Buying Data from Consumers

The Impact of Monitoring Programs in U.S. Auto Insurance

Yizhou Jin* Shoshana Vasserman†

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Abstract

This paper studies the design and impact of auto-insurance monitoring programs, in which insurers incentivize consumers to have their driving behavior monitored for a short period of time. We acquire proprietary datasets from a major U.S. auto insurer, matched with price menus of the firm's main competitors. We first estimate structural parameters for consumers' monitoring opt-in choice and for their insurance demand using rich data variation in insurance claims, prices, contract space, and monitoring status. We then conduct counterfactual simulations using a dynamic pricing model that endogenizes the firm's information set. We find three main results. (i) Data collection changes consumer behavior. Drivers become 30% safer when monitored, which boosts total surplus and alters the informativeness of the data. (ii) Safer drivers are more likely to opt in. But monitoring take-up is low due to both consumers' innate disutility for being monitored and attractive outside options from other insurers. Nonetheless, introducing monitoring raises both consumer welfare and total surplus. (iii) Proprietary data facilitate higher markups but protect the firm's ex-ante incentives to produce the data. A counterfactual equilibrium in which the firm must share monitoring data with competitors harms both profit and consumer welfare. This is because the firm offers smaller upfront incentives for monitoring opt-in, so that fewer drivers are monitored in equilibrium.

*UC Berkeley, corresponding author (scholar.harvard.edu/jin). †Stanford University (shoshanavasserman.com).
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Introduction

New technologies and data privacy regulations have led to a proliferation of *direct transactions of consumer data*. Firms directly incentivize consumers to voluntarily reveal information, while keeping the collected data as proprietary. How does this type of data collection influence prices, firm profit, and consumer welfare?

In this paper, we develop an empirical framework to quantify the economic impact of an auto-insurance *monitoring program* ("pay-how-you-drive") in the U.S., a prominent example of direct transactions of consumer data. New customers are invited to plug a simple device into their cars, which tracks and reports their driving behavior for up to six months (Figure A.1). In exchange, the insurer uses the data to better assess accident risk and adjusts future premiums accordingly. Unlike most traditional pricing factors such as age or claim history, monitoring data is not shared with other firms. In 2017, insurers serving over 60% of the $267 billion U.S. auto insurance industry offered monitoring programs.[1] Similar programs have been introduced in other industries, such as life insurance and lending (Figure A.2).[2] Despite this growing relevance, empirical evidence on the economic impact of monitoring programs or other types of direct transactions of consumer data is sparse.

We acquire proprietary datasets from a major U.S. auto insurer that detail drivers' characteristics, the price menu they face, insurance contracts purchased, and realized insurance claims. A monitoring program is introduced during our research window. For each driver who opts in, we observe a monitoring score that the firm uses in determining premium adjustments. To understand competition, we further match each observation with price menus of the firm's main competitors in each state. Taken together, our analysis uses a panel dataset of over 1 million drivers and 50 million insurance quotes.

We take a three-step approach in our empirical analysis. First, we quantify the degree to which monitoring can both incentivize safer driving and reveal drivers' risk types (Akerlof 1970; Fudenberg and Villas-Boas 2006; Einav, Finkelstein, and Schrimpf 2010). Second, consumers self-select into monitoring. We therefore estimate structural parameters that underpin complex correlations between consumers' monitoring opt-in, insurance coverage, and insurer choices, as well as the cost to insure them. This allows us to evaluate the impact of monitoring by simulating a counterfactual without it. Third, the firm can use proprietary data from monitoring to raise markups, but they also incur costs to "produce the data in the first place" (Posner 1978). We capture both factors with a dynamic and multi-product pricing model that endogenizes the firms' information set. This characterizes equilibria in counterfactual simulations, helping us understand optimal pricing and the impact of regulations that curb proprietary data.[3]

We find three main results: (i) Data collection changes consumer behavior. Drivers become 30% safer when monitored, which boosts total surplus and alters the informativeness of the data. (ii)

[1] According to 2017 data published by the National Association of Insurance Commissioners.

[2] The Vitality program from life insurer John Hancock tracks and rewards exercise and health-related behaviors. Ant Financial incentivizes users to conduct more personal finance transactions in exchange for borrowing discounts.

[3] The General Data Protection Regulation (2016) in the EU aims to curb the accumulation of proprietary data by allowing consumers to rescind consent and take their data to other firms, and by requiring firms to be transparent about how consumer data is used in pricing (see EUGDPR (2018)). The National Telecommunications and Information Administration in the U.S. is considering similar regulatory proposals (see press release NTIA (2018)).

Safer drivers are more likely to opt in. But monitoring take-up is low due to both consumers' innate preference against being monitored and attractive outside options from other insurers. Nonetheless, compared to a counterfactual with no monitoring, consumer welfare and total surplus both increase. (iii) Proprietary data facilitate higher markups, but they also protect the firm's incentives to produce the data. A counterfactual regulation that forces the firm to share monitoring data with competitors harms both profit and consumer welfare. This is because the firm offers smaller upfront incentives for monitoring opt-in, so that fewer drivers are monitored in equilibrium.

Our empirical analysis starts with a pair of reduced-form facts. The first one shows that drivers become safer when monitored – an incentive effect. The monitoring program is only offered to new customers and ends within the first six-month period. We therefore directly compare claim rates of the same monitored drivers during and after monitoring. A difference-in-differences estimator is used in which the control group consists of unmonitored drivers. Taking into account additional variation in monitoring duration, we find that the average opt-in driver *becomes* 30% safer when monitored. Our estimates are robust to various control specifications. We also conduct a test for parallel trends in periods after monitoring ends.

Despite the behavioral distortion, we document that monitoring data still captures substantial differences in drivers' risk types that are previously unobserved. This may lead to adverse selection into higher insurance coverage and advantageous selection into monitoring. We look at cost differences across monitoring groups conditional on observables. Monitored drivers who score one standard deviation above the mean are 29% riskier in the subsequent (unmonitored) period. Further, the within-driver risk reduction we measured above only explains 64% of the risk difference across monitored and unmonitored groups in the first period.[4]

With the reduced-form facts in mind, we develop a cost model for consumer (claim) risk and the monitoring program. Each driver has a latent risk type that partially depends on his or her observables. This risk type can change when the driver is monitored. Meanwhile, new customers can choose to be monitored during the first period. Doing so sends an informative signal of their risk types exclusively to the monitoring firm.

Consumers' monitoring opt-in choice is more complex and captures the following intuition. First, drivers may anticipate risk reduction during monitoring. Second, drivers form expectations over potential renewal discount (from monitoring) based on their risk types. Safer drivers may therefore be more likely to opt in. But the monitoring signal is noisy, which adds to drivers' uncertainty over their future premiums and deter risk-averse drivers from opting in (reclassification risk). Lastly, drivers need to actively opt into monitoring and may incur privacy or effort costs. They therefore suffer disutility from being monitored.

We develop a demand model that features key parameters that drive the intuition above and link consumers' monitoring opt-in decision with their choices of insurer and insurance coverage as well as the cost of insuring them. We start from an insurance framework (Einav, Finkelstein, and Levin 2010) that features risk preference, heterogeneous inertia costs, expected renewal premium, as well

[4]Opt-in drivers are only monitored for fractions of the first six-month period, so the incentive effect (within-driver risk changes across periods) is only 23% in the data as opposed to the full 30% outlined in the above paragraph.

as the latent risk type from the cost model. We then parameterize consumers' disutility from being monitored as a random effect that varies based on both observables and unobserved latent risk type. Parameters in the cost and monitoring models are identified based on variance and covariance of claims and monitoring scores conditional on observables. Identification of demand parameters relies on rich variation in prices and contract space conditional on observables used in the firm's pricing rules. For example, attrition rates under different competitive pricing environments allow us to estimate consumers' inertia in switching firms. Eligibility for monitoring also depends on location and time. This, in addition to variation in the monitoring opt-in discounts, helps us pin down consumers' monitoring disutility.

To facilitate estimation, we augment the demand model to admit a mixed logit structure and use a simulated maximum likelihood approach (Train 2009). Our estimates produce a close fit to the empirical distribution of monitoring scores among monitored drivers, which is endogenously generated based on drivers' monitoring opt-in choices. We further cross-validate our demand model on a hold-out dataset in which the mandatory minimum coverage changed in one (U.S.) state. The model accurately predicts changes in monitoring opt-in rate, coverage share, and attrition rate from the firm.

Our demand estimates show that the average driver suffers a \$93 disutility from being monitored. However, monitoring disutility is lower for safer drivers (lower risk type). This means that, conditional on the objective financial rewards and risk from monitoring, safer drivers are yet more likely to opt in, exacerbating advantageous selection into monitoring. Meanwhile, the average driver forgoes \$284 financial gain per year from not exploiting outside options from competitors. Further, drivers are only modestly risk-averse in their auto insurance choices. Improving the monitoring score's signal precision therefore has little impact on monitoring demand. Our cost estimates are consistent with the reduced-form findings above.

We then conduct several counterfactual simulations. The first one compares the current regime with one without monitoring, holding fixed baseline prices.[5] Introducing monitoring raises both firm profit (by \$7.9 per driver annually, a 23.6% increase) and consumer welfare (by \$11.6, in certainty equivalent, or 1.5% of premium). Total surplus increases by \$13.3 (1.7% of premium), 64% of which can be attributed to the risk reduction during monitoring. In contrast, although monitoring strongly mitigates information asymmetry, allocative efficiency gain is suppressed due to mandatory purchase of auto insurance and large preexisting competitive price variation.[6]

Next, we propose a pricing model that endogenizes the production of monitoring data and therefore the firm's information set. This is used to derive market equilibrium (i) when the firm optimizes prices without constraint, and (ii) when the firm must share its proprietary data with competitors. In the data, firm prices are likely to be sub-optimal due to regulatory constraints. But the pricing levers used imply that optimal pricing balances two motives: "investing" in data production and "harvesting" from the collected data.[7] The latter receives far more attention from the literature: proprietary

[5] Appendix B includes analysis that demonstrates that the firm did not raise prices for unmonitored drivers when introducing monitoring.

[6] A large literature focuses on the impact of risk classification on insurance allocation and consumer welfare. Examples include Crocker and Snow (1986), Finkelstein, Poterba, and Rothschild (2009), and Handel, Hendel, and Whinston (2015).

[7] This pricing dynamic is common in markets with high switching costs, see Beggs and Klemperer (1992), Farrell and Klemperer (2007), Dubé, Hitsch, and Rossi (2009), and Shin, Sudhir, Cabral, Dube, Hitsch, and Rossi (2009).

data facilitate higher markups and raise the firm's share of the surplus created by monitoring.[8] In our equilibrium simulation, we find that the firm reaches optimal pricing by reducing rent-sharing with consumers by 19.6%. This creates a flatter discount-surcharge schedule, representing more aggressive price discrimination. But the firm must first produce monitoring data. To do so, it can offer opt-in discounts or surcharge the unmonitored pool. Without competition, the firm can use the latter to force drivers into monitoring because auto insurance is mandatory. In contrast, the optimal pricing includes a surcharge of only 2.7% on the unmonitored pool. Price competition therefore effectively limits the firm's ability to coerce drivers into monitoring. Instead, the firm should raise the monitoring opt-in discount to 22.1% from 5%. This benefits the firm by producing monitoring data and simultaneously reducing risk.

Lastly, we endogenize competitor prices and explore the equilibrium implications of a regulation that requires the firm to share monitoring data with competitors. This turns monitoring into a public good. However, monitoring can still benefit the firm through risk reduction (the incentive effect) and high firm-switching inertia (imperfect competition). Nonetheless, we find that the firm significantly scales back investment in the program by reducing the incentives it offers for monitoring opt-in. Compared to the equilibrium without the information sharing mandate, this leads to a large drop in monitoring opt-in rate. Although the firm charges lower markups on monitored drivers, consumer welfare and total surplus both decrease.

Related Literature Our research contributes to several literatures. First, we extend the empirical literature on adverse selection and imperfect competition. We investigate firms' strategy to acquire – and consumers' willingness to reveal – risk information. To do so, we are among the first to quantify the interaction between consumers' information and product (insurance) choices.[9] This endogenizes firms' information sets, allowing them to unilaterally mitigate adverse selection while enhancing their market power. We extend the existing literature that have largely focused on exogenous changes in public information in the market.[10] We are also close to a literature that studies information sharing across firms with incomplete information but not adverse selection (Gardete 2016).

Second, we are related to the literature on dynamic contracting and price discrimination.[11] Mon-

[8] If a driver is priced at \$100 by all insurers but is revealed to be 30% safer through monitoring, then the firm can offer a discount far lower than \$30 and still be confident about retaining her.

[9] See Cohen and Einav (2007), Fang, Keane, and Silverman (2008), Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2013), Handel (2013), Handel, Kolstad, and Spinnewijn (forthcoming), Bai (2018), Shapiro (2018), and Handel and Kolstad (2015) for various dimensions of unobserved consumer heterogeneity that lead to selection. We also allow consumers to be forward-looking, related to studies on reclassification risk (Hendel and Lizzeri 2003; Handel, Hendel, and Whinston 2015; Aron Dine, Einav, Finkelstein, and Cullen 2015).

[10] Regulations such as community-rating mandates (limits to risk categorization) are most common. See Finkelstein, Poterba, and Rothschild (2009), Einav, Finkelstein, and Schrimpf (2010), Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), Cox (2017), and Nelson (2018). Tadelis and Zettelmeyer (2015) exogenously alters information disclosure rules in a car auction experiment and find similar allocative efficiency benefits. Holding fixed information environment, Mahoney and Weyl (2017) posit that market power may further depress quantity under adverse selection, raising price and reducing total surplus, which is contradicted empirically by Crawford, Pavanini, and Schivardi (2018)'s study in the Italian small-business lending market. See also Dafny (2010), Einav, Levin, and Jenkins (2012), Hendren (2013), Ho and Pakes (2014), Shepard (2014), Veiga and Weyl (2016), and Ho and Lee (2017) for how firms can obtain market power and screen consumers through pricing, rejection, and product differentiation.

[11] We are close to the literature on usage-based pricing in which prices depend on usage of the product (Narayanan, Chintagunta, and Miravete 2007; Chung, Steenburgh, and Sudhir 2013; Lambrecht, Seim, and Skiera 2007; Liu, Montgomery, and

itoring allows the firm to learn about consumer risk over time (Hart 1983; Dewatripont and Maskin 1990; Hendel 2017).[12] We show that this has important implications on consumer behavior and firm profit. A related theory literature focuses on price discrimination enabled by consumers' online purchase histories. It predicts behavioral distortion but mixed impact on profit or consumer welfare.[13] Empirically, Hubbard (2000) studies required monitoring in labor contracts for truck drivers. He finds similar improvements in driving behavior and in the allocative efficiency (of jobs) as in our setting. Wei, Yildirim, Van den Bulte, and Dellarocas (2015) finds that the use of social network data in credit scoring distorts consumers' social interactions and diminishes the informativeness of such data. Soleymanian, Weinberg, and Zhu (2019) is closest to our setting.[14] They analyze driving data, as opposed to claim outcomes, from a U.S. auto insurance monitoring program and find that monitoring reduces several dimensions of unsafe driving but not the amount driven.

Third, we make two contributions to the literature on the economics of privacy. First, our empirical framework characterizes the equilibrium amount of information revealed by consumers. It embeds demand features common in information disclosure, such as imperfect advantageous selection,[15] inside a model of product market competition. This allows us to extend the literature by studying not only consumers' privacy choices,[16] but also how their choice environments are endogenously affected by pricing and competition.[17] Second, we bring back and empirically validate an argument in the literature that has received little attention: proprietary data is a form of privacy given to the data-collecting firm. Posner (1978), in particular, cautions the government to protect firms' data property right in order to preserve their incentives to produce socially valuable information.[18]

The rest of the paper proceeds as follows. Section I describes our data and provides background information on auto insurance and the monitoring program we study. Section II conducts reduced-form tests that measure monitoring's ability to reduce risk and to mitigate information asymmetry. Section III presents our structural model, identification arguments, and estimation procedures to recover key demand and cost parameters. Section VI discusses estimation results and counterfactual simulation procedures for welfare analyses. Section V proposes a model of monitoring pricing and investigates equilibrium implications for optimal pricing and information sharing. Section VI concludes.

Srinivasan 2014; Nevo, Turner, and Williams 2016). The main differences are the temporary nature of monitoring and its dynamic pricing impact, which turn our problem from a standard moral hazard one into one with a signaling equilibrium.

[12] Monitoring is a form of asymmetric learning: the monitoring discount is a form of voluntary renegotiation after the firm–and not its competitors–learns more about consumers' risk type. See also Rajan (1992), Nilssen (2000), and Cohen (2012).

[13] See also Rossi, McCulloch, and Allenby (1996), Acquisti and Varian (2005), Taylor (2004), Fudenberg and Villas-Boas (2006), and Stole (2007).

[14] Bordhoff and Noel (2008) and Reimers and Shiller (2018) use aggregate data to analyze auto insurance monitoring.

[15] See Milgrom (1981), Jovanovic (1982), Jin and Leslie (2003), Dranove and Jin (2010), and Lewis (2011).

[16] See Goldfarb and Tucker (2011), Goldfarb and Tucker (2012), Tucker (2012), Acquisti, John, and Loewenstein (2012), Burtch, Ghose, and Wattal (2015), Acquisti, Taylor, and Wagman (2016), and Kummer and Schulte (2019).

[17] There is a broad consensus across fields that consumers' privacy choice is highly context-dependent. See Nissenbaum (2009), Martin and Nissenbaum (2016), and Athey, Catalini, and Tucker (2017).

[18] His analysis defines privacy as concerning the efficient ownership of socially valuable information. See also Stigler (1980) and Hermalin and Katz (2006).

1 Background and Data

In this section, we provide background information on U.S. auto insurance and the monitoring program we study. We also describe our datasets.

1.1 Auto Insurance

Auto insurers in the U.S. collected $267 billion dollars of premiums in 2017.[19] There are two main categories of insurance: liability and property. Property insurance covers damage to one's own car in an accident, regardless of fault. Liability insurance covers injury and property liability associated with an at-fault accident. In all states we study, liability insurance is mandatory, the required coverage ranging from $25,000 to $100,000.[20]

Insurance prices are heavily regulated. Major insurers collect large amount of consumer information in risk-rating, most of which is public or shared across firms. Firms are required to publish filings that detail their pricing algorithms. In most states, the insurance commissioner needs to approve such filings.[21] An important focus of the regulator is deterring excessive price discrimination based on demand elasticity.[22] In general, a pricing rule can be summarized by the following structure, where price p for a (single-driver-single-vehicle) policy choosing certain liability coverage (limit) is:[23]

$$\begin{aligned} p = \text{base rate} \times \text{driver factor} \times \text{vehicle factor} \times \text{location factor} \\ \times \text{tier factor} \times \text{coverage factor} + \text{markups and fees} \end{aligned} \tag{1}$$

Within each firm, price variation is based on observable characteristics and choices. Base rates vary only by state and calendar time. Driver, vehicle, and location factors include age, vehicle model, and zipcode-level population density, etc. This information is often verified and cross-referenced among various public or industry databases. Tier factors incorporate information from claim and credit databases, which include accident, traffic violation (DUI, speeding, etc.), or financial (delinquency, bankruptcy, etc.) records in the past.[24] Conditional on the factors above, choosing a higher coverage (liability limits) scales prices by a positive factor. Lastly, firms charge a fee that includes markups and overhead for operational and marketing expenditures.[25]

A typical period for new customers is summarized in Figure 1a. At time $t = 0$, new customers arriving at the firm are required to report observable characteristics. This information facilitates risk

[19]This is according to the National Association of Insurance Commissioners. This number is calculated as premiums from property annual statements plus state funds.

[20]All states that we study follow an "at-fault" tort system and mandate liability insurance. In reality, liability insurance is specified by three coverage limits. For example, 20/40/10 means that, in an accident, the insurer covers liability for bodily injuries up to $40,000 overall, but no more than $20,000 per victim; it also covers liability for property damage (cars or other infrastructure) for up to $10,000. We quote the highest number here.

