the minimum mandatory liability limit ranges between 39% and 78%. This statistic points toward the presence of self-selection into companies because the liability coverage is a mandatory feature of all contracts. Regarding demographics, there are mild differences in age—the average policyholder is between 46.2 and 49.7 years old—and in the fraction of male policyholders across companies. The variation in the driving record captured by the bonus-malus class is limited: the minimum and maximum mean BM class equal 1.7 (company D) and 2.19 (medium companies), while the number of accidents on record exhibits substantial variability, ranging from 0.113 to 0.165. The switching rate is also heterogeneous: 15.1% of the policyholders covered by a small insurer change companies versus company E's switching rate of 9.2%. Table 27 reports several means related to claims: the average number of claims at-fault—for brevity, accident rate at-fault—equals 5.5% and ranges from 4.7% to 6.1% across the 7 groups of insurers, the mean indemnity corresponding with third parties in accidents at-fault equals 3,101 euros and ranges from 2,703 (A) to 3,502 euros (medium companies), and 16.9% of the claims at-fault involve bodily injuries. The average accident rate not at-fault equals 5.6%, and the indemnity received by the policyholder averages 2,941 euros and ranges from 2,403 to 3,268 euros. 67.5% of the claims are covered by CARD system and, again, there exists

considerable variation, ranging from 48% to 73.6%.

A more immediate visualization of the relationship between premiums and frequency/-severity of claims at the insurer level is shown in the scatter plots in figures 30 and 31. As expected, a positive correlation between the average number of claims at-fault and premiums emerges (panel A of figure 30), while the correlation between insurance rates (ρ) and size of the claims at-fault (panel B) is weaker ($\rho = -0.08$). Importantly, the figures show the large degree of variation in the premium(315-456 euros), accident rate at-fault (3.58-8.66%), and indemnities to third parties ($1,775$-$12,425$ euros) in the market. The same pattern emerges within the accidents not-at-fault, although the correlation between the premium and accident rate is weaker.

INSERT FIGURES 30 and 31

A.2. **Intermediation Channel.** Insurance contracts are underwritten in the Italian market either through sales agents—the so-called traditional companies—or by phone/internet, the so-called direct companies. About 12 percent of the market is covered by direct companies.

I compare direct and traditional companies in table 25. Distinctive differences between these two types of insurers emerge. First, direct insurers are characterized by lower administrative and claims servicing loading costs than traditional insurers—81.3 vs. 57.9 and 341.4 vs. 256.25 euros—which is consistent with the idea that not relying on sales agents allows these insurers to adopt a "lighter" cost structure.
Second, drivers covered by direct companies are charged, on average, 41 euros less than those covered by traditional companies (direct insurers pay considerable smaller fees (36 vs. 2 euros) on contracts); they hold a poorer driving record (the average bm class equals 2.4 vs. 1.81 at the traditional companies and the average number of claims on the AR equals 0.18 vs. 0.16); and they are about 4 years younger. Also, the frequency and severity of claims is higher within direct insurers. In terms of insurance plans, 14.5 percent of contracts underwritten by direct insurers feature the free driving clause vs. 52.25 percent; however, 44.2 percent of the "direct" ("traditional") insurees choose the minimum liability coverage. That is, lower(higher) coverage against accidents (not) at-fault is purchased by drivers covered by traditional (direct) insurers.
The data also show two more interesting facts: (i) the retention rate at the direct companies is about 7 percentage points lower than at the traditional companies, and (ii) the average profit per contract made by direct insurers is lower than that made by traditional insurers.[68]

[68]In fact, according to the BSD direct(traditional) insurers lose(gain) 5(37) euros, while using IPER and the BDS I obtain that direct(traditional) insurers lose(gain) 21(62) euros.

TABLE 25. Traditional and Direct Insurers

	Traditional		Direct	
	Mean	St. Err	Mean	St. error
	Data from IPER			
Premium	456.32	(0.102)	415.00	(0.233)
Fees	36.37	(0.009)	2.79	(0.013)
BM class	1.81	(0.001)	2.40	(0.004)
No. acc AR	0.16	(0.000)	0.18	(0.001)
Perc. male subscribers	59.3	(0.000)	57.18	(0.001)
Age	52.60	(0.008)	48.15	(0.018)
Perc. with free driving	52.52	(0.000)	14.49	(0.000)
Perc. with min. liab. coverage	71.62	(0.000)	44.24	(0.001)
Switching rate	11.16	(0.000)	18.38	(0.00)
Car's Power (KW)	65.98	(0.014)	70.10	(0.036)
	Balance Sheet Data			
Admin. cost	81.29	(0.009)	57.92	(0.018)
Liq. cost	341.43	(0.066).	256.25	(0.126)
Profit	37.77	(0.020)	-5.17	(0.07)
Perc. claims liquidated	79.24	(0.002)	77.50	(0.01)
	Data on Claims from BDS			
Perc. contract with claims AF$\geq$ 1	4.86	(0.000)	6.22	(0.00)
Perc. contract with claims NAF$\geq$ 1	5.14	(0.000)	6.24	(0.00)
Indemnity claims NAF	2,622.39	(56.04)	3,361.49	(149.61)
Indemnity third parties claims AF	2,883.73	(74.63)	3,337.28	(170.70)
Profit from BDS+IPER	62.17	(3.40)	-21.29	(15.06)

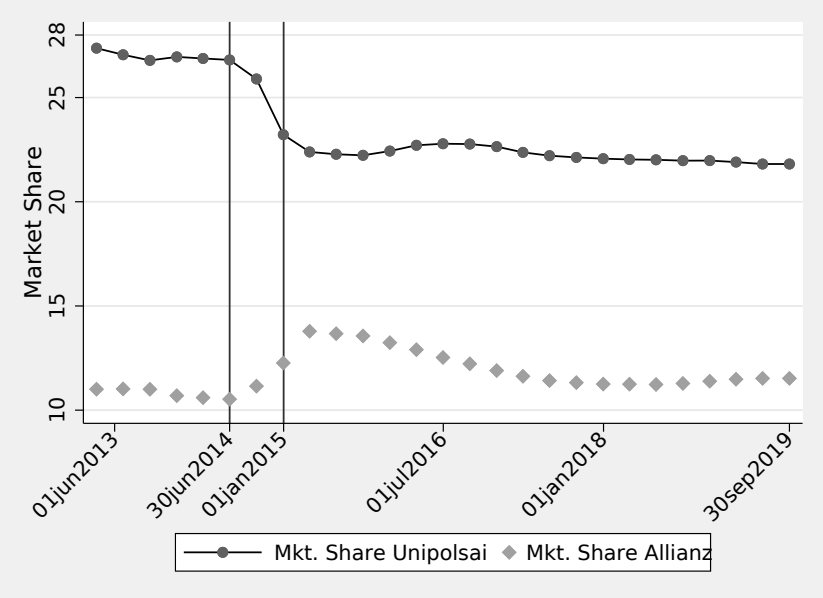
Notes. This table reports weighted means from the contracts underwritten by direct and traditional companies. AF stands for "at fault", while NAF for "not at fault." The perc. of claims liquidated measures the proportion falling into the CARD system occurred and liquidated in the same year. Profits computed using IPER and BDS are calculated consistently with the CARD formula.

All in all, these data indicate that (i) drivers covered by direct insurers are more expensive to cover than those by traditional insurers, (ii) because premiums are low and claims payout is high in relative terms, the reduced loading costs do not guarantee direct insurers a higher profit margin with respect to traditional companies, and, in fact, they lose money.

A.3. **Event history analysis.** I leverage on a mandatory divestiture as an instrument for the switching decision. The idea is that policyholders covered by the company acquired are somehow "forced" to switch by this exogenous event. Within the industry dynamics characterizing the Italian auto insurance market during the period under consideration, one event stood out as particularly useful for this purpose. Because the Italian antitrust law stipulates that each insurer cannot cover more than 30 percent of the market at the national and province level, following an investigation by the Italian antitrust authority, insurer A agreed to divest a share of its portfolio to another top-5 insurer, call it B. Figure

22 offers a visualization of the variation of the market shares held by the two insurers.[69] As

FIGURE 22. Effect of the Mandatory Divestiture



Note: This figure illustrates the trend of the market shares held by insurer B and insurer A in the period 2013-Q3:2017.

illustrated by the figure, the action undertaken by the antitrust authority caused insurer A to lose 4 percent of its market shares to insurer B. The divestiture occurred from July 2014 through the end of 2014. Unfortunately, the data do not contain direct information on which contracts underwritten by insurer A to cover 2013-2014 and subsequently underwritten by insurer B in 2014-2015 were directly affected by the mandatory divestiture. Nevertheless, a reasonable imputation is that *all* switchers from insurer A to insurer B between 2014 and 2015—16,602 contracts—are "exogenous" switchers. I refer to switchers from A to companies different than B as the "endogenous" switchers.

In order to isolate the role of moral hazard from self-insurance and to take into account the endogenous nature of the switching decision, I examine the pattern of the hazard rate within the sample of exogenous switchers.[70]

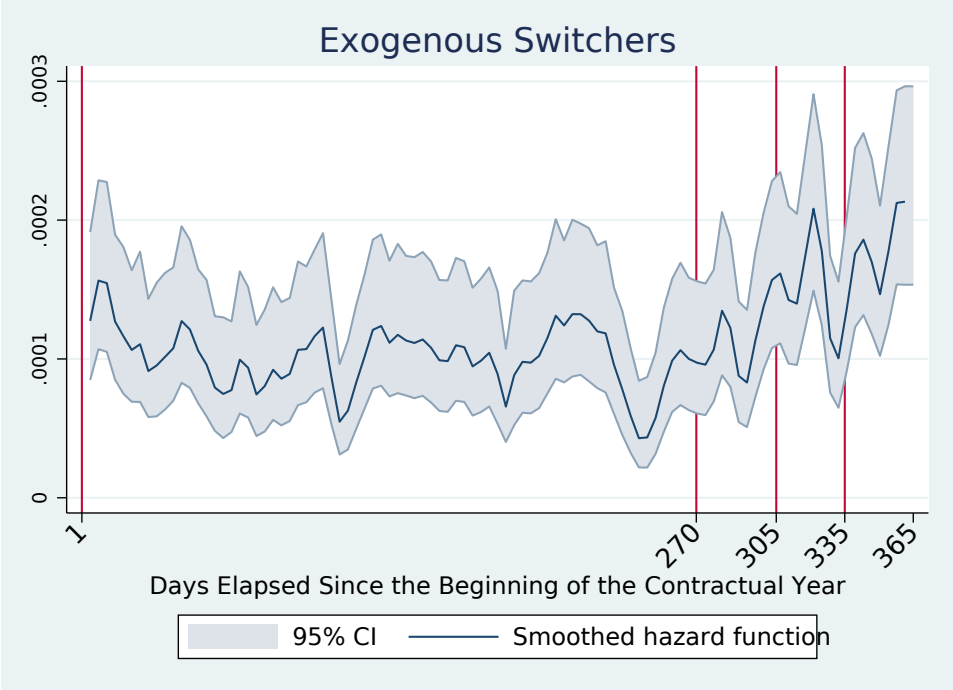
Figure 23 illustrates the hazard rate of exogenous switchers; it can be observed that the

[69]Before the divestiture the market shares held by insurer A and insurer B in Q2:2014 were equal to 26.8 percent and 10.53 percent, respectively. In Q1:2015 insurer A and insurer B covered 22.4 percent and 13.78 percent of the market, respectively. Among the other figures of this operation, insurer B acquired a distribution channel funneled by 700 sales agents in charge of managing a portfolio of contracts worth 1.1BN euros; furthermore, about 500 employees dedicated to the management of these assets became insurer B's employees.

[70]A necessary condition to infer moral hazard from the sample of exogenous switchers is that the grace period effect is still active after the divestiture; that is, accidents during the last 60 days by those covered by insurer A and exogenously migrated to insurer B disappear from the record. I verified that this is the case.

grace period effect is less pronounced with respect to the sample of "endogenous" switchers, suggesting that reverse causality is partially but not fully responsible for the increase in the last 60 days.

FIGURE 23. Hazard Rate within Exogenous Switchers



Notes. This figure illustrates the hazard rate of exogenous switchers 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)

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 (**?**)

$$\lambda(\tau|X_{ik}) = \lambda_0(\tau)\exp(\beta X_{ik}) \tag{24}$$

where X_{ik} includes a rich set of controls related to intrinsic risk: the driver and vehicle characteristics, the driving record, company and province fixed effects, a dummy for whether the driver had an accident the previous year—I control for state dependence this way—contractual clauses, dummies for the number of installments, contractual year, and contracts' starting month fixed effects. Also I control in a crude way for potentially missing pricing variables by including the residualized premium, obtained by retrieving the fitted OLS residuals of the OLS regression of (log) premium on controls.

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.[71] 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 in 60-day intervals until day 270, and in 30-day intervals afterward.[72] 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 insurer k is as follows:

$$\lambda_{ijk}(\tau|\tau_{j-1} \leq \tau \leq \tau_j) = \lambda_j \exp(\beta X_{ik}) \tag{25}$$

with $j = 1, \ldots, 12$. This model is known as the piecewise exponential model (PEM)—see **?**—because the distribution of the survival time within any interval is exponential, implying an interval-specific constant hazard rate λ_j. The large number of contracts available is instrumental to precisely estimating the λ_j's in 30-day intervals, allowing for 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.[73]

[71] This specification is consistent with a model in which policyholders choose their driving effort on a daily basis.

[72] 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-day grid is approximately 90 GB.