[21]Some states follow a "use-and-file" system, which means that insurers can seek pricing approval ex-post as long as any price changes are reflected in public filings.

[22]"Price optimization" on top of risk rating is typically not allowed by state insurance commissioners.

[23]See Appendix F, e.g. Figure F.1.

[24]See Appendix F, Figures F.7 and F.8

[25]The latter is often referred to as the loading factor in the literature.

rating, based on which the firm generates individualized price menu. Consumers can take one of the coverage options offered or go to other firms.

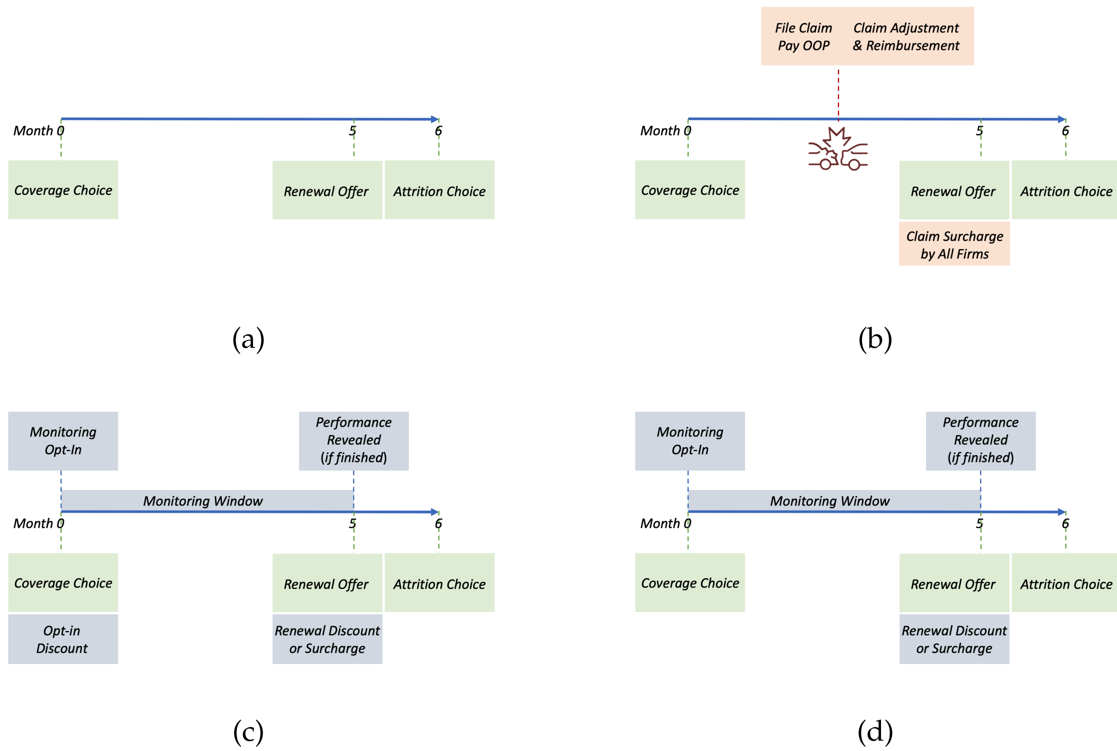

Figure 1: Timing Illustration of Auto Insurance Contracts and the Monitoring Program

There is no long-term commitment in U.S. auto insurance. In our setting, each period lasts for six months. At the end of month five, firms provide their customers with renewal quotes. Drivers decide whether to renew at the end of month six. During the policy (six-month) period, if an auto accident occurs (Figure 1b), the insured files a claim immediately and, depending on the claim type, pays some costs out-of-pocket. Insurance adjusters will then evaluate the accident and determine reimbursement and pay-out. As soon as a claim is filed, this information is recorded in industry databases in real time. As a result, the driver will likely face a claim surcharge renewing at the current firm or switching to other firms.

Dataset 1 - Panel data from an auto insurer Our first dataset comes from a national auto insurer in the U.S. that offers a large monitoring program. It is a panel that spans 2012 to 2016, and covers 22 states. For tractability, we narrow the scope of our analyses to *single-driver-single-vehicle* insurance policies sold online or via phone. Nonetheless, we observe more than 1 million drivers, for an average duration of 1.86 years (3.73 periods)[26]. The date range spans periods pre- and post-introduction of monitoring.

[26]The panel is right-censored, but the censoring is plausibly uninformative.

At the beginning of each period, we observe each driver's observable characteristics[27] as well as the price menu offered, which include all available options from the firm and their prices. We also see the driver's coverage choice. For simplicity, we limit our attention to *liability coverage* (limits). Not only is it the most expensive coverage (for the average driver), its mandatory nature also strongly influences firms' competitive strategy and monitoring's allocative benefit. These cover auto accidents involving two or more parties, in which the policy holder is at least partially at-fault. As such, our focus also mitigates concerns about under-reporting.[28]

During renewals, those with a claim will experience a surcharge that ranges from 10% to 50% (Figure A.4. The variation depends only on your existing claim and traffic violation records, which is summarized in points.). Otherwise, the average driver experiences close to no price change in a typical renewal period. Overall, about 5% to 20% of drivers leave the firm after each period.[29]

Table 1 presents summary statistics of prices, coverage levels, and claims. It also lists key observable variables. The average driver is 33 years old, drives a 2006 vehicle, lives in a zipcode area with average annual income of $142,000, and had 0.3 at-fault accidents in the past 5 years. Per six-month period, he pays $380 in liability premium and files 0.05 liability claims. We also observe his assigned risk class, which is the premium calculated for him before coverage factor and markups and fees.

Table 1: Summary Statistics of Premium, Coverage and Claims

Statistic	Mean	St. Dev.	Min	Median	Max
Total Premium (6-month)	631.50	364.02	69	548	22,544
Liability Premium	379.95	208.23	32.00	335.88	10,177
Risk Class	254.73	172.22	50.00	212.23	9,724
Liability Coverage ('000)	126.16	118.86	25	60	500
Mandatory Minimum Ind.	0.36	0.48	0	0	1
Liability Coverage Ranking	2.10	1.15	1	2	8
Renewal Count	1.76	2.01	0	1	9
Calendar Month	6.25	3.43	1	6	12
Calendar Year	2.66	1.38	0	3	5
Number of Drivers	1	0	1	1	1
Number of Vehicles	1	0	1	1	1
Claim (6-month)	323.47	2,821.78	0	0	544,814
Liability Claim	164.49	2,209.17	0	0	513,311
Claim Count	0.18	0.67	0	0	12
Liability Claim Count	0.05	0.32	0	0	7

Notes: This table reports summary statistics of our main panel data. Risk class is defined as the net premium calculated for each policy's liability coverage before markups and fees.

[27] Main observables include driver gender, age, martial status, education, out-of-state status, home-ownership, vehicle model, year, and financing, license and vehicle history, violation and accident records, credit history, prior insurance history, and zipcode population density. See Table A.1 for a list of observables used in our estimation procedure.

[28] In contrast, claim filing for single-car accidents is almost entirely discretionary.

[29] The first renewal is somewhat different, as some one-time discounts are removed. These are mostly cost-based discounts, such as e-signature or online quoting discounts. It therefore sees a higher attrition than subsequent ones.

Dataset 2 - Price menus of competitors based on price filings To understand competition, we need to account for drivers' outside options. Therefore, we complement our main dataset with competitors' price menus that drivers face when making insurance and monitoring choices. It includes quotes from all liability coverage options offered by the firm's top five competitors in each state. As seen above, price filings contain these information, and we harness it using Quadrant Information Services' reputable proprietary software. Each observation in our first dataset is matched with the competitive price menu the driver faces at the time of choice. We are able to achieve precise matches based on main observable characteristics, including state and calendar time.[30] In Table 2, we compare the quotes for the five most common liability coverage options across competitors. This is done on all our data in one large U.S. state.

Table 2: Summary Statistics by Coverage

Liability Coverage Limits	40	50	100	300	500
Quotes	335.14	343.43	382.03	422.13	500.48
- Competitor 1	482.68	506.11	564.34	626.81	730.56
- Competitor 2	263.14	279.15	314.46	347.69	405.22
- Competitor 3	319.42	348.97	388.48	428.64	464.36
- Competitor 4	511.24	567.58	613.74	682.87	790.83
- Competitor 5	421.84	363.96	403.64	433.17	497.79
NA Ratio	0.61	0.00	0.00	0.00	0.00
- Competitor 1	0.62	0.00	0.00	0.00	0.00
- Competitor 2	0.62	0.00	0.00	0.00	0.00
- Competitor 3	0.62	0.00	0.00	0.00	0.00
- Competitor 4	0.61	0.01	0.01	0.01	0.01
- Competitor 5	0.62	0.00	0.00	0.00	0.00
Claim	256.87	285.27	306.68	297.73	293.96
	(9.15)	(7.10)	(11.72)	(15.04)	(46.80)
Liability Claim	154.98	155.54	154.16	143.43	107.54
	(7.31)	(5.31)	(8.89)	(12.56)	(23.83)
Claim Count	0.09	0.10	0.10	0.10	0.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Liability Claim Count	0.05	0.05	0.04	0.03	0.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share within Firm	0.19	0.39	0.20	0.19	0.03

Notes: This table reports summary statistics by liability coverage. We report average quotes of own and top 5 competitors in one U.S. state. This is because different states have different sets of coverage options. In this state, mandatory minimum changed from \$40,000 to \$50,000. The NA ratio calculated the portion of plan that cannot be rated. This is mostly due to the mandatory minimum increase, as well as location-based rejection. The bottom panel reports summary statistics of claim variables.

Looking ahead, observing competitor prices allows us to identify parameters such as consumers' inertia to switch firms based on observed attrition choices in renewal periods. In counterfactual anal-

[30]We match based on variables in Table 1, plus other traffic violation records, zip-code, vehicle make and model.

yses, competitive prices can also help us enumerate our sample of new customers of the firm to the full market. Our ability to do so is further enhanced by prior insurance records.[31] On average, 48% new customers switched from another firm, about half from one of the top five competitors. We default the other switchers into the largest insurer of each state. 33% of new customers are previously uninsured (including new drivers), and 19% have a rewritten policy (by far the most common reason being an out-of-state move).

1.2 Monitoring Program

Our research focuses on the firm's one-time monitoring program for new customers.[32] The monitoring process is summarized in Figures 1c and 1d. When customers arrive, they choose whether to opt into monitoring right before seeing their price menu. They are provided with information on the kinds of driving behavior that are tracked and rewarded, although the exact discount schedule is opaque. Specifically, high mileage driven, driving at night, high speed, and hard braking are highlighted as monitored behavior. Across several monitoring programs offered by large U.S. auto insurers, drivers can expect a renewal discount of up to 20-50%. They can also receive a surcharge of up to 5-20% for poor performance. In some states and calendar times, drivers are given an up-front discount for opting into monitoring, ranging from 1 to 20%.

Should a driver opt into monitoring, a monitoring device is mailed within the next week. She then has until the end of month five to accumulate around 100-150 days of monitored driving. If completed, the firm will evaluate her performance and include an appropriate renewal discount when giving out renewal quotes. In the case of an accident, monitoring data is not used in claim adjustment or reporting. Monitoring continues after any disruptions from the accident.

27% of drivers who start monitoring do not finish. Our main analysis ignores these drivers and focus on analyzing consumers' decision to start and finish monitoring. Non-finishers likely have incorrect beliefs about the potential discounts they get or the costs they incur from monitoring. Most of them drop out during a two-month grace period in which they can learn about the monitoring program and their own risk.[33] Our analysis therefore does not account for the costs and benefits associated with this learning process.

During the monitoring period, monitored drivers receive real-time feedback on their performance. Different monitoring programs have different methods of communication. Insurers often post daily summary of key statistics of recorded trips online and via mobile apps, particularly on the highlighted behaviors mentioned above. They also offer more active reminders, some sends text messages or mobile app notifications, while others design devices that beep whenever it records a hard brake.

Nevertheless, monitoring data is *proprietary* information to the firm that administers the program. Firms face both practical and regulatory hurdles in rating monitoring information from another firm. First, it is hard to verify a customer's claim that she has gotten certain monitoring results from another

[31] This is part of tier information and is verified by the firm. It carries significant pricing weight.

[32] The firm has also offered a continuous monitoring program, but not during our research period.

[33] Drivers can drop out of the monitoring program for the first two months without penalty. Afterwards, dropping out results in the maximum amount of renewal surcharge.

firm. Even if verified, each firm's monitoring program and preexisting risk algorithm are idiosyncratic. Therefore, it is very difficult for an insurer to determine and publicly file a discount for a driver who has received a monitoring score of, say, 24 from a competitor (e.g., Figure F.9). Furthermore, according to the privacy policy and usage terms agreed to when opting into monitoring, no personally identifiable data can be resold. It is no surprise, therefore, that each firm only prices based on its own monitoring information according to price filings.

For the same reason, we are not able to empirically account for competitive monitoring programs in our analyses. Public filings contain very limited information on these programs; even monitoring start dates often do not coincide with the proposed dates in public filings. However, during our research window, monitoring in general takes up a small fraction of the market, especially around its introduction. We therefore do not consider this as a significant factor influencing our empirical results. In addition, the firm is the only one offering monitoring in some states and time periods. We replicate our empirical results in these subsamples for robustness.

Dataset 3 - Monitoring Our data on the firm's monitoring program includes its pricing schedule, drivers' opt-in choices, and monitoring scores and renewal discounts for finishers. The firm's monitoring pricing is discussed in Section 6 as well as in Appendix B. Across calendar time and states, the average monitoring finish rates are around $10 - 20\%$.

Monitored drivers' performance is summarized by a score, the distribution of which is plotted in Figure 2. The more punishable behavior recorded for a given driver, the *higher* her score. Drivers who received a zero score plugged in the device continuously for enough days but did not drive. We ignore these drivers in all subsequent analyses.

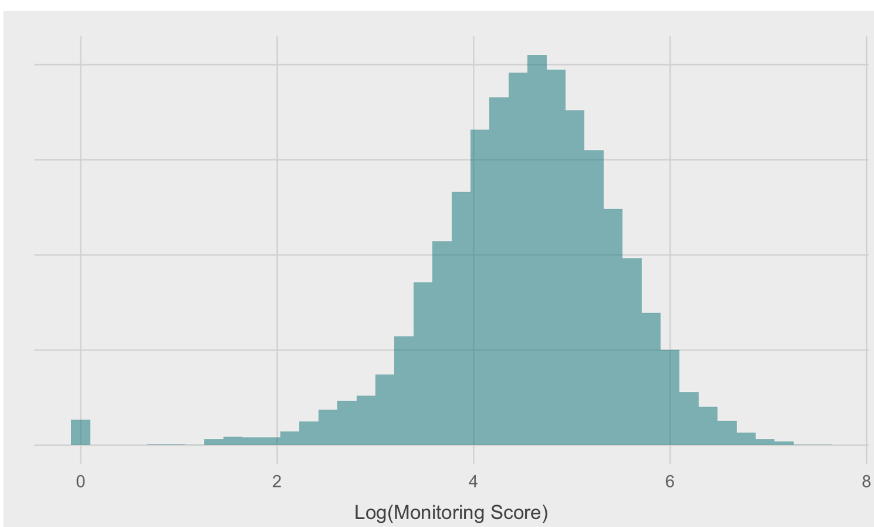

Figure 2: Distribution of monitoring scores

Notes: This graph plots the density of the (natural) log of monitoring score for all monitoring finishers. The lower the score the better. Drivers that received zero score plugged in the device continuously for enough days but did not drive. We ignore these drivers in all subsequent tests.

We treat this score as the output of the monitoring technology. It represents the firm's belief about *future* accident risk, based on a monitored driver's performance in the first (and monitoring) period. To see this, Figure 3 plots the average claim count in period two ($t = 1$, after monitoring) across monitoring groups. Compared to unmonitored drivers, those who finished monitoring are 22% safer. Among finishers, the quintile of their monitoring score strongly predicts their second-period risk, which ranges from 60% better to 40% worse than the opt-out pool.

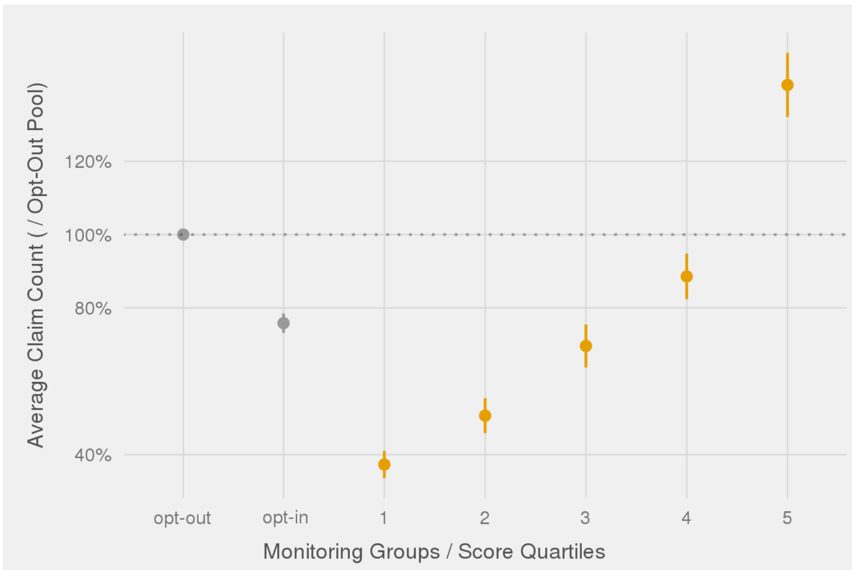

Figure 3: Comparison of subsequent claim cost across monitoring groups

Notes: This is a binned-scatter plot comparing average claim count of the first renewal period ($t = 1$, after monitoring ends) across various monitoring groups. The benchmark is the unmonitored pool, which is the "opt-out" group. Group "opt-in" includes all monitored drivers that finished the program per definition in section 1.2. Groups "1" to "5" breaks down the "finish" group based on the quartile of the drivers' monitoring score. Lower monitoring score means better performance.

Monitoring finishers face the same renewal choices as other drivers, except that their renewal quotes include appropriate monitoring discounts or surcharge. Figure 4 compares the distribution of first-renewal pricing change across monitoring groups. We benchmark the baseline price change to center around one. On average, monitored drivers received a 7% discount. Moreover, the monitoring discount is persistent after monitoring ends (Figure A.3). This is consistent with the firm's upfront communication with consumers during their opt-in decision.

Figure 4: First Renewal Price Factor by Monitoring Group

Notes: This graph plots the benchmarked (per firm request) distribution of renewal price change during the first renewal, by monitoring group. 1x represents mean renewal price change factor for the unmonitored group. Initial/upfront monitoring discount is not counted towards this. So that monitoring price change is discounted monitored price divided by undiscounted new business price. "Mon" and "UnMon" are monitored and unmonitored groups, while "Mon (pre-disc)" represents the renewal price change for monitored drivers without the monitoring discount.

2 Reduced-form Evidence

This section documents two reduced-form facts. First, drivers that opt into monitoring becomes safer when they are monitored. Despite this change in behavior, monitoring still reveals previously unobserved risk differences across drivers, which can lead to selection in consumer demand for monitoring and for insurance.

2.1 Risk Reduction and the Incentive Effect

If monitoring technology is effective, drivers may want to appear safer when monitored.[34] If this incentive effect is important and if drivers' risk is modifiable, then we should expect the *same* drivers to be riskier in unmonitored periods than in the monitored one.