[73] This approach is analogous to **?**, who studies the effect of unemployment benefits on the duration of unemployment, and to **?**, who adopt a PEM to examine the annuitant survival rate after purchasing an annuity.

Multiple events.— Although having more than one accident in a year is an extremely rare event, 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.[74] 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 **?** (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 an accident $k - 1$ or no accident.[75]

Results.— Panel A of table 28 reports the estimates of the baseline hazard rates using different samples, described in the note of the table. The estimating samples are restricted to contracts underwritten in the first contractual year. Panel B reports the percentage change of the baseline hazard rates between two adjacent intervals. In order to visualize the grace period effects, figure 24 depicts the pattern of the estimated baseline hazard rates within the exogenous and endogenous switchers (within A). Both the figure and a closer inspection of panel B of table 28 indicate that a grace period effect also exists within the sample of exogenous switchers. The increase is less pronounced than within the sample of endogenous switchers—column (3) of table 28—but the patterns of the hazard rates are similar. In particular, in the sample of exogenous and endogenous switchers, the hazard rate increases between the ninth and eight months by 44 and 49 percentage points, respectively. This is consistent with the possibility of also eliminating from the record accidents that occurred right before the grace period. The main quantitative difference has to do with the increase of the hazard rate in the last 30 days relative to the second-to-last month, which equals 26 percent within the sample of exogenous versus 57 percent within the sample of endogenous switchers. I interpret these results as evidence that the bulk of the grace period effect is due to moral hazard rather than to self-insurance and is not an artifact of the selective nature of the switching decisions.[76] As a result, the conditional analysis leaves me unable to reject the hypothesis of moral hazard.

[74] **?** describes the various methods to model repeated events and how to implement them in Stata. **?** provides a survey on variance-correction models.

[75] 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 **?**). I adopt the gap time approach; nevertheless, the shape of unconditional hazard arising from the two models turns out to be nearly identical.

[76] Is worth observing that the grace period effect among the switchers covered by insurers other than A is larger: the baseline hazard rate between the last 30 days and second-to-last month increases by 64 percentage points within the switchers from other companies (column (4) of panel B of table 28).

FIGURE 24. Pattern of the Estimated Baseline Hazard Rates within Switchers

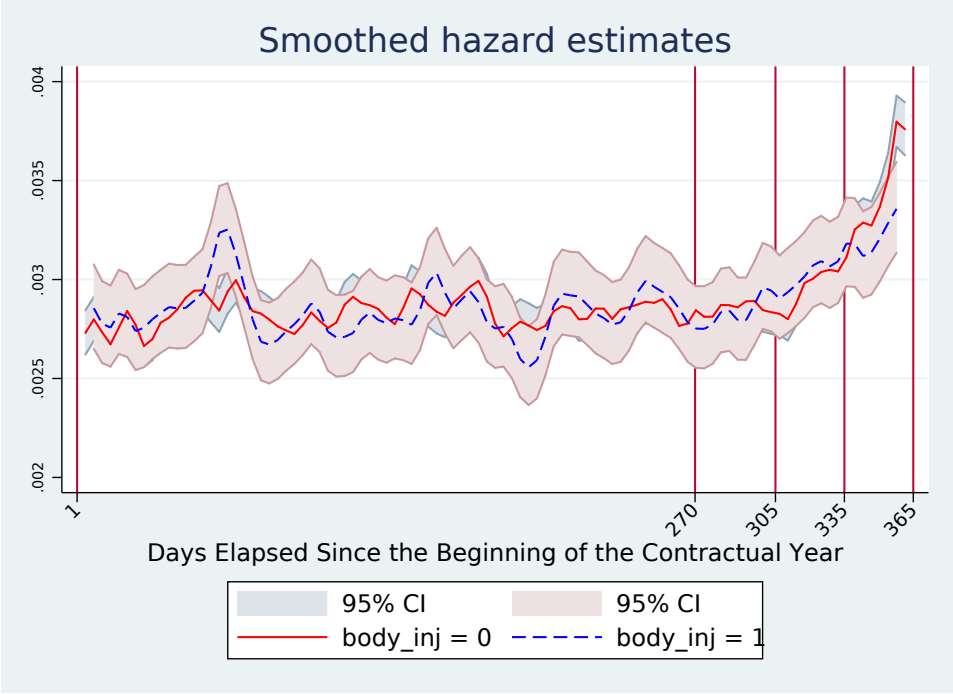


Note: The left and right panels depict the estimates of the interval-specific hazard rates within the sample of exogenous and "endogenous" switchers. The estimates are reported in columns (1) and (3) of table 28, respectively.

I now discuss three confounders: misreporting/frauds, learning, and seasonality effects.

Misreporting and frauds.— 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 actually 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 26 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 29). To extent that fraudulent claims are unlikely to involve bodily injuries, this descriptive evidence also suggests that the grace period effect does not arise from a concentration of fake accidents at the end of the year.

FIGURE 25. Hazard Rate During the Contractual Year Conditional on the Presence of Bodily Injuries

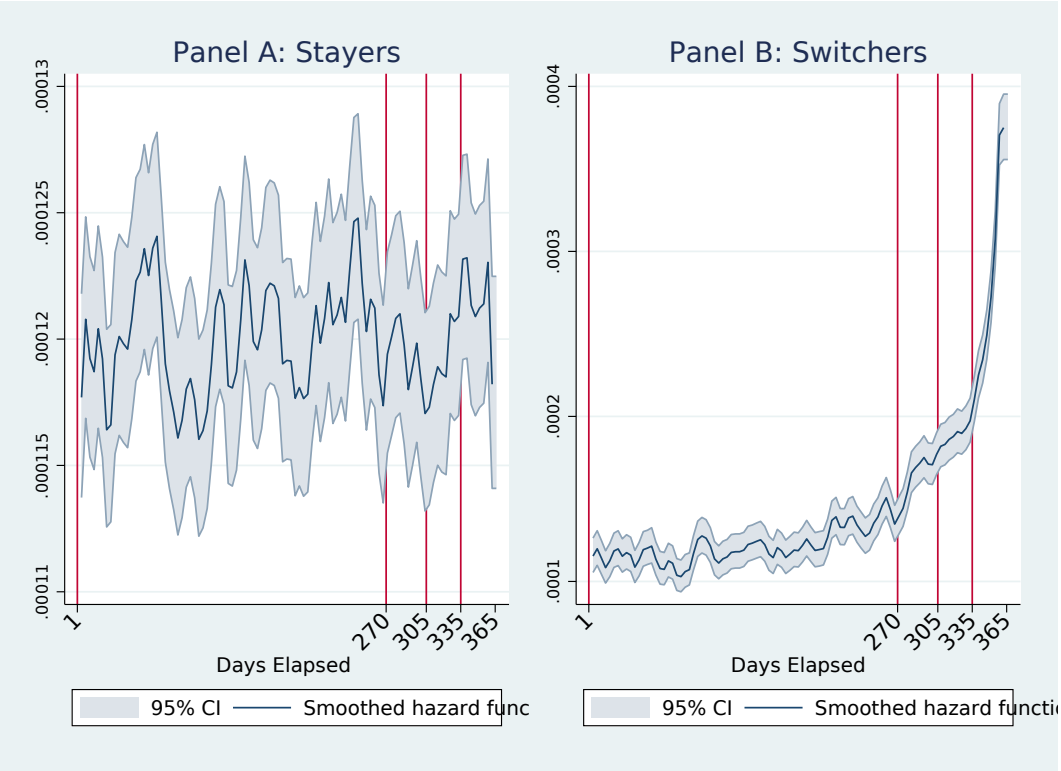


The hazard rates are bounded by the 95 percent confidence interval. A Gaussian kernel is used to smooth the hazard rates. The sample is restricted to contracts associated with one or more claims during the contractual year. The continuous (dotted) line represents the hazard rate of claims with (without) bodily injuries.
Sample: contracts covering years 2013-Q3:2017.

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 $\geq$ 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 28 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.

FIGURE 26. Hazard Rate within Switchers and Stayers



Note. This figure depicts the hazard rates of one or more accidents, bounded by the 95 percent confidence interval. A Gaussian kernel is used to smooth the hazard rates. Sample: contracts covering years 2013-Q3:2017.

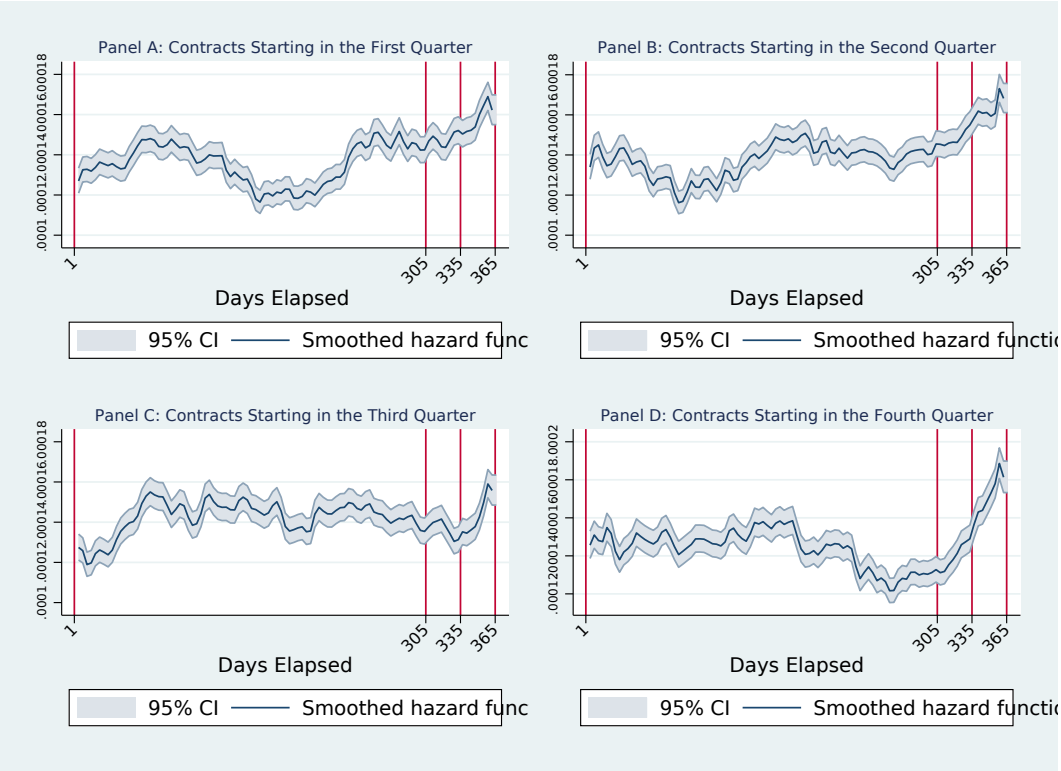
A.4. **Switching Probability and Dynamic Selection.** To investigate the effect of the driving record on the decision to switch, I specify the following linear probability model:

$$s_{ijkt} = \sum_{k=1,\ldots,9} \beta_k^{BM} BM_k + \sum_{n\in\{1,2\}} \beta_n^{AR} n_{it} + \beta^b bb_{it} + \beta^X \mathbf{X}_{it} + \beta^Z \mathbf{Z}_{kt} + \tau_t + \zeta_{kt} + \widehat{\xi}_{it} + \theta_{it} \quad (26)$$

where the dependent variable s_{ijkt} takes value 100 if driver i living in province k covered by company j during year t switches companies at the end of the year, and zero otherwise; bm_k and $accAR_n$ are indicators taking value one if the policyholder is assigned to class k—the omitted category is BM classes 10-18—and has n accidents on record, respectively. I am primarily interested in β_k^{bm} and β_n^{AR}, the effect of the driving records on the switching probability.

Panel A of table 33 presents the estimates using different specifications, the odd and even columns containing the estimates obtained by the OLS and CF-FE estimator, respectively; in columns (1)-(2) I summarize the driving record into a single clean record indicator, while in columns (5)-(6) I restrict the sample to contracts underwritten by A. The first pattern in this table is that the OLS estimates are downward biased relative to the CF-FE estimator, suggesting unobservable heterogeneity correlated with driving records. Second, drivers with a clean record experience a 1 percent reduction of the switching

FIGURE 27. Hazard Rate Conditional on the Quarter



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.
Sample: contracts covering years 2013-Q3:2017.

probability: by inspecting columns (3) and (4), it can be observed that the positive effect of the number of accidents on record is counteracted by the negative effect of the BM class.

Panel B reports the effect of the black box on the retention probability. The coefficient on the black box is negative and implies that adopters are 15 percent less *likely* to change companies relative to non-adopters (column (4)). To understand the relationship between driving habits and switching, columns (5) and (6) of table 33 distinguish between first adopters and distance bands from the second year onward within policyholders covered by A. First adopters are 3 percent less likely to change companies, and within the 5-distance bands the relationship between driving habits and switching is non-monotonic, whereas within the 7-distance bands a negative relationship emerges: low-distance drivers are less likely to change companies (relative to non-adopters).

Taken together, these findings suggest that low-risk types are over-represented in company-specific panel data as a consequence of the dynamic selection mechanism. This analysis does not support the assumption that company-specific samples are random *at all points in*

time, implying that fixed-effect strategies to measure moral hazard using company-specific sample of contracts are unlikely to deliver unbiased results.

Appendix B. 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 **?**). The stratification variables are region (20), city size (small, medium, large), and age group (< 25, [25,35), [35,45), [45,60), and ≥ 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.