Since monitoring is temporary, we can directly measure this effect by comparing claim outcome for the *same* monitored drivers before and after monitoring ends. This exercise requires us to balance

[34] This effect is studied in Fama (1980) and Holmström (1999). A similar setting is online tracking of consumers' purchase history (Taylor 2004; Fudenberg and Villas-Boas 2006). If consumers know that buying expensive items online may label them as inelastic shoppers and lead to higher prices in the future, they may refrain from purchasing those items online.

our panel. We focus on the first three periods (18 months).[35] There may be spurious trends in claim rate across periods that are irrelevant to monitoring. We account for this effect with exhaustive observable controls and a difference-in-differences approach. Among monitored drivers, we take the first difference in claim counts[36] between post-monitoring and monitored periods. This difference is then benchmarked against its counterpart among unmonitored drivers (control group).

$$C_{it} = \alpha + \tau m_i + \omega \mathbf{1}_{post,t} + \theta_{mh} m_i \cdot \mathbf{1}_{post,t} + \mathbf{x}'_{it}\beta + \epsilon_{it} \tag{2}$$

Here, i, t index driver and period in our panel dataset. C denotes claim count, and m_i is a driver-specific indicator for whether i has finished monitoring. x is a rich set of observable characteristics that the firm uses in pricing.[37]

Our main specification includes only monitored drivers who finish monitoring in the first period. To test for parallel trends of the monitored and unmonitored groups, we conduct the same test in subsequent periods after monitoring. In reality, some monitored drivers do not finish monitoring until subsequent periods.[38] To make use of this plausibly exogenous variation in monitoring duration and timing across the first and subsequent periods, we introduce another specification, adding additional variation in relative monitoring duration in the pre-period, z_i. It is calculated as the fraction of days monitored in the first period minus the same fraction in post periods.[39]

Results are reported in Table 3. We find a large and robust incentive effect. Column (3) corresponds to the specification in Equation 2, with the addition of insurance coverage fixed effects.[40] It shows that monitored drivers' average claim count is 0.009 or 23% lower during the monitoring period, compared to after it. Adjusting for the average monitoring duration of first-period monitoring finishers (142 days), a fully-monitored period would be 29.5% less costly to insure for the same driver. Incorporating additional variations in monitoring duration generates similar results (Column (6)). We test for parallel trends between the monitored and unmonitored groups by repeating the baseline specification in subsequent (unmonitored) periods. As shown in Columns (7-10), no differential claim change across periods can be detected between the two groups.

We discuss two important caveats of our results. First, monitoring provides a way for drivers to build a reputation for their risk (but only to the monitoring firm) (Fama 1980; Holmström 1999).

[35] In our robustness check, we show results with only two periods. Attrition is about $10 - 15\%$ per period and our data is right-censored, so balancing the panel eliminates 46% of our data.

[36] Throughout our reduced-form analyses, we use claim count as our cost proxy. This is because claim severity is extremely noisy and skewed. This is also common practice in the industry, where many risk-rating algorithms are set to predict risk occurrence only. We therefore present our estimates mostly in percentage comparison terms.

[37] See Table 1 for a list of main observable characteristics. We also include controls for trends and seasonality including third-order polynomials of the calendar year and the month when each driver i starts period t with the firm.

[38] Based on interviews with managers, among finishers, delays in finishing is predominantly caused by device malfunction or delayed start of monitoring due to mailing issues, etc.

[39] As discussed above, some drivers started monitoring but dropped out without finishing. This would bias our results if claims itself leads to non-finish. Out of more than 10,000 claims we observe among monitored drivers, only 13 occurs within 7 days before or after monitoring drop-out. In Table D.1, we further test the robustness of our results by repeating our main analyses on all drivers who started monitoring. This implies larger moral hazard effect adjusting for monitoring duration. However, if some monitored drivers drop out as they discover that they cannot change their risk, the incentive effect estimate would be contaminated by this selection effect.

[40] This soaks up any coverage adjustments between periods.

Table 3: **Estimates From Moral Hazard Regression**

	dependent variable: claim count (C)								
explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	Parallel Trend/Placebo		
constant	0.045***	0.002	0.003	0.046***	0.003	0.004	0.001	0.002	0.002
	(0.000)	(0.005)	(0.005)	(0.000)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
post monitoring indicator	−0.001*	−0.003***	−0.003***	−0.001**	−0.003***	−0.003***	0.001*	−0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
monitoring indicator (m)	−0.013***	−0.012***	−0.012***	0.008***	0.005***	0.005***	−0.005***	−0.005***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
monitoring duration (z)				−0.026***	−0.020***	−0.020***			
				(0.002)	(0.002)	(0.002)			
interaction ($\mathbf{1}_{post} \times m$)	0.008***	0.009***	0.009***	−0.005**	−0.005***	−0.005***	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
interaction ($\mathbf{1}_{post} \times M$)				0.015***	0.016***	0.016***			
				(0.002)	(0.002)	(0.002)			
observables controls (x)	N	Y	Y	N	Y	Y	Y	Y	Y
coverage fixed effects	N	N	Y	N	N	Y	Y	Y	Y
implied risk reduction (%)	28.0	29.4	29.5	27.5	29.4	29.6			
pre- / post-periods - "1st diff"	0 / 1-2						1 / 2	2 / 3	3 / 4
treatment / control - "2nd diff"	$t = 0$ finisher / unmonitored			all finishers / unmonitored			$t = 0$ finisher / unmonitored		
number of drivers per period	755,614			809,784			755,614	539,296	397,642

Notes: This table reports results of equation (2). The estimate on the interaction term ($\mathbf{1}_{post} \times m$ or z) measures the "treatment effect" of monitoring ending on claim count across periods. We first balance our panel data to include all drivers who stay till the end of the third semester ($t = 3$). This gives us two renewal semesters ($t \in \{1, 2\}$) after the monitoring semester ($t = 0$). We control for a full set of observables, including driver and vehicle characteristics and tiers (past records of violations or claims). It also includes third-order polynomials of calendar year and month. Continuous observable characteristics are normalized. We report estimates with and without these controls.

Columns (3) and (6) are our main specification. Column (3) focuses on monitored drivers who finished within the first period, while Column (6) introduces additional variation in monitoring duration and timing and looks at all monitoring finishers. Columns (1,2,4,5) show robustness of our estimates to observable and coverage fixed-effect controls. The right-most columns are placebo tests for parallel trends among treatment/control groups after monitoring ends. We first try to detect a similar change from $t = 1$ to $t = 2$. We drop all observations from period 0, and roll the post-period cutoff one period forward, so that $1_{post,t} = 1 \iff t \geq 2$ (changed from $t \geq 1$). Naturally, we look at the future trends of monitored drivers who finished within the first semester and drop other monitored finishers. We find similar results by repeating this test in subsequent periods. As we need to balance panels, number of drivers drop in these tests.

Moral hazard is therefore mitigated by drivers' concern over their future reputation as opposed to by directly contracting on effort as in a continuous monitoring setting. The magnitude of risk reduction can be different in the latter setting.[41] On the flip side, our result provides evidence that at least some drivers are forward-looking and respond greatly to future incentives. This means that uncertainty in dynamic premium (reclassification risk) may be nontrivial.

Second, our estimate measures a treatment-on-treated effect. If significant heterogeneity in the incentive effect exists across drivers and that it influences consumers' opt-in decision, then we would face external validity concerns in counterfactual simulations. In equilibrium, the firm assesses the signal monitored drivers send based on future claim records when drivers are no longer monitored, which corresponds to the renewal discount it gives. Therefore, risk reduction is compensated only to the extent to which it is correlated with drivers' future risk type. If safer drivers' risk levels are also more responsive to incentives, as suggested by a pure effort cost model for example, selection on the incentive effect can be important.[42] In this case, the effect we find will be larger than the population average (or the average treatment effect) (Einav, Finkelstein, Ryan, Schrimpf, and Cullen 2013). In our counterfactual analyses, we therefore maintain the opt-in structure of the monitoring program and do not extrapolate to scenarios where the market monitoring rate is high.

2.2 Private Risk and the Selection Effect

Are drivers who choose monitoring safer than those who do not? Table 4 reports the results of regressing claim count in the first period ($t = 0$) on monitoring indicator, controlling for the same variables as in Column (3) of 3. The incentive effect only accounts for 64% of the risk differences across the two group. Had the monitored drivers not been monitored in the first semester, they would still be safer than the average unmonitored driver. It thus suggests that drivers possess private information on their own risk. Therefore, there may be strong advantageous selection into monitoring.

Selection into monitoring suggests that the technology is effective at capturing previously unobserved differences in drivers' risk types, further allowing the firm to dynamically select safer drivers. The following regression examines both factors. It shows how average costs in future (unmonitored) periods vary based on monitoring choice and score among all drivers.

$$C_{it} = \alpha_t + \theta_{m,t} m_i + \theta_{s,t} s_i + \mathbf{x}_{it}' \beta_{\mathbf{t}} + \epsilon_{it} \tag{3}$$

Again, $m = 1$ for monitored drivers who finished within the first period. s denotes monitoring score, which is normalized among monitored drivers and set to 0 for others. Figure 6 reports $\hat{\theta}_t$ for renewal periods $t = 1$ to 5 (three years), translated into percentage difference terms.[43] Looking at the main specification (left grey series), the estimate for $\theta_{s,t}$ implies that a monitored driver which scores one

[41] We are also unable to disentangle the "Hawthrone effect" from drivers' responsiveness to financial incentives in our estimate. Since consumers must be aware of the data collection to be incentivized for it, we consider this effect as part of the incentive effect.

[42] Perfect revelation of a continuum of risk types is possible, as characterized in Mailath (1987), with a monotonicity condition similar to the single-crossing condition. However, consumers likely have multidimensional heterogeneity in reality, so drivers' performance during monitoring may not perfectly reveal their risk types (Frankel and Kartik 2016).

[43] Regression on a balanced panel of drivers (who stayed till the end of period 5) produces similar results.

Table 4: First Period Claim Comparison

	Dependent variable:
	Claim Count ($t = 0$)
constant	-0.004^{**}
	(0.009)
monitoring indicator	-0.014^{***}
	(0.001)
observable controls	Y

Notes: This table reports results of a regression where the dependent variable is first period claim count, and the independent variables are the monitoring indicator and observable controls. This is done within all first-period finishers of the monitoring program. This variable is consistent with the monitoring indicator in the incentive effect regression (2) (Table 3), so as to facilitate comparison and decomposition. *p<0.1; **p<0.05; ***p<0.01

standard deviation above the mean has a 29% higher average claim count in the first renewal (after monitoring ends). However, this informativeness diminishes dynamically, and disappears after 3 years. Further, controlling for claims does not alter our estimate much. This suggests that although claim realization is a direct measure of risk, its sparsity may significantly limit how informative it is of risk in the short run. In Figure 5, our results also show that the monitored pool is persistently safer in periods after monitoring ends.

These results are shaped not only by the selection into monitoring, but also by selective attrition due to more accurate risk rating. We may see the monitored pool becoming safer as risky drivers receive higher prices and leave the firm at higher rates. Regardless, both effects suggest that monitoring technology is effective at capturing previously unobserved driver risk.

In reduced-form analyses, it is difficult to disentangle these two effects or to detect coverage-level adverse selection. In general, exogenous and *unilateral* variation in the pricing of policies and monitoring is rare in our setting. As shown in Equation 1, price revisions often trigger changes in various inter-dependent prices that activate several demand margins at once. Therefore, in the next section, we propose a structural model to jointly account for several demand margins, including firm, coverage, and monitoring choices.

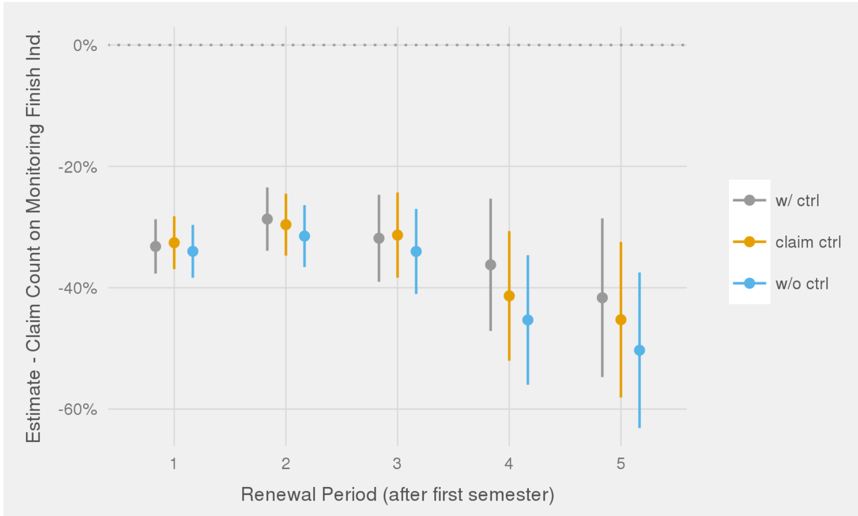

Figure 5: Regression results - dynamic informativeness of monitoring participation

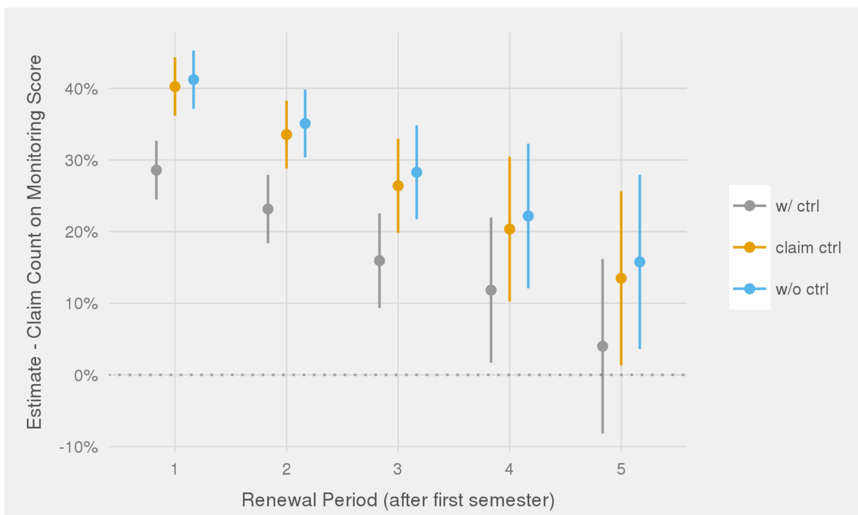

Figure 6: Regression results - dynamic informativeness of monitoring score

Notes: Figures 5 and 6 report the estimate for θ_t and γ_t from regression (3), translated into percent increase terms. Monitoring participation is defined as an indicator for finishing monitoring. For each $t > 0$, we take all drivers who stayed with the firm till at least the end of period t. θ_t is the coefficient of claim count of driver i in period t on monitoring score of i, and γ_t is that on monitoring finish indicator of i. Monitoring score is normalized, and defaulted as 0 for unmonitored drivers. So θ_t measures the effect of getting a score one standard deviation above the mean during the monitoring period ($t = 0$). γ_t compares unmonitored drivers with the average monitoring finisher. To further translate these effects into percent increase terms, we divide the estimate of θ_t and γ_t by the average claim count in period $t$of all *monitored* drivers. The horizontal axis represents different regressions for different renewal period $t > 0$.
Different colors and positions within each t value represent different specifications of control variables (x_{it}). The grey (left-most) series represents estimates from regressions with the full set of x_{it}; the orange (middle) one includes only claim records revealed since $t = 0$; the blue (right) series includes no control.

3 Cost and Demand Models of Auto Insurance and Monitoring

This section develops a structural model for consumers' monitoring opt-in choice in relations to their choices of insurer and insurance coverage as well as the cost of insuring them. We start from the canonical insurance framework, which consists of models for consumer preference and how their choices influence insurer costs. We then introduce additional features to incorporate drivers' opt-in decision and how monitoring technology can reveal driver risk. This allows us to link consumer demand in the information market with product (insurance) market fundamentals.

We describe our model in two parts. First, we outline a choice model conditional on the realization of claim and monitoring score. It features risk aversion, out-of-pocket expenditure, firm-switching inertia, as well as disutility from being monitored and expected price renewals. We then describe the data generating processes for claims and for monitoring scores in a cost model that features risk heterogeneity, the incentive effect, and monitoring score's signaling precision. This unifies the cost and demand factors under an rational expectation expected utility framework and introduces selection effects. Lastly, we provide an informal discussion of model identification.

3.1 Choice model

In our setting, consumers make firm, coverage, and monitoring participation choices. Drivers, periods,[44] and choice options are indexed by i, t, and d, respectively. Conditional on the realization of claims C and monitoring score s, the choice model specifies realized utilities $u_{idt}(C, s)$.[45]

Besides consumers' risk type, our choice model highlights three factors. (i) Risk aversion governs both preference for insurance and disutility from price fluctuations. (ii) Demand frictions: firm-switching inertia leads to imperfect competition among insurers. Consumers' disutility from being monitored accounts for factors such as privacy or effort cost associated with monitoring. They also sustain partial pooling equilibrium, in which only a fraction of the population is monitored. (iii) Future prices contain most of the benefit of monitoring and depends on claims and monitoring score.

Drivers have standard von Neumann-Morgenstern preferences $u(\cdot)$. We assume that they are twice continuously differentiable and globally increasing and concave, which pin down drivers' absolute risk aversion, denoted by γ. Each driver-period i, t starts with annual income w_{it}. Different choice options are denoted by $d = \{f, y, m\}$, where f, y, and $m \in \{0, 1\}$ index firm, coverage, and monitoring choices, respectively. For the same driver-period, differentiation in choice options is purely financial

[44] Monitoring takes place in the first period ($t = 0$).

[45] We model u structurally for two reasons. First, key structural quantities outlined below are of interest. Second, the model must explain consumers' choice to be monitored consistently with their insurance choice. As monitoring introduces additional uncertainty in future prices, we need to understand the micro-structure of how consumers handle risk.

and impact utility through the consumption term h_{idt}.

$$u_{idt}(C,s) = u_\gamma\left(w_{it} + h_{idt}(C,s)\right) \tag{4}$$

$$h_{idt}(C,s) = -p_{idt} - \underbrace{\mathbf{1}_{d,t-1} \cdot \psi_{idt}}_{\text{friction}} - \underbrace{e(C,y_d)}_{\text{oop}} - \underbrace{p_{idt} \cdot R_{idt}(C,s)}_{\text{renewal price}} \tag{5}$$

$$\text{where } \psi_{idt} = \underbrace{\mathbf{1}_{d,t-1} \cdot \eta_0}_{\text{baseline inertia}} + \underbrace{\mathbf{1}_{f_d,t-1} \cdot \eta(x_{it};\theta_\eta)}_{\text{firm-switching inertia}} + \underbrace{\mathbf{1}_{m_d} \cdot \mathbf{1}_{t=0} \cdot \xi(x_{it},\lambda;\theta_\xi)}_{\text{monitoring disutility}} \tag{6}$$

Consumption h includes four main components. Drivers pay prices p and friction costs ψ up front. The latter is broadly defined as a cost to change choices compared to the previous period ($\mathbf{1}_{d,t-1} = 1$). Drivers also form expectations over the realization of claims and of monitoring score. These influence out-of-pocket expenditures, e, and changes in renewal prices, R. Like prices, the out-of-pocket expenditure (oop) covers two periods, so that the overall consumption term h is of a one-year horizon.[46]

Demand friction (ψ_{idt}) includes heterogeneous disutility consumers experience from being monitored, $\xi(x_{it},\lambda)$, since monitoring is only offered to new customers of the firm. We allow it to vary across both observable characteristics and risk λ. Including the latent risk type λ is important in fitting selection into monitoring well. In its absence, the differential benefit of monitoring across safe and risky drivers is deterministic conditional on expected renewal prices. This may not accurately capture both the popularity of monitoring and the (risk) selection pattern into monitoring.

Demand friction also includes consumers' inertia associated with adjusting choices. We model them as implied monetary costs. The baseline inertia η_0 prevents consumers from making any choice adjustments. Heterogeneous firm-switching inertia $\eta(x_{it})$ further deters consumers from exploiting financially lucrative outside options. These terms capture imperfect competition that supports the observed attrition rate given price dispersion in the data (2). They capture the effect of search and switching costs consumers face when adjusting firms across periods as well as potential brand differentiation (Farrell and Klemperer 2007; Honka 2012; Handel 2013).