Appendix C. Description of the Variables

I now describe in detail variables I use in the empirical analysis and whose means are shown in tables 7 of the main text and in table 26:

- 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 ≥ 60.
- accidents on AR: number of accidents 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 if 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, if 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 accidents 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 to 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

C.1. **Tables Online Appendix.**

TABLE 26. Means of the Covariates Among Companies

	A	B	C	D	E	Medium	Small
	The Premium and Its Component[c]						
Premium	480.448	501.150	472.429	435.927	384.310	473.898	448.311
Discount	121.786	70.742	74.469	148.887	109.779	91.588	78.447
Fees	35.437	42.653	39.921	37.865	31.916	30.936	28.702
Taxes	58.755	61.580	58.249	53.698	47.321	58.379	54.540
Contr. to Italian Health System	40.078	41.769	39.353	36.327	32.026	39.437	37.230
	Gini Index						
Premium	0.23	0.243	0.22	0.226	0.238	0.235	0.233
	Clauses[b]						
Inspection	0.000	0.000	0.003	0.000	0.000	0.000	0.000
Repairing	0.298	0.159	0.202	0.050	0.000	0.046	0.053
Increasing	0.331	0.733	0.519	0.501	0.000	0.223	0.310
Decreasing other	0.000	0.121	0.000	0.546	0.000	0.001	0.015
Corporate agreement	0.000	0.806	0.036	0.362	0.200	0.127	0.118
Black Box	0.318	0.068	0.161	0.010	0.000	0.077	0.058
Exclusive Driving	0.021	0.005	0.037	0.021	0.000	0.141	0.025
Expert driving	0.377	0.743	0.235	0.324	0.824	0.351	0.279
Free driving	0.466	0.205	0.701	0.648	0.172	0.499	0.675
Other driving	0.136	0.046	0.027	0.007	0.004	0.008	0.021
Protected onus	0.423	0.203	0.016	0.000	0.283	0.088	0.244
Min.liability coverage	0.738	0.441	0.779	0.713	0.390	0.673	0.654
Liability Coverage[e]	8.797	28.999	6.804	7.390	18.372	7.955	8.518
Deductible[c]	17846.648	166.369	258.000	263.158	170.946	351.516	447.960
	Type of Contract						
Bonus-malus	0.999	0.776	1.000	1.000	0.994	0.955	0.990
Deductible	0.000	0.001	0.000	0.000	0.005	0.002	0.003
Mixed(bonus-malus+deductible)	0.001	0.222	0.000	0.000	0.001	0.043	0.007
	Installments						
No. installments	1.469	1.464	1.547	1.489	1.543	1.455	1.394
One installments[b]	0.553	0.540	0.461	0.511	0.475	0.553	0.611
Two installments[b]	0.432	0.457	0.533	0.488	0.516	0.441	0.385
Three installments[b]	0.015	0.003	0.006	0.001	0.009	0.006	0.004
	Demographics						
Age	49.771	49.955	48.909	48.111	46.284	48.189	48.267
18-24[b]	0.021	0.011	0.034	0.024	0.029	0.032	0.028
25-34[b]	0.149	0.138	0.172	0.175	0.205	0.164	0.169
35-44[b]	0.227	0.257	0.208	0.239	0.254	0.245	0.245
45-60[b]	0.348	0.336	0.341	0.347	0.340	0.338	0.331
>60[b]	0.256	0.259	0.244	0.214	0.172	0.221	0.226
Male[b]	0.581	0.600	0.564	0.572	0.615	0.569	0.574
	Driving Record						
BM class	1.926	1.894	1.981	1.707	1.942	2.190	1.970
BM 1[b]	0.780	0.783	0.771	0.808	0.776	0.740	0.764
BM 2-3[b]	0.091	0.086	0.090	0.087	0.092	0.094	0.095
BM 4-10[b]	0.111	0.113	0.120	0.096	0.105	0.136	0.120
BM 11-18[b]	0.018	0.016	0.019	0.009	0.022	0.028	0.018
No. acc. on record	0.165	0.120	0.153	0.113	0.173	0.177	0.154
1[b]	0.122	0.092	0.117	0.094	0.127	0.125	0.114
2[b]	0.014	0.010	0.013	0.007	0.016	0.017	0.014
> 2[b]	0.052	0.041	0.044	0.031	0.056	0.058	0.048
	Tenure Effects						
Days since first contract	1360.411	1384.781	1051.271	1022.016	1058.793	1258.258	1055.304
Switch at the end of the year[b]	0.121	0.123	0.097	0.118	0.092	0.132	0.151
	Car's charact.						
Power[d]	65.514	67.625	65.529	65.995	67.221	67.722	66.724
Years since registry	8.506	8.854	8.444	8.717	8.425	8.223	8.492
Cubic cilinder	13.885	14.257	13.815	14.093	14.124	14.125	14.045
Diesel[b]	0.431	0.445	0.399	0.449	0.493	0.439	0.441
Petrol[b]	0.527	0.516	0.557	0.510	0.465	0.517	0.516
GPL[b]	0.033	0.028	0.035	0.033	0.033	0.034	0.034
Hybrid[b]	0.002	0.002	0.002	0.001	0.001	0.003	0.002
Other type of power supply[b]	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Location of Residence						
North[b]	0.448	0.460	0.526	0.463	0.371	0.511	0.533
Center[b]	0.202	0.151	0.216	0.194	0.305	0.210	0.211
South[b]	0.233	0.280	0.190	0.239	0.195	0.183	0.155
Islands[b]	0.117	0.109	0.067	0.103	0.129	0.096	0.101

NOTES: This table reports unweighted means of the premium and its components, as well as of the pricing variable associated with the contracts underwritten in the period 2013-Q3:2017.
b] $0-1$ Dummy.
c] Euros.
d] Power of the vehicle in KW.
e] Million Euros.

TABLE 27. Claims and Indemnities

	(1) Net premium	(2) Fee	(3) No. claims F	(4) Indemnity TP	(5) Bodily Injury	(6) No. claims NF	(7) Indemnity	(8) Bodily Injury NF	(9) CARD NF
Market	358.33	32.35	0.055	3101.43	0.169	0.056	2941.65	0.162	0.675
	(0.07)	(0.01)	(0.000)	(68.33)	(0.001)	(0.000)	(68.33)	(0.001)	(0.001)
A	371.46	34.31	0.052	2703.66	0.162	0.055	2617.77	0.162	0.711
B	390.72	41.91	0.056	3023.59	0.184	0.056	2850.79	0.175	0.480
C	362.13	38.58	0.054	3337.44	0.167	0.048	3121.22	0.162	0.736
D	338.39	37.04	0.047	3043.93	0.185	0.053	2954.02	0.166	0.664
E	295.59	30.88	0.053	2647.71	0.169	0.058	2403.11	0.156	0.686
Medium	353.93	25.71	0.061	3502.57	0.164	0.060	3268.95	0.158	0.672
Small	345.96	27.72	0.055	3036.89	0.173	0.055	2966.40	0.164	0.712

NOTES. This table reports weighted means of the premium net of taxes and contribution to the health system (1), sales agents fees (2), average number of claims at fault (3), the average indemnity corresponded to third parties in claims not at fault (4), the proportion of claims at fault involving bodily injuries (5), the average number of claims at not at fault (6), the average indemnity associated with claims not at fault (7), the proportion of claims not at fault involving bodily injury (8), and the proportion of claims not at fault covered by the CARD system (9).