Renewal prices are influenced by a baseline price change factor (R_0) that can be influenced by monitoring results, as well as by claim surcharges (R_1). We separately model the two components to capture the correlation between out-of-pocket expenditures and renewal prices.[47]

$$R_{idt}(C,s) = R_{0,idt}(s) \cdot R_1^C \tag{7}$$

Monitored drivers gets a renewal price discount based on score s. We use a Gamma distribution to

[46] We assume that consumers are myopic but have a one-year (two-period) horizon, during which they do not consider changing choices after the first period. This is the simplest model that captures different types of costs and benefits of monitoring programs to consumers. In particular, dynamic premium risk (reclassification) is incorporated, as higher uncertainty in renewal prices diminishes ex-ante utility. It is unclear whether a two-period or fully dynamic model can be separately identified. Our model can also be interpreted as approximating a two-period dynamic model with infinite adjustment costs.

[47] Notice that R_1 changes R_{idt} for all d, including those at other firms. In reality, it is between 1.1 and 1.5 (Figure A.4). In contrast, monitored drivers are reclassified within the monitoring firm only. However, our myopia assumption diminishes this difference. We consider it as a realistic assumption because, as we will show later, the average switching cost is much larger than the potential surcharge that a monitored driver can receive.

model renewal price change R_0.[48] It is influenced by observables x and, if monitored, the monitoring score.[49] Notice that monitoring only impact own firm ($f^\star$) options.

$$R_{0,idt}(s) \sim \text{Gamma}(\alpha_{R,m}(x_{it}, s; \theta_{\mathbf{R}}), \beta_R) \tag{8}$$

By definition, out-of-pocket expenditure e is non-decreasing in claim, but non-increasing in the amount of coverage y.[50] Similarly, renewal price R is *non-decreasing* in both of its arguments. The choice-specific utility v_{idt} is simply the expectation of u over C and s.

$$v_{idt} = \mathbb{E}_{C,s}\left[u_{idt}(C, s)\right] \tag{9}$$

Lastly, we adopt a mixed logit structure (Train 2009) to model discrete choice.

$$d_{it} = \arg\max_{d \in D_{it}} \{v_{idt} + \varepsilon_{idt}\} \tag{10}$$

$$\text{where } D_{it} = \begin{cases} \mathcal{F}_{it} \times Y_{\mathcal{F},it} & t > 0 \text{ or } i \text{ ineligible} \\ \mathcal{F}_{it} \times \{Y_{-f^\star,it}, Y_{f,it} \times \{0,1\}_m\} & t = 0 \text{ and } i \text{ eligible} \end{cases} \tag{11}$$

The choice space D can vary based on driver-period i, t, but always includes firm space $\mathcal{F}$ and the corresponding coverage space Y. It covers all firms we observe, including the monitoring firm $f^\star$. As discussed in Section 2, we assume that no other firms offer monitoring, for which only new customers that come to the firm after monitoring introduction are eligible. In addition, we abstract away from monitored drivers that drop out; the opt-in indicator m therefore represents drivers' decision to finish monitoring. Lastly, ε follows a type 1 extreme value distribution with scale σ.

Our *demand parameters* include risk aversion, baseline inertia, intercept and slope parameters for heterogeneous firm-switching inertia, monitoring disutility, as well as the (expected) renewal pricing rule:

$$\Theta_d = \{\gamma, \eta_0, \theta_\eta, \theta_\xi, \theta_{\mathbf{R}}, \beta_R, \sigma\}.$$

3.2 Cost model

Let λ be defined as the expected claim count (C) per period. We model λ as follows:

$$\lambda_{imt} = \mu_\lambda(x_{it}, m; \theta_\lambda) + \epsilon_{\lambda,i} \tag{12}$$

$$\ln \epsilon_{\lambda,i} \sim \mathcal{N}(0, \sigma_\lambda) \tag{13}$$

$$C \sim \text{Poisson}(\lambda) \tag{14}$$

[48] Figure 4 shows the actual distribution of the first-renewal price-change factor.

[49] In subsequent renewals, prices are very stable. We therefore assume that $\alpha_R = \beta_R$ in those periods so that, in expectation, prices do not change without claims.

[50] We abstract away from strategic reporting behavior.

We interpret $\epsilon_{\lambda,i}$ as the persistent private risk of driver i with variance σ_λ.[51] We further assume that it is distributed i.i.d. log-normally.[52] Let M denote the set of monitored drivers. Then advantageous selection into monitoring implies that:

$$\mathbb{E}[\epsilon_{\lambda,i}|i \in M] < \mathbb{E}[\epsilon_{\lambda,i}|i \notin M] \tag{15}$$

The incentive effect may reduce monitored drivers' risk during the monitoring period. We adopt a reduced-form approach towards modeling this effect to avoid making further assumptions about the underlying structure of effort provision and risk determination. We assume that the incentive effect is homogeneous across drivers and that it enter risk in an mechanical and additive-separable fashion:[53]

$$\mu_\lambda(x_{it}, m = 1) = \mu_\lambda(x_{it}, m = 0; \theta_{\lambda,\mathbf{0}}) + \theta_{\lambda,m} \cdot \mathbf{1}_{t=0} \tag{16}$$

In order to get out-of-pocket expenditure, we need to model not only the severity of claims, but also that of accident loss conditional on occurrence. Let ℓ denote the latter quantity, which is assumed to be independent from claim count arrival and drawn from a Pareto distribution:

$$\ell_{idt} \overset{\text{i.i.d.}}{\sim} \text{Pareto}(\ell_0, \alpha_\ell) \tag{17}$$

α_ℓ is the main (shape) parameter. In the primary specification, we assume that α_ℓ is homogeneous across drivers. Importantly, we assume that there is no unobserved heterogeneity in the conditional loss severity.

Monitoring Technology (Score) We model monitoring score s as an informative signal of private risk ϵ_i. Monitoring score is driver-specific and is revealed once for monitored drivers after the first semester ($t = 0$).

$$\ln s_i \sim \mathcal{N}\left(\mu_s(x_i, \ln\lambda; \theta_{\mathbf{s}}), \sigma_s\right) \tag{18}$$

We assume that the signal noise has a log-normal distribution with mean μ_s and and precision σ_s, similar to the latent risk type λ that it tries to capture. When $\frac{\partial \mu_s}{\partial \lambda} \neq 0$ and σ_s is finite, the realization of s is informative of λ conditional on observable x. On the other hand, s perfectly reveals λ as $\sigma_s \to 0$.

Overall, we can define the *cost parameters* as the intercept and slope parameters for unmonitored latent risk type λ, the incentive effect parameter, the spread of latent risk type conditional on observables, intercept and slope parameters for conditional accident loss, the intercept and slope parameters for monitoring score, and montioring score precision.

$$\Theta_c = \{\theta_{\lambda,\mathbf{0}}, \theta_{\lambda,m}, \sigma_\lambda, \alpha_\ell, \theta_{\mathbf{s}}, \sigma_s\}$$

[51] In our estimation, we allow σ_λ to vary based on driver tenure (Ansari, Jedidi, and Jagpal 2000).

[52] Risk parameters are non-negative. Cohen and Einav (2007) and Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2013) use the same distributional assumption. We also investigate a robustness check with normally distributed λ.

[53] For more careful treatment of moral hazard and risk determination, see Jeziorski, Krasnokutskaya, and Ceccarini (2014).

3.3 Identification

We now provide an informal discussion of the data variation and model structure that allow us to identify cost and demand parameters.

Cost parameters All parameters contained in Θ_c can be identified with cost data alone. Variations in average claim count and monitoring scores across observable groups identify θ_λ and $\theta_{\mathbf{s}}$ (slope parameters). $\theta_{\lambda,m}$ is identified with the same data variation outlined in the reduced-form section in Equation 2. As in Cohen and Einav (2007), σ_λ is identified when sufficient number of drivers file for multiple claims per period, conditional on observables. In addition, the monitoring score brings additional restrictions to the distribution of private risk, conditional on signal precision σ_s. Therefore, σ_s and σ_λ are jointly identified in our setting by the variance of claim counts and monitoring score conditional on observables and on one another.

In modeling and identifying loss severity, we attempt to accurately capture both insurer cost, which we observe, and out-of-pocket expenditure in consumers' expectation, which is unobserved. The Pareto distribution does a good job balancing these two objectives. With appropriate location parameter, it fits the average claim amount well. At the same time, it is sufficiently long-tailed so that loss events significantly larger than coverage limits still have non-degenerate support in consumer's expectation. This is important in fitting the share of large coverage limits.

Demand parameters Our demand identification largely relies on price and contract space variation. Controlling for the observable characteristics used in firms' pricing rules, the remaining price variation depends on location and calendar time. We specifically model consumers' risk differences across these dimensions by including each consumers' assigned risk class in the cost model. We further include controls for yearly trend, seasonality, and zipcode characteristics including income and population density in our demand parameters. Therefore, we are left with price changes associated with the firm's and its competitors' rate revisions (back-end changes in pricing rules) as well as cross-location differences that are plausibly exogenous from consumer demand. Specifically, the firm also changed monitoring opt-in discount over time.

We also observe variation in consumers' contract space conditional on observables. Specifically, monitoring eligibility differs based on state, time, specific vehicle models, and renewal period. For instance, drivers arriving before monitoring introduction in their states or with vehicles older than 1995 are not eligible. Monitoring is also only available to new customers. Meanwhile, mandatory minimum coverage also changed in two states within our research window. We use one in our demand estimation (see Table 2) and reserve the other for cross-validation (see Table 6).

Our primary concern is in identifying monitoring disutility (ξ) well. Given cost parameters and risk aversion, we can determine the relative attractiveness of the same coverage option with and without monitoring based on objective financial risk and rewards. However, just because a driver can financially benefit from monitoring does not mean that she will opt in. The monitoring disutility is pinned down by the observed monitoring share (under different pricing environments) given cost parameters and risk aversion. The slope parameter on risk type ($\theta_{\xi,\lambda}$) further turns the monitoring disutility term into a risk-specific shifter that flexibly controls the share of each risk type opting into monitoring. It therefore helps us fit both the share of monitoring and selection based on risk.[54]

Another parameter of interest is risk aversion γ. For a given i, t, different γ values imply different gradient of Δv_{idt} across the multiple coverage options we observe in the data.[55] Therefore, conditional on risk parameters, risk aversion can be identified by how the empirical coverage share changes given contract space and pricing environment.[56] In our demand estimation, the Pareto severity parameters can also affect changes in coverage attractiveness. However, we restrict the Pareto distribution to approximate the actual (truncated) claim severity that we observe.

We also need to separately identify baseline inertia (η_0) and consumers' firm-switching inertia (η). Conditional on observables, different levels of these parameters imply unique combinations of the share of drivers who adjust coverage versus leaving the firm at renewals. We also observe rich variation in competitive pricing environments conditional on observables. Under a given pricing environment, these parameters imply a corresponding threshold under which drivers would stay with the firm, and another one under which drivers would not adjust choices at all.

4 Estimation

In this section, we propose econometric specifications in order to take our model above to the data. We also discuss identification, our estimation procedure, the model fit, and cross-validation results.

4.1 Econometric Specifications

Intercept and slope parameters We parameterize heterogeneous latent parameters linearly:

$$\begin{aligned}
\eta(x_{it}) &= (1, x_{it})' \, \theta_\eta \\
\xi(x_{it}) &= (1, x_{it}, \ln\lambda)' \, \theta_\xi \\
\alpha_{R,m}(x_{it}) &= \begin{cases} \mathbf{x}_{it}^{R\prime} \theta_{\mathbf{R},\mathbf{0}} & m_d = 0 \\ \left(\mathbf{x}_{it}^{R}, s\right)' \theta_{\mathbf{R},\mathbf{1}} & m_d = 1 \end{cases} \\
\mu_\lambda(x_{it}, m = 0) &= (1, x_{it})' \, \theta_{\lambda,\mathbf{0}} \\
\mu_s(x_i, \lambda) &= (1, \ln\lambda_i, x_i^s)' \, \theta_{\mathbf{s}}
\end{aligned}$$

[54]Simply raising baseline monitoring cost for all risk types (conditional on observables) enhances selection but also necessarily reduces monitoring share.

[55]This is conditional on the fixed effect for the mandatory minimum plan (ψ_1). The fixed effect adds an additional degree of freedom to more flexibly fit the gradient of willingness-to-pay across coverage options.

[56]Specifically, based on the company's pricing rule in Equation 1, the price gradient across coverage options only depends on the actuarial risk class assigned to each consumer and the coverage factor. The latter is heavily regulated. Each state offers an official guidance on the coverage options that auto insurers should offer and the corresponding coverage factors. Firms need to provide actuarial support to deviate from the guidance in order to avoid regulatory scrutiny. Empirically, coverage factor is rarely changed in our demand estimation states based on rate revision filings.

Broadly consistent with actual firm pricing rules, x_{it}^R and x_i^s only include a polynomial and the log of risk class, which represents firm's risk assessment without monitoring information.

Nest structure Incorporating additional alternative-level random effects can further enrich our model. In our primary specification, we add a random coefficient, ζ, on all choices within $f^\star$. This allows us to capture correlations between choices within the firm. Here, we assume ζ is an independently normally distributed with mean zero and standard deviation σ_ζ (Train 2009). This allows us to escape the Independence of Irrelevant Alternatives property of a simple logit model. The model can therefore achieve better fit on attrition rate differences across consumers facing different contract spaces across states or when mandatory minimum changes.

Taylor approximation approach for nonlinear utility Next, following the literature on auto insurance choices (Cohen and Einav 2007; Barseghyan, Molinari, O'Donoghue, and Teitelbaum 2013), we start with an approximation approach to model the utility function . Assuming that third- or higher-order derivatives are negligible, the utility function can be expressed by a second-order Taylor approximation of the utility function around income w. Normalizing by marginal utility evaluated at w, we get the following expression, in which γ is the absolute-risk-aversion term:

$$v_{idt}(\lambda, \zeta) = \mathbb{E}\left[h_{idt} \right| \lambda, \zeta] - \frac{\gamma}{2}\mathbb{E}\left[h_{idt}^2 | \lambda, \zeta\right] \tag{19}$$

This further simplifies product differentiation into consumption bundles with different mean and variance profiles. It also allows us to interpret v in monetary values, as the second term of Equation 19 is exactly the risk premium, while the first is expected consumption. We are currently running robustness checks for alternative utility assumptions such as CARA and CRRA, as well as to allow for richer heterogeneity in risk preference.

4.2 Estimation

Our model includes random coefficients that enter utility nonlinearly. Private risk, in particular interacts with various observed monitoring and coverage characteristics (renewal price, out-of-pocket expenditure), as well as unobserved demand parameters (risk aversion and monitoring cost). Therefore, we use a simulated maximum likelihood approach (Train 2002; Handel 2013). In particular, the mix logit structure implies that the choice probability is numerically integrated as follows:

$$\begin{aligned}\Pr(d_{it}|\lambda) &= \Pr(\epsilon_{idt} - \epsilon_{id't} > [v_{idt}(\lambda) - v_{id't}(\lambda)] \ \forall d' \neq d \\ &= \frac{\exp\left[v_{idt}(\lambda)/\sigma\right]}{\sum_{d'} \exp\left[v_{id't}(\lambda)/\sigma\right]} \qquad (20)\\ \Pr(d_{it}) &= \int \Pr(d_{it}|\lambda) f_\lambda(\lambda) d\lambda \qquad (21)\end{aligned}$$

In general, for each parameter proposal Θ_d, we simulate 50 independent draws of private risk

(ϵ_λ) and the zero-mean firm dummy (ζ).[57] Then, we compute the likelihood for observed choices, claim count and severity, monitoring score, and renewal price change. These are averaged over to get the simulated log likelihood. The estimator $\theta^\star$ maximizes the log likelihood. Notice that the Taylor approximation allows us to derive closed-form solutions for the first two moments of out-of-pocket expenditures and renewal prices.[58] We therefore do not simulate claim losses or monitoring scores within each draw of random coefficients.

As discussed above, our cost model is easier to estimate but requires a large amount of data to estimate precisely. Our demand model faces the opposite challenge, being computationally demanding but also making use of rich variations in choice environment and outcome. Therefore, we adopt a two-step estimation procedure. First, risk and monitoring score parameters ($\theta_\lambda, \sigma_\lambda, \theta_s, \sigma_s$) are estimated in the full dataset (except the loss severity parameter, per the discussion above). We then feed the estimates into the demand models as truth.[59] We lose precision by doing so, but both models are identified standalone.

4.3 Fit and cross-validation

We demonstrate that our demand model is flexible enough to produce accurate fit for four critical moments of the data in table 5 and figure 7. We present two specifications: a basic one that excludes a firm dummy (ζ random coefficients) or private monitoring cost ($\theta_{\xi,\lambda}$), and a comprehensive one that includes these variables. As Table 5 shows, we match monitoring and coverage shares within our firm well. Further, first-renewal attrition rates – the share of outside option – is also broadly consistent. More importantly, the primary specification is able to accurately fit the expected monitoring score. This demonstrates that the model is capable of capturing selection as well as the effectiveness of the monitoring score. Figure 7 confirms this graphically: we calculate the expected monitoring score for each driver over all random-coefficient draws. The red line plots the simulated score weighted by the corresponding monitoring choice probability in each draw. The orange line plots the full distribution of expected monitoring scores, had everyone in the data finished monitoring.

Using these estimates, we can calculate the expected unmonitored risk type (no incentive effect) of *monitored* drivers in the first period. Specifically, when we numerically integrate over private risk ϵ_λ, we simply weight it by the choice probability of monitoring. This gives us the expected (unmonitored) risk type in the monitored pool. Vice versa for the unmonitored pool. The selection effect is therefore a ratio between the two. The 21% ratio between the two pools is similar to the 17% back-of-the-envelope calculation we did in the reduced-form section.

[57] We test the effect of increasing the number of draws in estimation on a 10,000 sub-sample. The effect of going from 50 to 200 draws is minimal.

[58] Further, we restrict α_ℓ to be larger than 2 so that the mean and variance of the distribution are both finite, as both moments enter consumers' utility. The mean of the Pareto distribution is thus no more than $2\ell_0$. Therefore, to fit the average cost to the firm well, we set $\ell_0 = 3000$, roughly half the empirical mean of the claim distribution. This parameter is selected in cross-validation, om which we compare model performance in a hold-out dataset by directly calculating the likelihood. In a robustness check, we are also fitting a Gamma model for calculating the firm's cost only.

[59] Standard errors for the demand estimates are current not adjusted for two-step estimation. In a robustness check, we are correcting those standard errors and implementing a joint estimation.

Table 5: Demand Model Fit

	Basic Specification	**Primary Specification**	**Data**
Monitoring share (when eligible)	17.7%	15.6%	15.3%
Expected score	5.46	4.25	4.30
Selection effect (risk)	6.7%	21.2%	-
Coverage share			
30K	13.7%	12.5%	12.7%
40K	9.1%	8.2%	8.5%
50K	53.2%	49.8%	47.1%
100K	13.0%	15.4%	17.0%
300K	9.3%	11.9%	12.3%
500K	1.8%	2.3%	2.4%
First renewal attrition (indexed)	133.0%	102.9%	100.0%

Notes: This table reports the fit of our demand model as described above. The primary specification is outlined in our econometric model section. Monitoring share is conditional on eligibility. For coverage shares, our demand estimation data pools across three states with different mandatory minimum. One state changed mandatory minimum from 30K to 50K; estimation data is drawn from only the pre-period of that state to capture monitoring introduction. First renewal attrition rate is benchmarked to data per the firm's request (reporting percent differences, not percentage point differences).

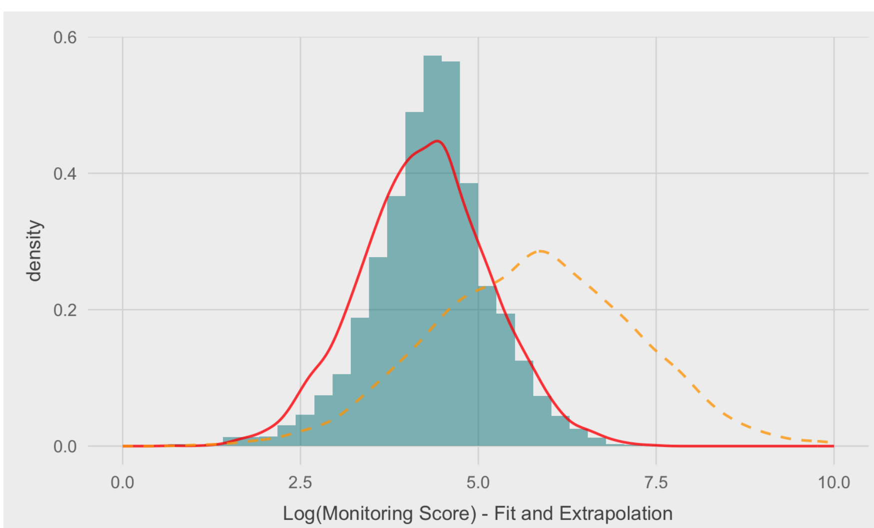

Figure 7: Monitoring Score - Fit and Extrapolation

Notes: The green histogram is the empirical distribution of monitoring score for monitoring finishers in our demand estimation data. The red line plots the fitted distribution as outlined above. The orange dotted line plots the density of the extrapolated distribution of monitoring scores had all drivers finished monitoring.

The availability of un-used demand data allows us to perform cross-validation. In particular, one state in our dataset increased its mandatory minimum from $30,000 to $50,000. In our demand estimation, we draw from only the pre-change period for this state. The hold-out sample, however, contains all drivers in that state arriving in the post-period. As shown in Table 6, our model performs well out of sample.

Table 6: Cross Validation

	Basic Specification	**Primary Specification**	**Hold-Out Data**
Monitoring share (when eligible)	21.2%	17.9%	17.6%
Expected score	5.23	3.97	4.17
Selection effect (risk)	5.2%	23.7%	-
Coverage share			
30K	-	-	-
40K	9.4%	7.6%	7.2%
50K	66.3%	60.5%	58.1%
100K	13.4%	17.5%	19.6%
300K	9.7%	10.9%	12.8%
500K	1.3%	3.6%	2.4%
First renewal attrition	132.2%	104.2%	100.0%

Notes: This table reports our cross-validation result. All measures are calculated analogously as Table 5. For the state that changed mandatory minimum, the hold-out data include all post-period data. For the other two states, the hold-out data include all observations that are not in our demand estimation data.

5 Estimation Results and Welfare Calculations

The raw estimates of our models are reported in Tables A.1 to A.2. In this section, we highlight some key results and provide intuition. In particular, we use a simulation exercise to demonstrate the relative importance of different demand factors. We also conduct welfare calculations. Importantly, all simulation exercises in this section hold observed prices as fixed.

The magnitude of private risk and the monitoring score's signal precision are presented in the left panel of Table A.2. Compared to Cohen and Einav (2007), we find significantly more unobserved heterogeneity in driving.[60] This can be attributed to our ability to capture information contained in an additional signal of private risk – the monitoring score. New drivers who do not have past claim records see particularly high spread of private risk. our estimates also capture the monitoring

[60] Our private risk spread is 0.43 ($\exp(\ln \sigma_\lambda)$) for non-new drivers, compared to Cohen and Einav (2007)'s estimate of 0.15.

technology and the firm's renewal prices well. In particular, monitoring score rises with driver risk, as do renewal prices for monitored drivers (Table A.3).

Figure 8 benchmarks our risk-aversion parameter against the literature. Our primary specification assumes homogeneous risk aversion and the estimate is broadly consistent with the literature.[61] In the graph, risk aversion is interpreted as the indifference value between inaction and taking a 50-50 bet on gaining $1000 versus losing that value.

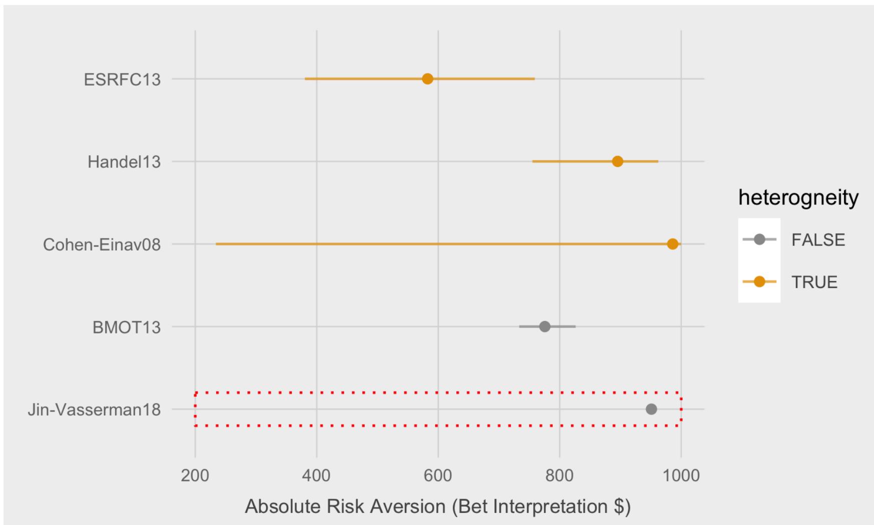

Figure 8: Risk Aversion Parameter Estimates - Benchmark

Notes: This figure benchmarks our risk aversion parameter estimate to the literature. Heterogeneity indicator means that the author allows risk aversion to vary across people, in which case we plot the range of risk aversion paramters in the population. Otherwise we plot the 95% confidence interval of the homogeneous risk aversion parameter.

Also consistent with prior literature, demand frictions are empirically important. This implies that many drivers who can benefit from monitoring do not participate. In Table 7, we show the empirical distribution of both firm-switching and monitoring costs in the population. The average driver foregoes $283 of gain by not choosing an outside option from other firms, which is 44% of annual premium (two periods). Monitoring cost is also large and is heterogeneous across drivers. In particular, the average driver needs to expect a gain of $93 to participate in monitoring.

Moreover, monitoring disutility increases with private risk.[62] This further accelerates advantageous selection into monitoring, while suggesting that observed renewal prices alone are not enough to explain the empirical selection pattern. At the same time, we see that older and more educated drivers tend to have lower monitoring costs, as well as those with newer cars, better prior insurance records and less traffic violation points.

Looking at the right panel of Table A.2, the fixed inertia cost that drivers need to overcome when adjusting coverages is $134. This adds to firm-switching and monitoring costs and further prevents

[61] Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2013), in particular, differentiate between probability distortion (wrong belief about one's own risk) and risk aversion.

[62] Column (2) of table A.1 in the appendix reports the slope parameter for private risk.

Table 7: Latent Parameters

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Firm-switching Inertia							
$\eta(x)$	283.63	35.39	157.71	264.85	286.46	307.11	406.56
(/ annual premium)	0.44	0.17	0.11	0.31	0.41	0.55	0.55
Monitoring Disutility							
$\xi(x, \lambda)$	92.83	19.21	9.52	79.97	92.54	105.21	187.20
(/ annual premium)	0.14	0.06	0.01	0.10	0.13	0.18	0.25
Claim Risk λ	0.05	0.05	0.001	0.02	0.03	0.06	1.48

Notes: This table reports the distribution of heterogeneous latent parameters in our dataset. We simulate a distribution of private risk and calculate these parameters based on our demand estimates.

safe drivers from being monitored. All else equal, the average driver only prefers the mandatory minimum coverage by \$26, which seems low given that the plan commands almost 50% market share. This suggests that the rational amount of coverage for many drivers may be below the mandatory minimum, which restricts how monitoring can affect allocative changes across coverage.

5.1 Fixed-price Counterfactuals and Welfare Calculations

In this section, we use several simulation exercises to understand the demand and profit impact of removing different elements of the demand model as well as the welfare impact of introducing monitoring. We hold prices fixed here, and study equilibrium implication in the next section.

Simulation methodology Consistent with our demand model, we take a one-year horizon. The following procedure is used to calculate ex-ante and expected realized (ex-post) quantities.

1. For each driver i, simulate random coefficients (private risk and firm dummy) $L \in \mathbb{N}^+$ times.
2. For each draw $l \in \{1, ..., L\}$, calculate ex-ante utility directly and the corresponding certainty equivalent.[63] First-period choice probabilities are also calculated, which gives us the monitoring share. Expected cost of the first semester can be calculated directly. But we also need to form an expectation of the second-period cost (and prices) in order to calculate total surplus (and profit):
3. Simulate $K \in \mathbb{N}^+$ draws of first-period claim occurrence and monitoring score based on private risk.[64] Each draw pins down the renewal price change that driver i would face in the second

[63]Due to our Taylor approximation, this should be the negative root of the polynomial.

[64]For simplicity, we assume that R_0 is deterministic conditional on C and s. In reality, the spread of baseline R_0 without claims and monitoring may have subtle nonlinear effects on consumer choice, which we assume away.

period. All other prices remain constant. For each first-period choice d, we can then calculate the second period choice probability and the corresponding expected cost.

Sample enumeration Since we observe new customers' origins, as well as the competitive prices they face when coming to the firm, we can use our model to enumerate a full sample of potential new customers (Train 2009). To do so, we first calculate the probability of each new customer arriving at the firm. We then follow the same procedure as outlined above, but weight each driver by the inverse of the calculated probability. The simulation is carried out assuming that monitoring is available for all new customers.[65] Overall, our simulated dataset is expanded by a factor of 4.03, which gives us a market share (among the top six firms for which we have data) close to the reality in the states we study.[66] This also allows us to derive a realistic proxy for competitor profit under a symmetric cost assumption; that is, the distribution of risk that we estimate in our dataset is valid when extrapolated to the simulated market.

In order to enumerate the market, we need to extrapolate the estimated attrition elasticity the firm faces to understand how the firm competes with other firms in the first period. To do so, we make a *no-brand-differentiation assumption*: liability insurance contracts offered by different firms only differ financially. This means that our firm-switching inertia estimate consists only of search and switching costs that are state-dependent (on consumers' preexisting firm choice) and that consumers have no unobserved preference for our firm, which is not state-dependent. In the context of our counterfactual simulations, this assumption essentially maintains that the price elasticity the firm's competitors face when the firm tries to poach customers away from them (in the first period) is the same as the price elasticity the firm faces when trying to retain existing customers.

This assumption follows naturally from our data limitation: we do not observe comprehensive micro-level choice or quantity data for the firm's competitors. But it is also supported by empirical evidence. Honka (2012) uses a survey dataset that includes individual consumer choices across auto insurers. She is then able to tease out switching cost from firm-specific preferences. She finds that the mean firm preferences are not significantly different from 0 for all companies.[67]

Counterfactual demand models In this section, we show simulation results of removing key components of the demand model, as an illustration of their relative importance in determining monitoring share and the firm's profitability.

[65] Part of the estimation data is pre-monitoring introduction. We use the average opt-in discount for these drivers.

[66] We winzorize the re-weighting scaling factor to be between 1 and 20 to deal with outliers.

[67] Her estimate of search and switching cost is lower than our estimate. However, for the firm from which our administrative dataset comes from, the reported attrition rate in her dataset is more than three times as large as what we observe. Her estimate is therefore likely biased downwards.

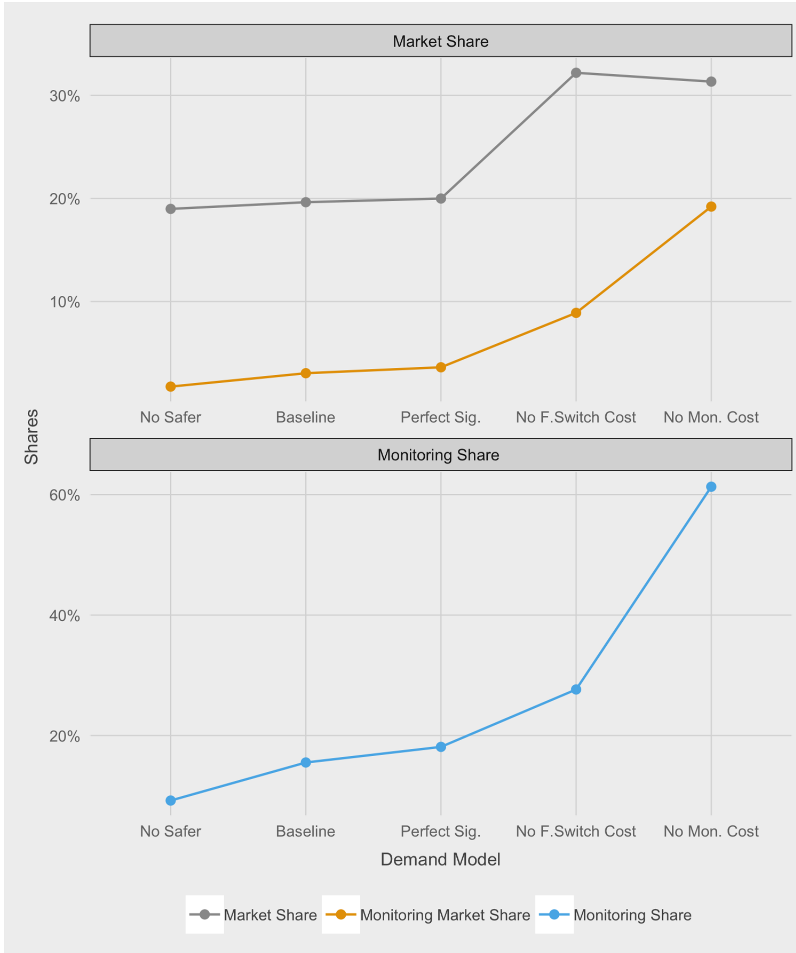

Figure 9: Demand Share Simulation Across Demand Model Assumptions

Notes: These figures correspond to our analyses in 5.1. The top graph plots the counterfactual market share of the firm, as well as the unconditional share of monitored drivers in the market, when prices are fixed but the demand model changes. The bottom graph plots the conditional monitoring share within the firm. See main text for definitions of each model - importantly, changes in model features are *not* cumulative from left to right. We also enumerate our sample of new customers to the full market with model-predicted likelihood of each new customer being in our dataset.

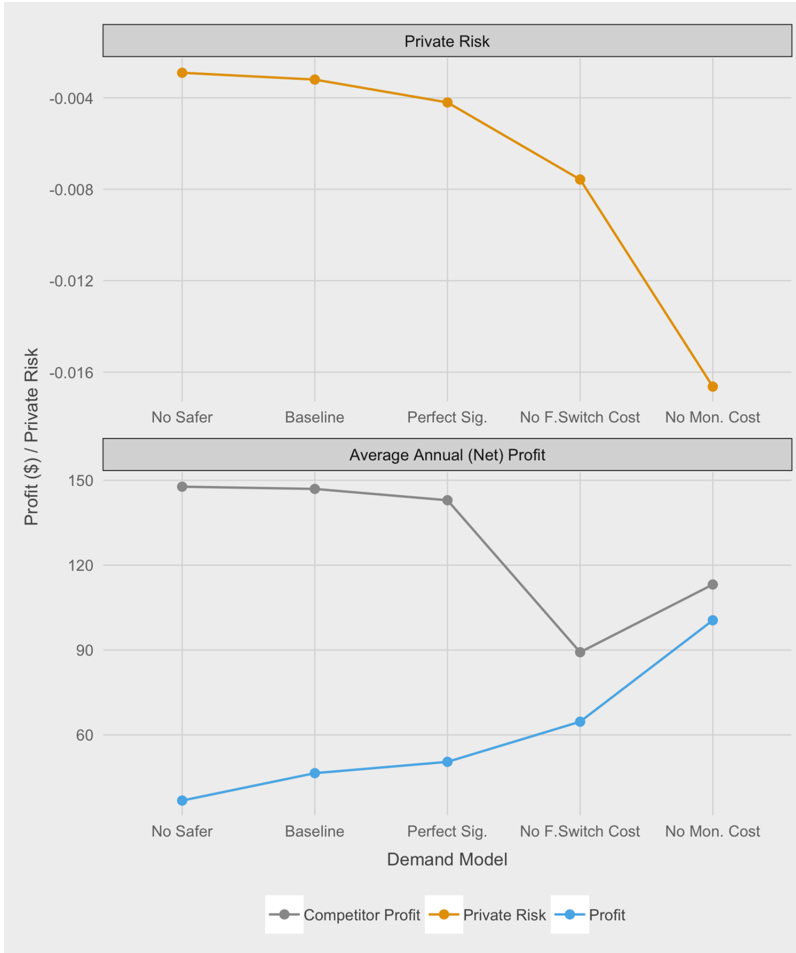

Figure 10: Simulation - Profit Under Different Demand Model Assumptions

Notes: Corresponding to the figure above, these graphs plot firm profit and competitor profit, holding prices fixed. The top graph plots the expected private risk among the firm's customers. Notice that private risk has mean zero in the population. It is numerically integrated over in the counterfactual simulations. With each draw, we weight each person's private risk with her probability of arriving at the firm to get the number shown above. It therefore represents both the monitored and the unmonitored pools of the firm.

First, compared to the baseline model, the "No Safer" model assumes that drivers do not take into account the incentive effect of monitoring on reducing their risk. As seen in Figure 9, monitoring share drops by 6.3pp.[68] Drivers substitute to the unmonitored pool and to competitors, leading to a 1.3pp drop in unconditional monitoring share but only a 0.6pp drop in market share.[69]

Second, the "Perfect Sig." model assumes that the monitoring signal is perfect in consumers' expectation by setting σ_s to zero. The market share, unconditional and conditional monitoring shares increase by 0.4pp, 0.6pp, and 2.6pp, respectively. In reality, our specification is consistent with a dynamic framework in which firm-switching is infinitely costly within a year. This will likely overstate the effect of reclassification risk. Nevertheless, the impact of a perfect signal on demand is small

[68]"pp" denotes percentage points.

[69]Market share here is calculated as the average choice probability for the monitoring firm $f^\star$ in the simulation.

compared to that of other forces.[70]

Demand frictions are the most important deterrent against monitoring participation. The third model removes firm-switching inertia, which dramatically lowers the barrier for drivers with good private risk to participate in monitoring. However, It also clears the way for drivers to explore attractive outside options. We find that the firm is able to gain market share by 12.6pp, while increasing its monitoring share by 12.1pp so that 5.9% of drivers in the market has monitoring. Lastly, we remove monitoring cost. This generates the biggest impact on monitoring by far. In particular, any driver with good private risk would prefer monitoring with any coverage within the firm. The monitoring share rises to 61.3%, with 16.2% of the market opting in the firm's monitoring program.

Firm profit is influenced not only by its market share, but also by risk selection. To directly visualize this, we isolate the risk selection effect from the overall profit impact in Figure 10. It plots the expected private risk parameter ($\epsilon_{\lambda,i}$, mean 0) for the firm's customers, both monitored and unmonitored. This clarifies the changes in the private risk of the marginal customers that come to the firm as we relax demand factors, which is crucial in understanding competition in selection markets. As the firm cream-skims better drivers in its monitored pool, the unmonitored pool in and outside of the firm deteriorates. These pool may therefore eventually unravel as firms adjust prices.

Welfare calculation We evaluate the welfare and total surplus of introducing monitoring by comparing the current monitoring regime to a simulated counterfactual where no monitoring is offered. As mentioned above, we take a certainty equivalent approach in calculating ex-ante welfare. Total surplus is the difference between welfare and total expected cost over two periods. Profits are given by observed prices (and renewal pricing parameters) minus the same expected cost. We also take into account the resource cost for the firm to administer monitoring. It is unobserved and is difficult to estimate since actual prices may be suboptimal. In our simulations, it is set at $35 per monitored period, based on interviews with the program manager and on industry estimates. It includes manufacturing, wireless data transmission, depreciation, inventory, and mailing costs as well as R&D, marketing, and other overheads.