TABLE 28. The Pattern of Baseline Hazard Rates

	(1) Exogenous Switchers	(2) Stayers	(3) Switchers Insurer A	(4) Switchers Other insurers
			Panel A	
$\lambda_{[1-60]}$	0.000152***	0.000208***	0.000111***	0.000231***
	[0.000091]	[0.000035]	[0.000056]	[0.000062]
$\lambda_{(60-120]}$	0.000114***	0.000208***	0.000111***	0.000231***
	[0.000069]	[0.000035]	[0.000056]	[0.000062]
$\lambda_{(120-180]}$	0.000143***	0.000202***	0.000099***	0.000247***
	[0.000086]	[0.000034]	[0.000050]	[0.000066]
$\lambda_{(180-240]}$	0.000141***	0.000198***	0.000132***	0.000236***
	[0.000084]	[0.000033]	[0.000067]	[0.000063]
$\lambda_{(240-270]}$	0.000098***	0.000189***	0.000119***	0.000273***
	[0.000060]	[0.000032]	[0.000061]	[0.000074]
$\lambda_{(270-300]}$	0.000141***	0.000195***	0.000177***	0.000322***
	[0.000085]	[0.000033]	[0.000091]	[0.000087]
$\lambda_{(300-335]}$	0.000198***	0.000182***	0.000197***	0.000392***
	[0.000119]	[0.000031]	[0.000100]	[0.000105]
$\lambda_{(335-365]}$	0.000249***	0.000214***	0.000310***	0.000642***
	[0.000150]	[0.000036]	[0.000157]	[0.000172]
			Panel B	
$[\lambda_{(60-120]} - \lambda_{[1-60]}]/\lambda_{[1-60]}$	-0.25	0.00	0.00	0.00
$[\lambda_{(120-180]} - \lambda_{[60-120]}]/\lambda_{[60-120]}$	0.25	-0.03	-0.11	0.07
$[\lambda_{(180-240]} - \lambda_{[120-180]}]/\lambda_{[120-180]}$	-0.01	-0.02	0.33	-0.04
$[\lambda_{(240-270]} - \lambda_{[180-240]}]/\lambda_{[180-240]}$	-0.3	-0.05	-0.1	0.16
$[\lambda_{(270-300]} - \lambda_{[240-270]}]/\lambda_{[240-270]}$	0.44	0.03	0.49	0.18
$[\lambda_{(335-300]} - \lambda_{[270-300]}]/\lambda_{[270-300]}$	0.4	-0.07	0.11	0.22
$[\lambda_{(335-365]} - \lambda_{[300-335]}]/\lambda_{[300-335]}$	0.26	0.18	0.57	0.64
previous year acc. FE	Yes	Yes	Yes	Yes
residualized premium	Yes	Yes	Yes	Yes
policyholder char.	Yes	Yes	Yes	Yes
clauses	Yes	Yes	Yes	Yes
driving record FE	Yes	Yes	Yes	Yes
car's charact.	Yes	Yes	Yes	Yes
region FE	Yes	Yes	Yes	Yes
fraud FE	Yes	Yes	Yes	Yes
no. of installments FE	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes
N	132,351	1,699,604	176,408	712,184

NOTES: The top part of this table reports the period-specific baseline hazard rates, from the piecewise exponential model specified in equation (24). The bottom part of the table reports the percentage change in the baseline hazard rates between two adjacent time-intervals. λ_{1-60} denotes the hazard rate between days 1 and 60.

The estimating sample in columns (1), (2), and (3) is represented by the sample of exogenous switchers, the sample of stayers covered by company A, and the sample of switchers covered by A, respectively. In column (4) the estimating sample is represented by policyholders changing companies covered by insurers different than A. The set of contracts used in estimation covers contractual years 2013-2014.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively. Standard errors are reported in parentheses and clustered at the province level.

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

	(1) OLS	(2) Q25	(3) Median	(4) Q75	(5) OLS	(6) Q25	(7) Median	(8) 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 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).

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 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).

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).

TABLE 32. Number of Distance-Bands Regimes

Number of Bands	2013	2014	2015	2016	2017
5	100	100	59.34	0	0
7	0	0	40.66	100	88.01
10	0	0	0	0	11.99
Number of Contracts	20,149	27,768	44,221	59,073	49,992

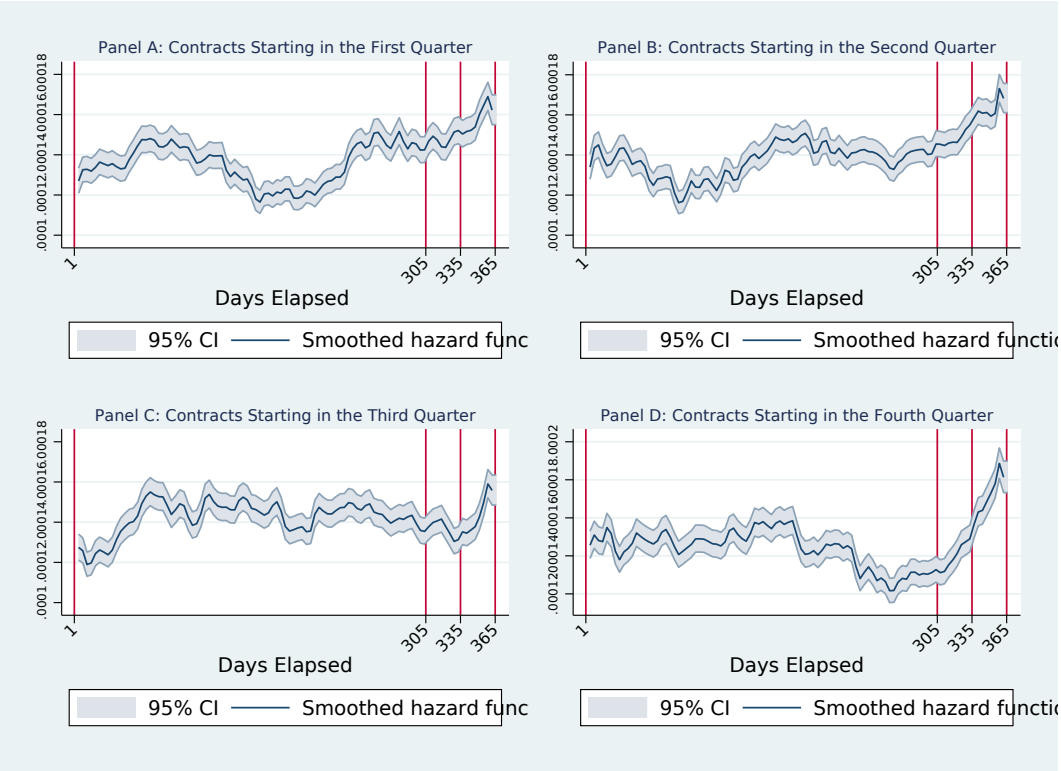
NOTES. This table reports the proportion of contracts assigned to each number of bands-regime at each contractual year, conditional on been monitored the previous year. In 2013(2014), all policyholders monitored in 2012(2013) are assigned to one of five distance bands. Discounts for contracts starting before(after) September of 2015 are based on a five(seven)-distance band regime.