Figure 11 plots the results in per-capita per-year terms. The average consumer gains $11.6 in certainty equivalent, or 1.5% of premium. Profit increases by $7.9 per capita, a 23.6% increase. Under our symmetric cost and no-brand-preference assumptions, competitors see a profit decline of $6.2. This isolates the impact of cream skimming by the monitoring firm because the firm can offer lower prices to some monitored drivers despite charging higher markups. The combined total surplus increases by $13.3 (1.7% of premium) over the no-monitoring scenario.

[70] A caveat is that we assume rational expectation in our model. This means that the effect of a systematic over- or underestimation of the monitoring signal's noise would show up in drivers' monitoring cost instead of be attributed to reclassification risk.

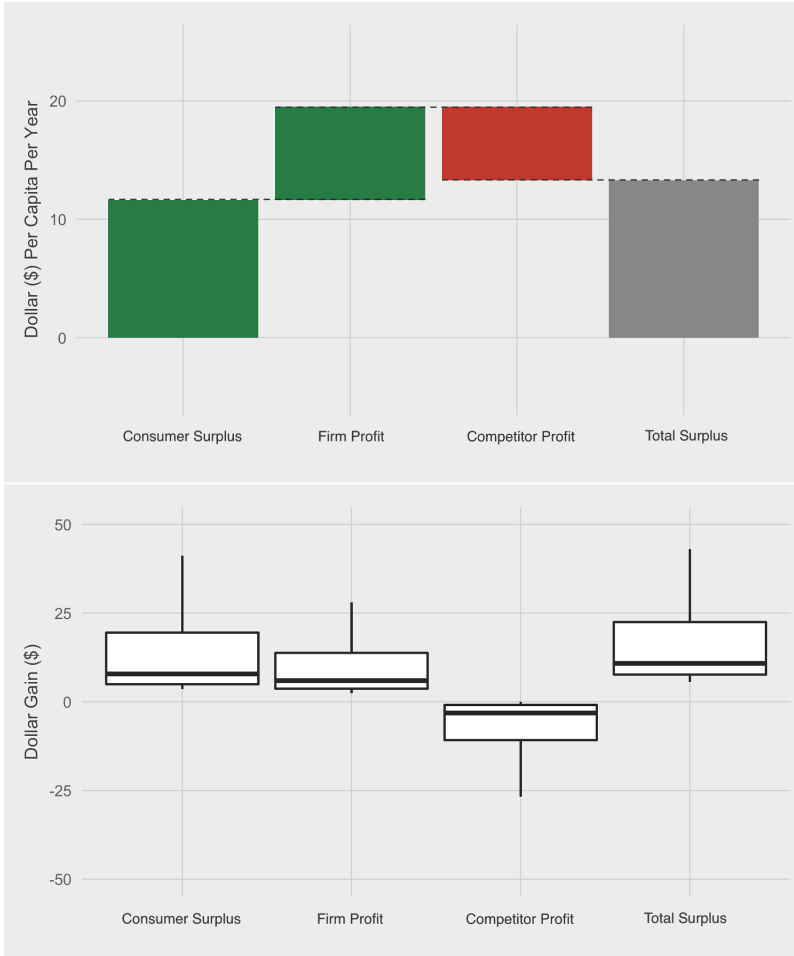

Figure 11: Welfare Calculations

Notes: These figures plot results from our welfare exercise outlined in Section 5.1. The amount denotes the change moving from a regime where no monitoring is offered to one we observe in the data. We plot the differences in ex-ante certainty equivalent, expected profit (across two-periods) for both the monitoring firm and its competitors, as well as total surplus (welfare minus expected cost). The top graph is a waterfall graph decomposing how the components of total surplus changes. The color green indicates an increase while red indicates a decrease. The box plot show 10/25/50/75/90 percentiles.

To disentangle the welfare consequence of the incentive effect (risk reduction) and allocative changes from mechanical monetary transfers across drivers, we first redo the welfare calculation without the incentive effect. Consumers' expected utility from monitoring and firms' expected cost for monitored drivers will both suffer, reducing the total surplus to $4.8 per capita. The top panel of Figure 12 plots this effect. This attributes almost 64% of total surplus gain to better driving, implying small allocative efficiency gains. To investigate this further, we look at changes in the quantity of insurance purchased, comparing the observed regime with the no-monitoring one. Because liability insurance is mandatory, the result we find here is entirely due to changes in coverage levels. Overall, insurance coverage increases, but only by 0.28%. Looking across various observable pools, the safer risk classes stand out despite the fact that they already pay lower premiums. Meanwhile, without risk reduction, overall profit in the industry falls as the monitoring firm offers lower prices to good monitored drivers at the expense of its competitors' profit.

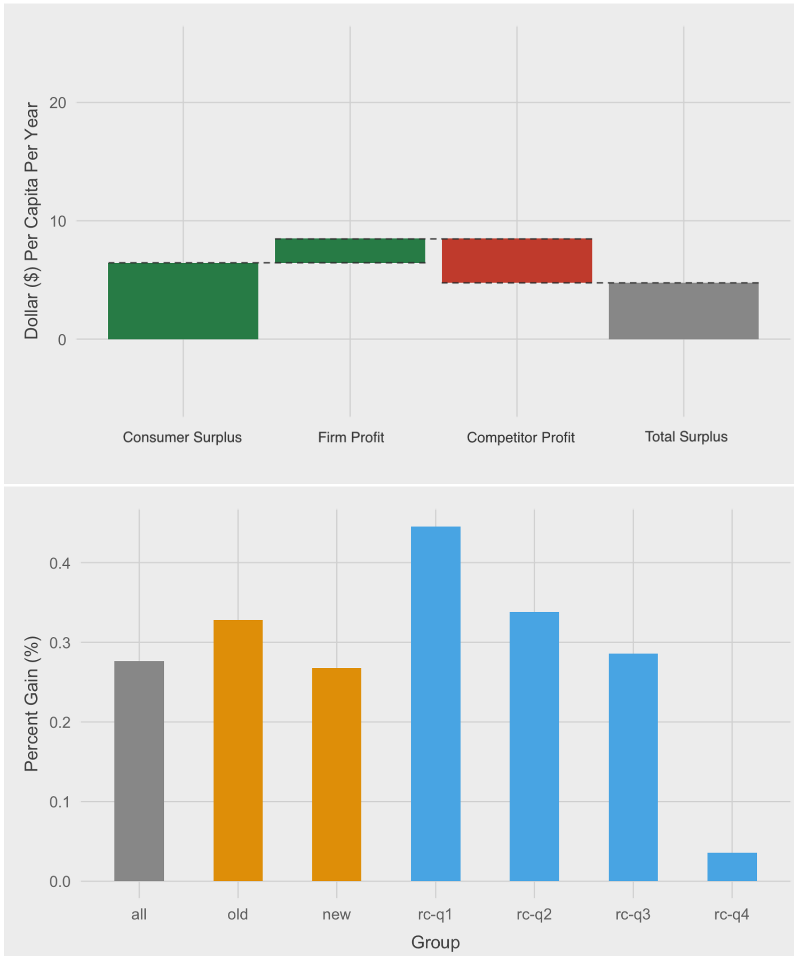

Figure 12: Incentive Effect and Coverage Reallocation

Notes: The top figure plots the same welfare calculation assuming away risk reduction during monitoring based on the incentive effect, per our discussion in the main text. The bottom figure plots average change in coverage amount in percentage across observable groups. "rc-q1" means risk class being in the first quartile at time of choice.

Importantly, our simulation in this section do not consider how the introduction of monitoring may have changed baseline firm prices for unmonitored drivers. This is because, as shown in Appendix B and Figure B.2, the firm did not raise prices on the unmonitored pool during the introduction of monitoring. Therefore, any cream-skimming effect in our simulation would reduce profit in the unmonitored pool as opposed to reduce welfare of unmonitored drivers. In the next section, we propose a model for pricing where the firm can freely surcharge unmonitored drivers.

6 Firm Pricing Model and Equilibrium Implications

In this section, we propose a dynamic multi-product model of firm pricing that links together firm's ex-ante incentive to produce information (monitoring data) and its ex-post incentive to extract rent from the data. The model endogenizes the firm's information set and allows us to simulate two counterfactual equilibria. First, we allow the monitoring firm to optimize prices without constraints, holding competitor pricing fixed. This highlights that profit maximization implies an "invest-and-harvest" pricing dynamic. Second, we endognize competitor prices and simulate an equilibrium in which the firm is required to disclose monitoring data to competitors. This helps us understand the impact of regulatory proposals that aim to curb markups by restricting proprietary data.

6.1 Firm Pricing

In our data, the firm uses two pricing levers for the monitoring program. First, it uses upfront discounts to encourage monitoring opt-in. Second, it uses non-uniform markups in giving monitoring discounts.[71] However, actual prices for monitoring may be suboptimal for profit maximization, largely because prices are heavily regulated in the insurance industry. In order to understand the broader equilibrium implications for an unregulated market, we propose the following *two-period, two-product* model for the firm's pricing of the monitoring program.

Suppose the firm's pricing rule is driven by a vector of parameters $\vec{\kappa}$ that maximizes profit Π, which depends on aggregate demand, heterogeneous costs, and competitor prices. For illustrative simplicity, we suppress coverage choice below.[72] The firm therefore has two products: insurance with and without monitoring. Further, since all prices already takes observables x into account, we suppress that notation.

$$\Pi(\vec{\kappa}) = \sum_i \int_\lambda \left\{ \sum_m \underbrace{\Pr\left(f^\star, m \middle| \lambda, \mathbf{p_m}, \mathbf{p}_{-f^\star}; \Theta\right)}_{\text{demand share}} \cdot \left[\underbrace{\left(p_{m,0}(\vec{\kappa}|\mathbb{I}_{0,i}) - c(\lambda, m) - m \cdot c_m\right)}_{\text{markup}} \right. \right.$$
$$\left. \left. + \delta \cdot \mathbb{E}_{C,s|\lambda} \left[\underbrace{\Pr\left(f^\star \middle| \lambda, p_{m,1}, \mathbf{p}_{-f^\star}; \Theta\right)}_{\text{retention rate}} \cdot \underbrace{\left(p_{m,1}(\vec{\kappa}|\mathbb{I}_{1,m,i}(C,s)) - c(\lambda, 0)\right)}_{\text{retention markup}} \right] \right] \right\} g(\lambda) d\lambda \tag{22}$$

The firm jointly optimizes two-period profit for all potential customers i whose latent risk types λ are distributed according to the distribution $g(\lambda)$. It forms expectations over the realization of stochastic claims C and monitoring scores s. In each period, it faces demand and incur cost to insure drivers ($c(\lambda, m)$) and cost to monitored drivers that choose to opt in ($c_m = 35$).

Our main focus is the pricing adjustments related to monitoring, $\mathbf{p_m} = \{p_{m,0}, p_{m,1}\}$, which can change the firm's information set as they influence demand for monitoring. In the first period, the

[71] See Appendix B for more details. In particular, we conduct an event study around monitoring introduction to show that the firm did not raise prices for the unmonitored pool. Meanwhile, we show that the retention elasticity drops as the firm gives more discounts.

[72] Coverage choice is incorporated in our simulation exercises and results.

firm's information set consists of observables x and consumers' monitoring choice m. In the second period, the firm gains additional signal about drivers by observing claim realization and, for monitored drivers, the monitoring score. Competitors' information sets do not include monitoring information.

$$\mathbb{I}_{0,i} = \{x_i, m\} \qquad \mathbb{I}_{-f^\star,0,i} = \{x_i\}$$
$$\mathbb{I}_{1,m,i}(C,s) = \{x_i, C, m \cdot s\} \qquad \mathbb{I}_{-f^\star,1,i}(C) = \{x_i, C\}$$

Next, we need to specify the pricing rule $\mathbf{p_m}(\vec{\kappa}|\mathbb{I})$ given the information set. The firm's complete pricing rule is extremely complex in reality. The price filings we obstain are frequently thousands of pages long. To make the pricing problem tractable, we start from the firm's existing price rule $p(\cdot)$ observed in the data and parameterize $\vec{(}\kappa)$ as simple adjustments related to the monitoring program.

In the first period, the firm faces price competition while aiming to produce valuable information. Based on its information set, on top of the existing price schedule $p(x)$, it can surcharge the unmonitored pool by κ_0 and discount the monitored pool by κ_1. Both of which can potentially nudge drivers towards monitoring, which intuitively represent the firm's "investment" in *information production*.

$$p_{m,0}(\vec{\kappa}|\mathbb{I} = x_i, m) = \begin{cases} \kappa_0 \cdot p(x_i) & m = 0 \\ \kappa_1 \cdot p(x_i) & m = 1 \end{cases} \tag{23}$$

In the second period, the firm continues to face competition, but among monitored drivers, it gains an information advantageous by observing the monitoring score s. For a monitored driver that is 30% safer than previously expected, the firm may be able to offer a discount much less than 30% and still be confident that she would not leave the firm. The firm essentially solves an optimal *rent-sharing* problem with the monitored drivers in order to "harvest" the value of the collect data.

Firm's monitoring price schedule becomes continuous with the revelation of monitoring score s, which is captured by our renewal price change model $R(C,s)$. For any given score s, conditional on observables x, the wedge between this and the unmonitored price change $R(C)$ represents the firm's rent-sharing schedule observed in the data. We use a single parameter κ_s to represent linear deviations from this rent-sharing schedule.

$$p_{m,1}(\vec{\kappa}|\mathbb{I} = \{x_i, C, s\}) = \begin{cases} p(x_i) \cdot R_{m=0}(C) & m = 0 \\ p(x_i) \cdot [\kappa_s \cdot R_{m=1}(C,s) + (1-\kappa_s) \cdot R_{m=0}(C)] & m = 1 \end{cases} \tag{24}$$

When $\kappa_s = 0$, the firm keeps all the rent and performance in monitoring has no impact on monitored drivers' renewal pricing. On the other hand $\kappa_s > 1$ means that the firm is sharing more rent with consumers than it does in the current regime.

6.2 Equilibrium Implication

Optimal pricing With the proposed model above, we can find the optimal pricing rule $\vec{\kappa}^{\star}$, taking demand and cost estimates as given. Profit is simulated using the procedures outlined in Section 5.3. Our results show that, in the first period, the firm should optimally surcharge the unmonitored pool by 2.7%, while offering a 22.1% upfront discount for opting into monitoring.[73]

Without competition, our model contains no outside option for consumers, given that auto insurance is mandatory. The firm can therefore arbitrarily surcharge prices for the unmonitored drivers. In contrast, our dataset only includes five competitors, yet the optimal pricing only includes a modest surcharge of 2.7% for the unmonitored pool. Price competition in the industry therefore significantly limits the firm's ability to coerce drivers into monitoring and to extract excessive rent. Instead, the large monitoring opt-in discount suggests that the firm can benefit from more investment in eliciting (producing) monitoring data, which not only enhances ex-post competitive advantage, but it also directly reduces the cost to insure drivers in the first period.

In the renewal period, we show that optimal pricing implies 19.6% less rent-sharing than observed in the data. This means less discount for good drivers and less surcharge for bad ones, which coincidentally implies more aggressive price discrimination: good drivers receive a discount only from the monitoring firm, and are therefore less likely to leave the firm; bad ones, however, face competitive pricing without a monitoring surcharge and are therefore more price-sensitive. This pattern is documented descriptively in Appendix B.

Overall, monitoring opt-in rate increases to 4.4% (unconditional for coming to the firm). Consumer welfare and market surplus both increase. Intuitively, although the firm is taking a larger share of the surplus, it also creates more surplus in the first place by eliciting more monitoring data.

Information sharing Building on the optimal pricing regime, we now endogenize competitor prices and impose a regulation requiring the firm to share its monitoring data with competitors. This turns the monitoring program into a public good. However, significant firm-switching inertia may form an effective barrier against other firms "cream-skimming" monitored drivers. In addition, the firm also directly benefits from the risk reduction during monitoring. In this section, we endogenize competitor prices and simulate an equilibrium in which competitors do not offer monitoring but can set alternative rent-sharing schedules to entice drivers who have finished monitoring.

We make two additional assumptions to facilitate this exercise. First, information sharing is complete and credible. Therefore, firms have symmetric knowledge about the expected cost of monitored drivers, given observables and monitoring score. Second, competitors do not adjust baseline prices. Instead, the focus is solely on competitors' cream-skimming motive, given the monitoring information revealed in the second period.[74] As a result, for this exercise, competitors need only determine a competing rent-sharing schedule $\kappa_{-f^{\star},s}$. This assumption is called for because re-optimizing competitors' baseline prices largely captures the effect of our symmetric cost assumption as opposed to their

[73]Consistent with our model, this discount is given for all drivers that *finish* monitoring.

[74]Consumers face higher reclassification risk when their monitoring information is made public. However, due to our myopia assumption, this does not influence the attractiveness of monitoring. We see this as a fairly innocuous omission given large firm-switching inertia and our demand simulations in section 5.1.

Table 8: Counterfactual Equilibrium Simulations

	Current Regime	**Optimal Pricing**	**Data Sharing**
Firm Profit	46.5	61.2	49.3
Competitor Profit	149.2	138.2	147.1
Consumer Welfare (CE)	-	+4.7	+2.2
Total Surplus	-	+8.4	+2.9
Monitoring Market Share	3.0%	4.4%	3.4%
Invest			
Unmonitored surcharge	0.0%	2.7%	1.6%
Opt-in discount	4.6%	22.1%	8.3%
Harvest			
Rent-sharing (κ_s)	1	0.80	1.14
Competitor rent-sharing ($\kappa_{s,-f}$)	-	-	1.81

Notes: This table reports results from our counterfactual equilibrium simulations in Section 6. The simulation procedure to calculate welfare, profits, and total surplus is outlined in Section 5.1. These quantities are reported in dollar per driver per year terms as we translate utility with a certainty equivalent approach. We further enumerate our sample of new customers to the full market by calculating driver weight as in Section 5.1. The time frame we report is one year (two-period). The level of consumer welfare and total surplus is not identified, so we report only the change in those values in counterfactual regimes compared to the current regime. "Optimal Pricing" represents our equilibrium simulation in Section 6.2. "Data Sharing" represents the equilibrium simulation in Section 6.2, where the monitoring firms is required to share monitoring data to competitors. The "Current Regime" uses monitoring pricing we observe in the data. The rent-sharing parameter (κ_s) is indexed against the one observed in the "Current Regime". Empirically, it is a scalar on top of the firm's existing monitoring renewal schedule. $\kappa_s = 0$ means no rent sharing with consumers (flat pricing schedule regardless of monitoring outcome). $\kappa_s > 1$ means a steeper monitoring discount schedule than observed. This represents more rent-sharing with the consumers. *p<0.1; **p<0.05; ***p<0.01

competitive response to the monitoring program. Similarly, we also do not conduct a counterfactual with competitive adoption of monitoring.[75]

The overall equilibrium is achieved when $\vec{\kappa}$ optimizes the firm's own profit while $\kappa_{-f^{\star},s}$ optimizes competitor profit. We use a best-response algorithm to compute Nash equilibrium. We start with the optimal pricing $\vec{\kappa}^{(0)}$ we derived above and calculate the optimal competitor response $\kappa^{(0)}_{-f^{\star},s}$. Taking the latter as given, we update the monitoring firm's optimal pricing to $\vec{\kappa}^{(1)}$, which is conditioned upon in calculating $\kappa^{(1)}_{-f^{\star},s}$. The algorithm converges after 16 iterations with a tolerance of a total of 1-percentage-point adjustment on all four markup parameters.