Table 33. Switching Probability

	(1) OLS		(2) CF-FE		(3) OLS		(4) CF-FE		(5) OLS		(6) CF-FE	
	Panel A: Driving Record and Installments											
clean record	-1.982***	[0.089]	-0.931***	[0.153]								
BM 1					-4.808***	[0.307]	5.888***	[0.770]	-1.889***	[0.393]	13.172***	[1.173]
BM 2					-3.420***	[0.346]	6.065***	[0.752]	-0.679	[0.468]	12.070***	[1.147]
BM 3					-4.032***	[0.270]	5.015***	[0.729]	-1.048**	[0.412]	10.856***	[1.113]
BM 4					-2.392***	[0.275]	4.328***	[0.701]	0.559	[0.485]	9.318***	[1.068]
BM 5					-1.840***	[0.267]	3.635***	[0.670]	1.255***	[0.452]	8.149***	[1.023]
BM 6					-1.648***	[0.265]	2.399***	[0.639]	0.758	[0.504]	5.386***	[0.978]
BM 7					-0.190	[0.287]	2.361***	[0.592]	1.318**	[0.589]	3.458***	[0.905]
BM 8					-0.875**	[0.336]	0.815	[0.521]	0.689	[0.585]	1.649**	[0.792]
BM 9					-0.055	[0.339]	0.728*	[0.434]	0.743	[0.679]	1.839***	[0.680]
one acc AR					-0.475***	[0.104]	1.587***	[0.188]	-0.962***	[0.186]	0.898***	[0.281]
two acc AR					-1.495***	[0.323]	2.424***	[0.449]	-0.145	[0.457]	3.725***	[0.668]
one install.	0.331	[0.333]	-7.548***	[0.851]	0.506	[0.341]	-7.595***	[0.851]	-1.019**	[0.513]	-2.316**	[1.136]
two install.	0.967***	[0.344]	1.886**	[0.844]	1.114***	[0.351]	1.857**	[0.844]	0.674	[0.503]	-0.361	[1.130]
	Panel B: Black Box and Driving Bands											
black box	-2.781***	[0.139]	-14.131***	[0.264]	-2.801***	[0.139]	-14.137***	[0.264]				
first year BB									-3.899***	[0.239]	-3.002***	[0.312]
BAND 1 out of 5									-4.369***	[0.332]	-1.019*	[0.539]
BAND 2 out of 5									-4.080***	[0.526]	-1.757***	[0.612]
BAND 3 out of 5									-3.353***	[0.333]	-1.296***	[0.427]
BAND 4 out of 5									-2.821***	[0.331]	-0.763*	[0.425]
BAND 5 out of 5									-2.293***	[0.504]	-0.110	[0.628]
BAND 1 out of 7									-2.156***	[0.355]	-1.983***	[0.497]
BAND 2 out of 7									-1.809***	[0.463]	-1.475**	[0.573]
BAND 3 out of 7									-1.243***	[0.367]	-1.040**	[0.451]
BAND 4 out of 7									-1.076***	[0.242]	-0.319	[0.375]
BAND 5 out of 7									-0.657*	[0.355]	0.195	[0.461]
BAND 6 out of 7									0.484	[0.702]	1.500**	[0.687]
BAND 7 out of 7									1.031	[0.706]	2.906***	[0.776]
policyholder char.	Yes		Yes		Yes		Yes		Yes		Yes	
clauses	Yes		Yes		Yes		Yes		Yes		Yes	
tenure FE	Yes		Yes		Yes		Yes		Yes		Yes	
proxy of fraud's incidence	Yes		Yes		Yes		Yes		Yes		Yes	
car char.	Yes		Yes		Yes		Yes		Yes		Yes	
area char.	Yes		Yes		Yes		Yes		Yes		Yes	
insurer FE	Yes		Yes		Yes		Yes		No		No	
province FE	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.038		0.179		0.039		0.179		0.042		0.074	
N	1,757,295		1,757,295		1,757,295		1,757,295		444,494		444,494	

NOTES. This table reports the effect of driving records and the black box on the switching probability from regression specification (26).
*, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively. Standard errors are reported in parentheses.

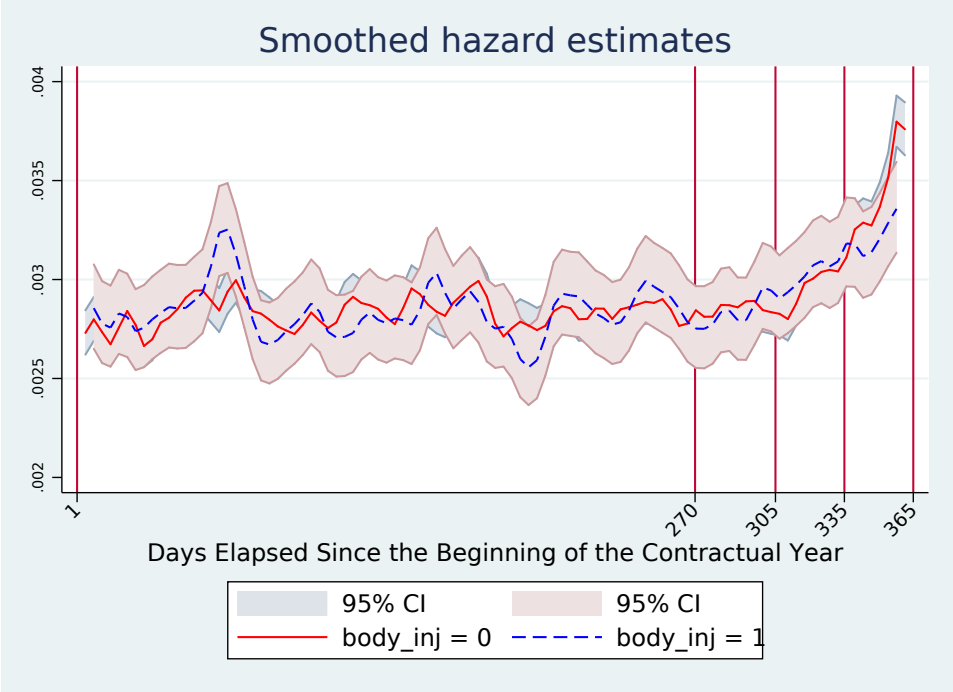
FIGURE 28. Hazard Rate Conditional on the Quarter