Results are presented in Table 8. We find that competitors offer an 81% "steeper" rent-sharing schedule than what the firm offers in the current regime. The firm is then forced to share more rent with monitored drivers, by 14% compared to the current regime and by 43% compared to the optimal pricing regime. In response, the firm also significantly scales back investment in the monitoring program, offering only 8.3% opt-in discount and surcharging the unmonitored pool by 0.8%. Overall, as profit reallocates across firms, consumer welfare and total surplus decreases slightly compared to the equilibrium without the information sharing mandate (optimal pricing regime). This implies that the positive impact of information sharing on curbing ex-post markups is outweighed by the firm's adjustments in investment level, which lowers monitoring participation. This suggests that existing price competition and consumer demand frictions already significantly limit the firm's pricing power. Data regulation on proprietary data should jointly consider their markup implications and firms' incentive to produce information in the first place.

Limitations There are several important limitations to our equilibrium simulations. First, our simplistic pricing framework may not fully capture the firm's pricing structure for the monitoring program. The latter can vary nonlinearly and interact with baseline prices in complex ways. Moreover, we maintain our assumption of symmetric cost across firms for monitored drivers. In reality, however, competitors have different preexisting belief about these drivers' risk based on their observables. Further, due to our utility assumptions, different regimes influence consumers' ex-ante welfare only by changing the prices and expected renewal prices they face at the monitoring firm. This is because they do not anticipate potential adjustments after the first period in our model; baseline competitor prices are also held fixed in the simulations. Therefore, our simulations will likely underestimate the changes in welfare and surplus across different regimes. In addition, firms' profit function do not take into account loading factor (overhead and administrative expenses unrelated to monitoring) on top of claim costs because we cannot separate loading factor from markups charged in our micro data. We therefore will exaggerate the firm's profitability from attracting customers. Lastly, we restrict our simulation to two periods, as we find that the value of monitoring data diminishes dynamically (see Figure 6).

[75] Dubé, Fang, Fong, and Luo (2017) studies competitive adoption of mobile geo-targeting by movie theaters. See also Xiang and Sarvary (2013). In our setting, competitive adoption can mitigate the benefit of introducing monitoring if competing programs cream skim a large portion of the market. But monitoring is voluntary and monitoring rates are very low in our simulations and empirically during our research window. Therefore, we believe that our results will be robust to competitive adoption of similar monitoring programs.

7 Conclusion

Firms are increasingly collecting consumer data in direct transactions. This influences social surplus and its division in complex ways. Beyond testing for the presence of various economic forces, it is important to quantify the underlying primitives and incentives to understand their interactions and joint effects.

In this paper, we acquire novel datasets that give us direct visibility into how valuable proprietary data are collected and used by firms. We also develop an empirical framework that links together the information market in which data transactions occur with the underlying product market. We conclude by revisiting three main results and discussing their real-world implications and caveats.

First, data collection changes consumer behavior. Drivers become 30% safer when monitored. We show that this is the primary reason why the monitoring program boosts social surplus in the short run. In other settings, consumer behavior may be distorted in a way that harms social surplus. For example, if consumers know that buying expensive items may label them as inelastic shoppers and lead to higher prices in the future, they may delay or refrain from purchasing those items. In general, firms learning about consumers can change consumer incentives and behavior, but the direction and magnitude of such distortion depends on how consumers perceive their information will be used by firms in the future.

Especially for selection markets such as insurance and lending, additional data on consumers cause differential price changes across consumers that alter allocation in the product market. In our setting, almost half of the drivers are in the state mandatory minimum plan, price adjustments therefore lead to only modest gain in allocative efficiency. This effect can be much greater in other selection markets that do not mandate participation, such as life insurance and student loans.

Second, we find that even though safer drivers are more likely to opt into monitoring, most drivers who would receive a monitoring discount (in expectation) do not. This low take-up rate is primarily driven by two factors. First, consumers suffer large disutility from being monitored. Our data does not allow us to identify the micro foundation of this disutility term. It may include "real" costs like privacy and effort costs. It can also incorporate the effect of systematic misconceptions of monitoring's benefit. In addition, it might also include the effect of salience issues related to an opt-in system. When considering a government mandate for monitoring or an opt-out mechanism, these costs will disappear. Nonetheless, our results show that in the context of direct transactions of consumer data, firms may face inelastic demand when incentivizing consumers to reveal information.

Competition in the product market also strongly influences the number of drivers choosing monitoring in equilibrium. Drivers have attractive outside options from other auto insurers due to fierce price competition. This limits the firm's ability to coerce drivers into monitoring by raising baseline prices. In many online settings, large firms hold significant market power and can afford to make their service contingent upon data collection without losing too many customers. For instance, after the EU's sweeping privacy regulation GDPR went into effect in 2018, the *Wall Street Journal* reports that large firms such as Google and Facebook achieved far higher consent rate for targeted ads than most competing online-ad services (Kostov and Schechner 2018). This further reinforces large firms' competitive advantage. In light of our results, the reason for their high opt-in rates is perhaps not only the value of their services but also the poor outside options consumers face.[76] More generally, our study shows that adding an additional informational demand margin can further amplify preexisting market power large firms have in the product market. Regulators should be cautious about this trade-off between consumer privacy and imperfect competition.

Lastly, the notion of privacy pertains not only to consumers' ownership of their data but also to firms' ownership of valuable proprietary data that they have collected. Our research develops a framework to jointly consider firms' incentives to "invest" in producing proprietary data and to "harvest" its value through higher markups. Our counterfactual simulation demonstrates that, in the short run, the government should protect the firm's ownership to the monitoring data in order to preserve its investment incentives to produce the data. In the long run, however, markup implications will likely dominate. The optimal regulation for proprietary data may therefore resemble a patent mechanism when the product market is sufficiently competitive and when data collection is costly but socially valuable.

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[76]See Schechner (2018) for the opt-in process used by large multinational firms following the implementation of the GDPR.

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A Additional Figures and Tables

Figure A.1: Examples of Telematics Devices in U.S. Auto Insurance

Notes: These are some examples of the in-vehicle telecommunication devices (or "telematics") technology used in monitoring programs in U.S. auto insurance. These devices can be easily installed by plugging them into the on-board diagnostics (OBD) port. The OBD-II specification that these monitoring devices rely on has been mandatory for all cars (passenger cars and light trucks) manufactured or to be sold in the U.S. since 1996.

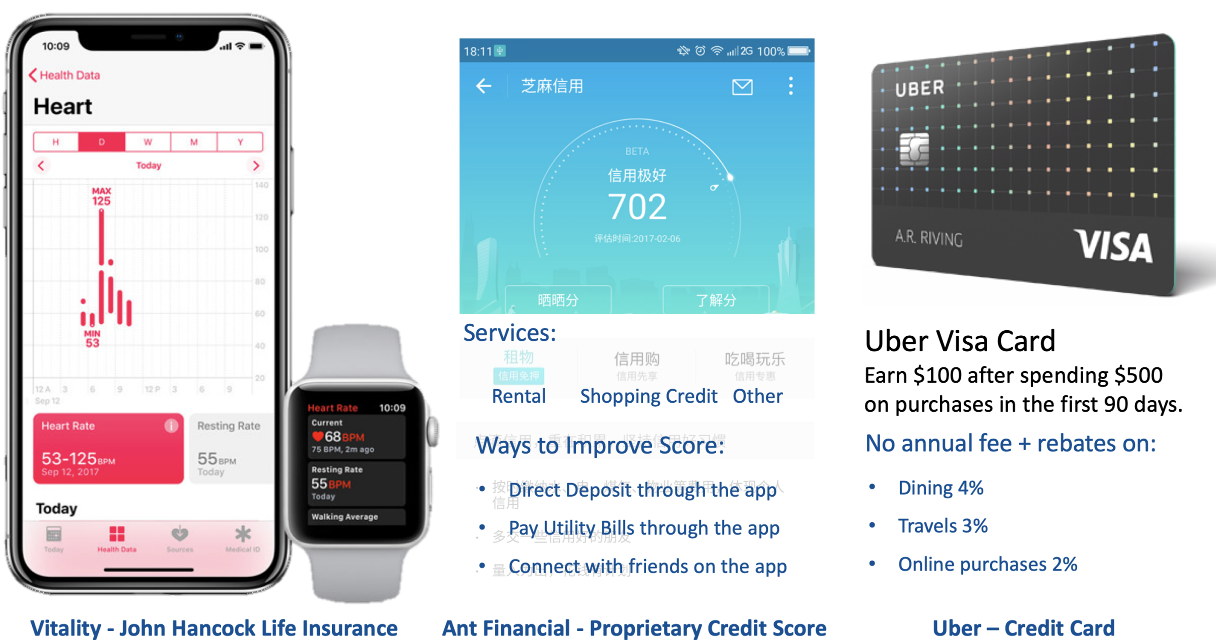

Figure A.2: Other Examples of Direct Transactions of Consumer Data

Notes: Examples of direct transactions of consumer data in other settings. The Vitality program from life insurer John Hancock tracks and rewards exercise and health-related behaviors in exchange for discounts on life insurance premiums. Ant Financial incentivizes users to conduct more personal finance transactions through the platform, such as setting up direct deposit or paying utility bills, in exchange for discounts on various borrowing and rental services. The Uber credit card offers much larger incentives for consumers to use it intensively than the transaction fees charged. One of the plausible business rationales is that the transaction data can be linked back to improve Uber's main businesses in ride sharing and in food delivery.

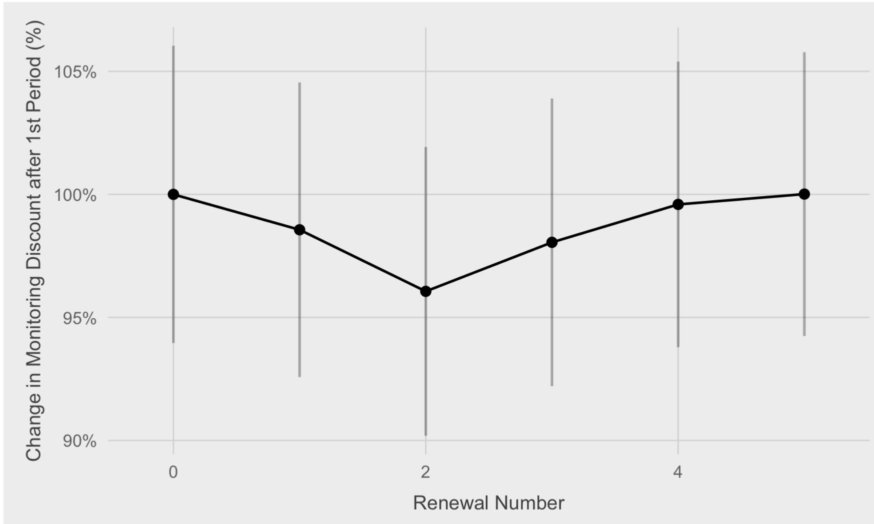

Figure A.3: Persistence of Monitoring Discount

Notes: This graph plots the empirical progression of monitoring discount for all monitoring finishers in one state that stayed with the firm till at least the end of the 5th periods (so we observe monitoring discount in the renewal quote for the 6th period). The benchmark is monitoring discount in the first renewal quote ($t = 0$). Fluctuations and noises are due to ex-post adjustments. Firm may change their discount schedule slightly. Monitored drivers can also report mistakes in their records and have their discount adjusted.

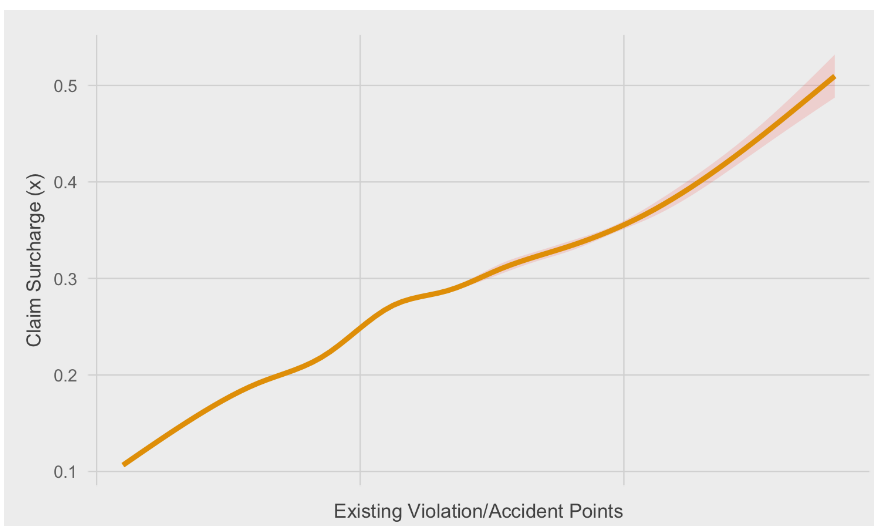

Figure A.4: Renewal Price Claim Surcharge

Notes: This graph plots the empirical claim surcharge function for at-fault accidents. Claim surcharge varies with existing violation points and calendar time. 0.1 means 10% surcharge. This differs from the filed factors because the latter is applied on the base rate only, while this function represents the surcharge percentage on top of overall premium. This is done by regressing renewal price change on violation point last period and current period at-fault claim, controlling for all other observables.

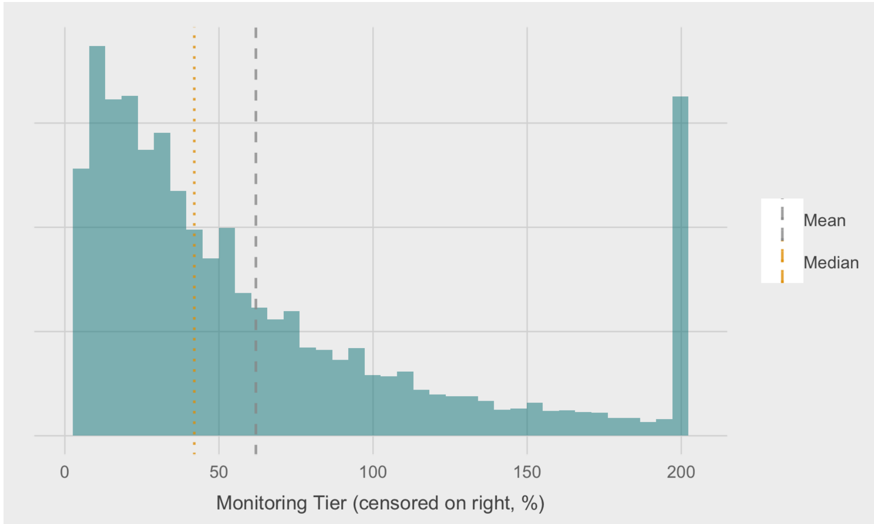

Figure A.5: Distribution of monitoring tier

Notes: This figure plots the empirical density of monitoring tier for all monitored drivers who finished monitoring. It is calculated as the quotient of realized monitoring score over ex-ante expected monitoring score. For monitored driver i, the expected score is derived based on the average driver in i's observable (x_i) group. It does not take into account the fact that i has selected into monitoring. The graph has a long right tail and is truncated at 200%.

Table A.1: Estimates: Heterogeneous Latent Parameters

	Log Claim Rate (μ_λ)	Monitoring Disutility (ξ/\$)	Firm-switching Inertia (η/\$)
Intercept	-3.294^{***}	96.773^{***}	228.559^{***}
	(0.080)	(2.813)	(6.213)
Private Risk		25.238^{***}	
		(1.657)	
Monitoring Ind.	0.404^{***}		
	(0.063)		
Monitoring Duration	-0.796^{***}		
	(0.081)		
Driver			
Driver Age	-0.240^{***}	-1.049^{**}	4.526^{***}
	(0.053)	(0.437)	(1.641)
– Square	0.156^{***}	-1.047^{***}	3.816^{**}
	(0.055)	(0.309)	(0.742)
Age < 25	0.081^{**}	0.326	-0.500
	(0.032)	(0.339)	(0.922)
Age > 21	-0.064	-0.059	3.195^{***}
	(0.053)	(0.403)	(0.449)
Age > 60	-0.046	-0.139	-0.275
	(0.068)	(1.689)	(0.340)
Year of Education	0.001	-2.452^{***}	-7.526^{***}
	(0.025)	(0.331)	(0.915)
College Ind.	-0.00001	-0.952^{***}	0.234
	(0.038)	(0.339)	(0.237)
Post Grad Ind.	0.005	-0.728	-1.547
	(0.039)	(1.644)	(1.686)
Female Ind.	0.099^{***}	-0.261	1.007
	(0.021)	(1.643)	(1.686)
Driver License Year	-0.018	-0.016	16.776^{***}
	(0.019)	(0.905)	(0.338)
Home Ownership	-0.020	-0.039	0.058
	(0.038)	(0.447)	(1.653)
Out-of-State License	-0.104^{***}	-0.380	-0.406
	(0.030)	(0.339)	(0.922)
Location			
Garage Verified Ind.	-0.069^{*}	0.008	1.847^{**}
	(0.036)	(0.521)	(0.922)
Population Density	0.076^{***}	0.359	-4.902^{***}
	(0.015)	(0.419)	(0.445)
Zipcode Income	-0.058^{***}	0.610	-2.936^{*}
	(0.017)	(1.615)	(1.677)
Log Zipcode Income	0.031^{***}	0.284	-0.808
	(0.008)	(2.949)	(1.850)
Vehicle			
Length of Ownership	0.017	-0.918	-0.084
	(0.012)	(0.887)	(0.338)

Vehicle on Lease Ind.	0.092***	−1.058	4.789***
	(0.024)	(1.677)	(0.343)
Model Year	−0.026*	−1.621***	3.211***
	(0.014)	(0.421)	(0.445)
ABS Ind.	−0.058*	0.034	−1.626***
	(0.035)	(0.741)	(0.422)
Airbag Ind.	0.014	0.199	1.225
	(0.021)	(1.644)	(1.686)
Class C Ind.	0.023	0.079	3.843**
	(0.053)	(0.448)	(1.655)
Tier			
Credit Report Ind.	0.044	0.414	1.832***
	(0.035)	(0.429)	(0.448)
Delinq. Score	−0.016	2.114***	10.959***
	(0.014)	(0.331)	(0.917)
Prior Ins. Length	−0.038**	−2.293	−3.993***
	(0.017)	(1.648)	(0.338)
Has Prior Ins.	−0.067*	−1.183***	−0.759*
	(0.035)	(0.427)	(0.448)
– w/ Lapse	−0.050	0.204	0.001
	(0.043)	(1.686)	(0.620)
Violation Points	−0.032	1.084***	4.333***
	(0.030)	(0.337)	(0.429)
Clean Record Ind.	−0.097***	−0.909	−1.392***
	(0.035)	(0.916)	(0.342)
Total Accident Count	0.115***	0.470	−0.139
	(0.029)	(1.638)	(1.690)
Total DUI Count	−0.233***	0.031	0.326
	(0.065)	(0.922)	(0.536)
Log Risk Class	0.275***		
	(0.046)		
Risk Class	0.042		
	(0.074)		
– Square	−0.124*		
	(0.073)		
– Cube	0.0002		
	(0.046)		
Seasonality	0.026**	−0.764**	−1.585***
	(0.011)	(0.331)	(0.427)
– Square	0.063	−0.364	−0.519
	(0.046)	(0.340)	(0.430)
Trend Year	0.083*	−1.570	7.417***
	(0.043)	(1.660)	(0.338)
– Square	−0.102***	−1.413	6.199***
	(0.039)	(1.830)	(1.674)

Notes: This table reports intercept and slope estimates for heterogeneous latent parameters. Continuous covariates are normalized (except λ and monitoring duration). Discrete variables with more than two values are normalized so that the minimum is zero. Deliq. (delinquency) Score is based on records from a credit bureau. Higher scores mean worse records. *p<0.1; **p<0.05; ***p<0.01