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)

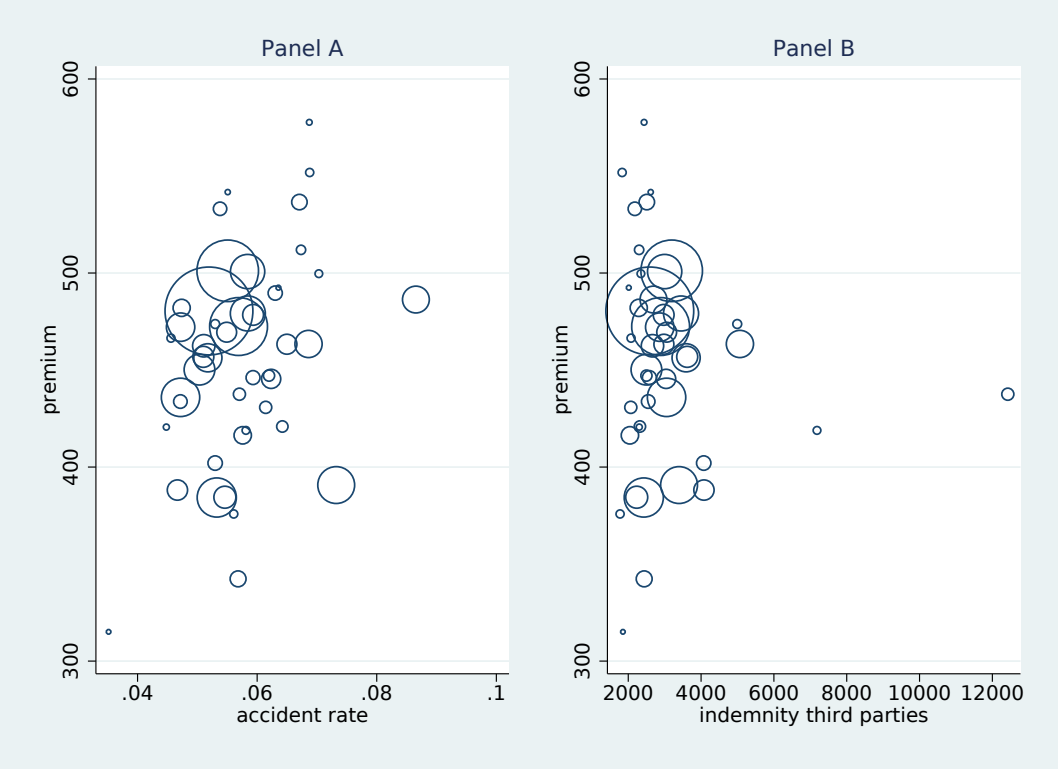
C.2. **Figures—Online Appendix.**

FIGURE 29. Hazard Rate During the Contractual Year Conditional on the Presence of Bodily Injuries



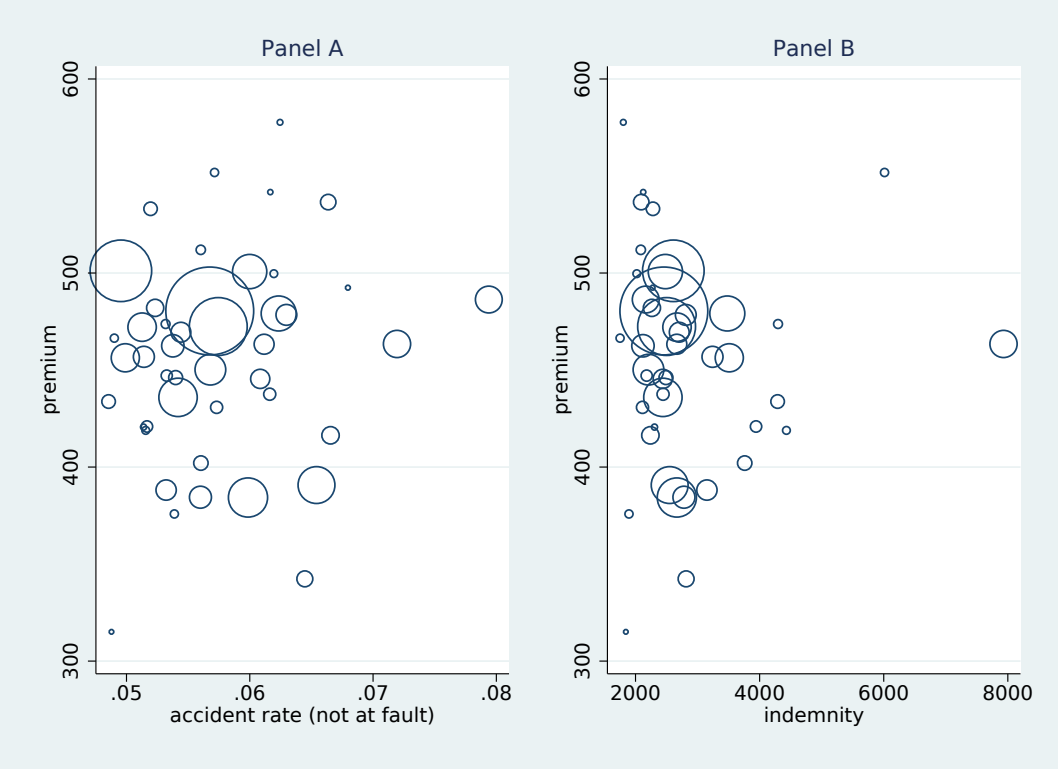
Note. The hazard rates are bounded by the 95 percent confidence interval. A Gaussian kernel is used to smooth the hazard rates. The sample is restricted to contracts associated with one or more claims during the contractual year. The continuous (dotted) line represents the hazard rate of claims with (without) bodily injuries.
Source: IPER (contracts covering years 2013-2014 and 2014-2015).

FIGURE 30. Relationship Between Accidents (At Fault)/Indemnities and Premia Across Insurers



NOTE: Panel A contains a scatter plot on the correlation between the average number of claims at fault and premiums across insurers. The coefficient of linear correlation equals 0.397.
Panel B contains a scatter plot on the correlation between the average indemnity corresponded to third parties for accidents at fault and premiums across insurers. The coefficient of linear correlation equals 0.08.
The size of the circles is proportional to the average market share held by each insurer over the period 2013-Q3:2017.

FIGURE 31. Relationship Between Accidents (Not at Fault)/Indemnities and Average Premium Across Insurers



NOTE: Panel A contains a scatter plot on the correlation between the average number of claims not at fault and premiums across insurers. The coefficient of linear correlation equals 0.195.
Panel B contains a scatter plot on the correlation between the average indemnity received and premiums across insurers. The coefficient of linear correlation equals 0.015.
The size of the circles is proportional to the average market share held by each insurer over the period 2013-Q3:2017.