Table A.2: Estimates: Homogeneous Parameters

	Cost		Score & Pricing		Demand
$\ln \sigma_{\lambda,\text{new driver}}$	-0.266^{***} (0.060)	$\ln \sigma_s$	-0.081^{***} (0.007)	$\ln \gamma$	-9.235^{***} (0.089)
$\ln \sigma_{\lambda,\text{old driver}}$	-0.840^{***} (0.070)	$\beta_{R,\text{new}}$	66.953^{***} (0.403)	η_0	134.262^{***} (2.228)
$\ln \alpha_\ell$	-1.480^{***} (0.063)	$\beta_{R,\text{monitoring}}$	59.680^{***} (0.902)	σ_ζ	98.989^{***} (2.303)
		$\beta_{R,\text{renw}}$	78.571^{***} (0.315)	σ	39.213^{***} (0.632)

Notes: This table reports estimates for homogeneous parameters of our structural model. *Cost*: spread of private risk $\sigma_{\lambda,\text{new driver}}$ and $\sigma_{\lambda,\text{old driver}}$ (new drivers are defined as those licensed in the past three years), claim severity Pareto distribution parameters ℓ_0 and α_ℓ (ℓ_0 is set at \$3,000 per discussion in the text). *Score and Precision*: monitoring score's signal precision σ_s, rate parameters for the renewal price change (R_0) Gamma distribution β_R's. *Demand*: absolute risk aversion coefficient γ, baseline inertia η_0 in dollar term, variance of own firm random coefficient σ_ζ, scale of the logit error σ. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Estimates: Renewal Pricing and Monitoring Score

	$\mathbb{E}[R_{0,m=0,t=0}]$	μ_s	$\mathbb{E}[R_{0,m=0,t=1}]$
Intercept	-0.362^{***}	11.367^{***}	-1.131^{***}
	(0.001)	(0.506)	(0.132)
Log Risk Class	-0.413^{***}	-0.384^{**}	-0.080^{***}
	(0.018)	(0.155)	(0.018)
Risk Class	0.367^{***}	-0.077	0.063
	(0.051)	(0.304)	(0.034)
– Square	-0.290^{***}	0.245	-0.155^{***}
	(0.054)	(0.308)	(0.036)
– Cube	-0.229^{***}	-0.039	0.031
	(0.022)	(0.140)	(0.019)
$\ln \lambda$		1.859^{***}	
		(0.094)	
$\log$(Monitoring Score)			0.150^{***}
			(0.005)

Notes: This table reports estimates for the renewal pricing and monitoring score model. Instead of modeling the Gamma shape parameters (α), we use a change-of-variables technique to directly estimate the expected renewal rate. It is modeled with a Sigmoid function between 0.5 (50% cheaper) and 2 (twice as expensive). That is, $\mathbb{E}[R_0] = \sigma(\mathbf{x}'\theta_R) \times 1.5 + 0.5$. We include the appropriate Jacobian adjustments in estimation, and winsorize away extremely large or small renewal price change. *p<0.1; **p<0.05; ***p<0.01

B Analysis of Actual Firm Pricing

Cream skimming effect Advantageous selection into monitoring may cream skim from the firm's unmonitored pool. As a result, firms may choose to raise prices in the unmonitored pool. In addition, they may also want to surcharge the unmonitored pool to indirectly encourage monitoring participation. To test the effect of monitoring introduction on the unmonitored pool more formally, we take advantage of the staggered introduction of monitoring across states. This gives rise to a regression discontinuity strategy that evaluates how prices and average cost changed in the *unmonitored* pool. We focus on a year before and after monitoring introduction; our observable characteristics also include state fixed effects and flexible controls for trends and seasonality. We only focus on the first semester ($t = 0$) to avoid contamination from attrition[77]. We therefore drop the t subscript, and run the following regression

$$dep.\ var._i = \alpha + \gamma Qtr_i + \kappa \mathbf{1}_{post,i} + \theta \cdot Qtr_i \times \mathbf{1}_{post,i} + \mathbf{x}_i'\beta + \xi_{y,i} + \epsilon_i \tag{25}$$

We use price p_i and claim count C_i as our dependent variable. Qtr is the running variable, which denotes the calendar quarter when driver i arrived at the firm[78]. $\mathbf{1}_{post}$ is an indicator for whether i arrived at the firm after the introduction of monitoring. $\mathbf{x}$ and a coverage fixed effect ξ_y soak up compositional changes in observable risk class and coverage plans. The coefficient θ reveals treatment effect of monitoring introduction on prices and claims in the unmonitored pool.

Estimates for $\hat{\theta}$ across various specifications are reported in figure B.2. The firm did not raise prices around monitoring introduction. We also find no evidence that the average cost of the unmonitored pool deteriorated by more than 2%.

In reality, monitoring is only a small fraction of the market. As our demand estimates will reveal in the next section, even when monitored drivers are significantly better, its influence on the unmonitored pool is significantly limited by its small size. Further, the firm does not make follow-up offers to customers who initially opted out monitoring, which is necessary for unraveling to occur empirically. Lastly, monitoring programs are subject to approval by state commissioners. And a new program that affects baseline pricing may be subject to more regulatory scrutiny. On the flip side, this suggests that the current monitoring regime is largely welfare-neutral for unmonitored drivers.

Dynamic and non-uniform pricing The firm is not required to offer monitoring, it therefore must benefit from it to justify administrative and R&D costs. Indeed, monitored drivers have 35% higher profitability overall, controlling for observables. On top of reduced moral hazard (during monitoring) and better risk rating (going forward), this can also be a result of higher profit margin and retention rate when information is revealed. We provide descriptive evidence on pricing and dynamic retention in this section.

First, the firm faces a dynamic pricing problem as information is revealed at the end of the first period. It offers a opt-in discount to encourage all drivers to participate in monitoring. This averages

[77] This regression does not include monitored drivers, so there is no contamination from moral hazard.
[78] It is normalized so that the quarter immediately after monitoring introduction is indexed as 0.

to around 5% across states and time.

When monitoring information is revealed, the firm can use it to set non-uniform prices. Here, the firm's pricing schedule is based on a monitoring tier that measures how "surprising" a given driver's monitoring score is to the firm. In figure A.5, we plot the empirical distribution of monitoring tier, which is realized monitoring score divided by firm's expected score given observables[79]. Consistent with our findings above, the average monitored driver performed much better than expected[80].

Figure B.3 presents the discount schedule the firm uses given the percentile of monitoring tier as defined above. Surprisingly good drivers are on the left, who are offered the highest renewal discount, while around 25% of drivers that performed poorly (compared to firm's expectation) received a surcharge.

Figure B.4 plots the corresponding retention rate. It is clear that as discounts approach zero or negative, retention rate drops significantly. In fact, we can regress renewal choice (binary) on prices with monitoring discount, controlling for observables and price level without the discount. θ then measures the slope of the residual (retention) demand.

$$\mathbf{1}_{renew,i} = \alpha + \delta p_i + \theta disc_i + \mathbf{x}_i' \beta + \epsilon_i \tag{26}$$

The estimates for $\hat{\theta}$ are reported in figure B.5. Without monitoring discount, a $\$1$ increase in price (decrease in discount given) causes the retention rate to drop by 0.07 percentage points (7 basis points). When firms give discounts, however, the slope of the demand decreases, and by 56% when the discount given is larger than 10%. This suggests that

[79]For monitored driver i, the expected score is derived based on the average driver in i's observable (x_i) group. It also does not take into account the fact that i has selected into monitoring. The graph has a long right tail and is truncated at 200%.

[80]It is important to note that a driver with a monitoring tier of 30% is not necessarily 70% safer than the average person in her pool, especially in renewal period. This is because monitoring score does not capture risk perfectly, and it is also stochastic. Our structural model quantifies these effects more formally.

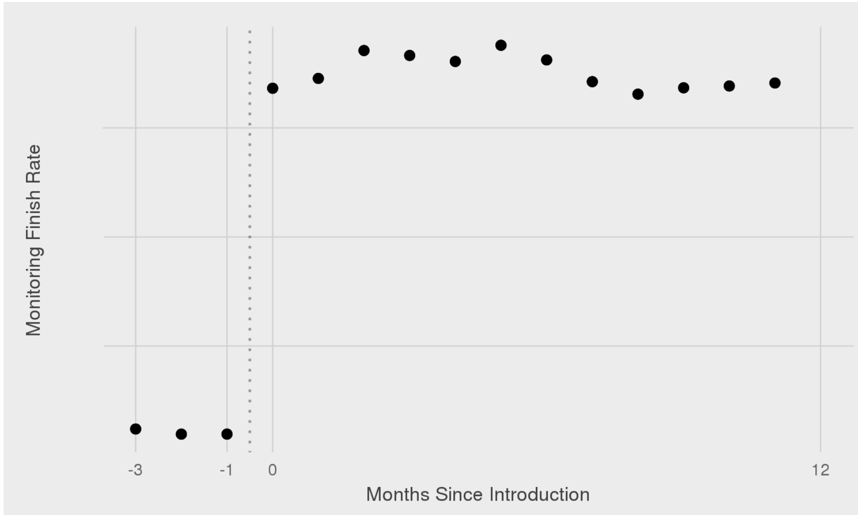

Figure B.1: Monthly monitoring finish rate around monitoring introduction

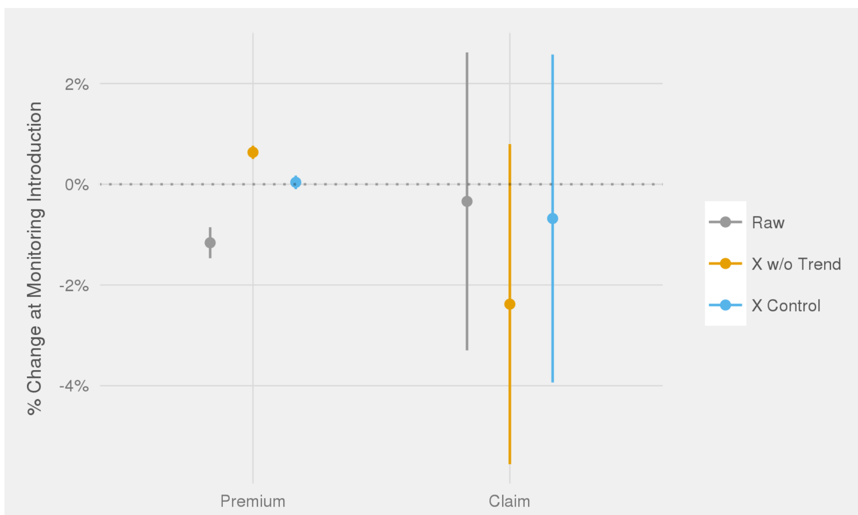

Figure B.2: Event Study: treatment effect of monitoring introduction on the unmonitored pool

Notes: figure B.1 the progression of monthly monitoring finish rate around the introduction of monitoring. The monthly finish rate are below 0.1% in all months before monitoring introduction. The reason why it is not exactly zero before monitoring introduction is due to small-scale trial and experimentation. We throw out states that introduced monitoring in the first three months or the last 12 months of our research window. This ensures that the trend we see do not pick up changes in state composition.
figure B.2 reports regression-discontinuity estimate θ of equation (25), where the horizontal axis distinguishes dependent variable used. These effects are translated in percentage terms by dividing the average of the dependent variable in the period immediately before monitoring introduction. We look at only first period outcomes, and include all *unmonitored* drivers arriving at the firm a year before or after the firm. States that introduced monitoring within a year after the beginning or a year before the end of our research window are excluded. The running variable is quarter since monitoring introduction. Different colors and positions represent different specifications of control variables (x_{it}). The grey (left-most) series represents estimates from regressions with the full set of x_{it}; the orange (middle) one includes a full set of observables, including flexible controls for trend and seasonality.

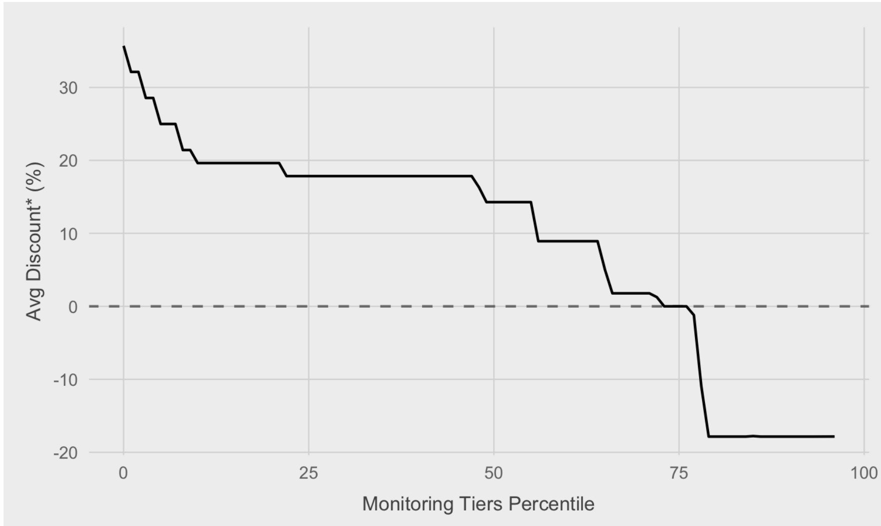

Figure B.3: Monitoring Discount Schedule

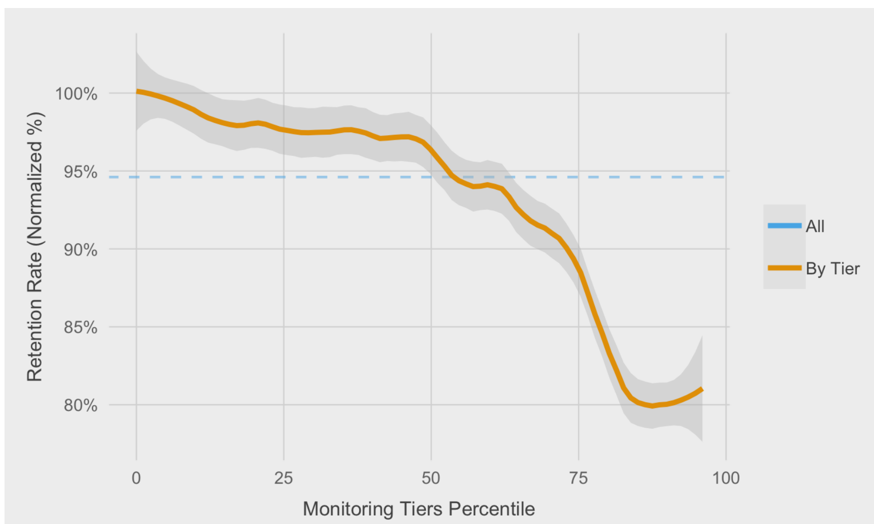

Figure B.4: Indexed Retention Rate

Notes: figure B.3 plots the firm's pricing schedule for giving monitoring discount. On the horizontal axis, we plot the percentile of monitoring tier, which is monitoring score divided by that expected by the firm given observables. 74% of people received a discount. The vertical axis is scaled by a factor between 0.5 and 1.5. This is to protect the firm's identity while demonstrating the scale and shape of the pricing algorithm. The firm went through two pricing schedules. This graph plots the second pricing schedule. The first one is similar, except that no surcharge was given.
figure B.4 uses the same horizontal axis, and non-parametrically plots the retention rate for the semester immediately after drivers finish monitoring (and thus when they first got monitoring discounts). Bandwidth is set as 5, and all numbers are benchmarked/normalized against the mean retention rate of the lowest 5 monitoring tiers. For 93% of monitored drivers, this is the first renewal period.

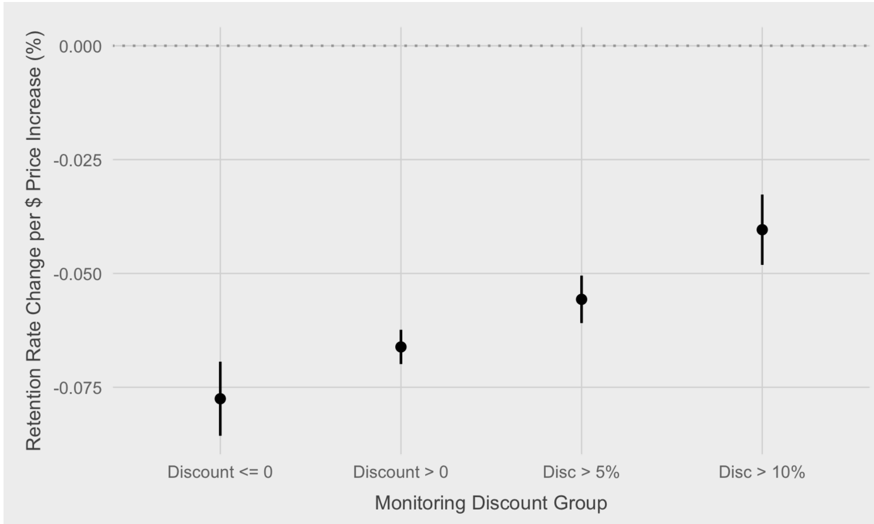

Figure B.5: Comparison of subsequent claim cost across monitoring groups

Notes: This figure plots the estimate of θ from equation (26) in various subsamples. These subsamples are represented on the horizontal axis. Notice that although we segment the data using discount percentage, we use the actual discount amount in the regression to measure demand elasticity. The results are scaled to percentage point terms. Therefore, -0.05 means that the slope of retention demand is such that a one dollar increase in price would lead to a 0.05 percentage point drop in retention rate.

C Simulation Analysis of the Informativeness of Monitoring Signal

We can conduct a simple simulation exercise to quantify the spread of private risk and monitoring's effectiveness. To do so, we first simulate a large risk pool by taking the mean of all observable characteristics and simulating each driver's private risk. Figure C.1 plots the density of simulated true risk.[81] Next, Figure C.2 plots the firm's prior mean for all drivers in the risk pool. The firm has a flat prior for all drivers in the first period, which is far from the perfect belief (represented by the dotted and zoomed in 45-degree line). In Figure C.3, we calculate the evolution of firm belief (posterior mean) in subsequent periods as the firm observes potential claim realization. The firm's belief evolves towards the truth as claim is a direct measure of risk. However, the sparsity of claims, especially among safe drivers, dramatically slows down the firm's belief updating.

Monitoring score provides an immediate signal for driver risk after the first period. In Figure C.4, we plot, in orange, how the firm's belief updates after observing a one-time monitoring score. It is clear that monitoring is far more informative than observing a period of potential claim realization (dark grey line). Monitoring is especially useful in distinguishing the large mass of safe drivers, in which claims are even rarer. To quantify this measure, we can calculate the absolute deviation of firm belief from the true risk in our simulated risk pool. Overall, observing the monitoring score gets the firm 12.3% closer to the perfect belief (45-degree line).

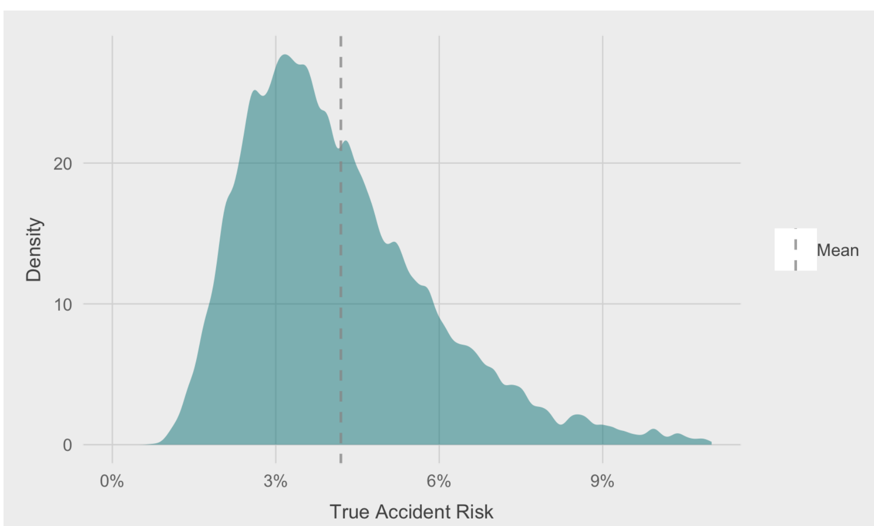

Figure C.1: A simulated mean risk pool given our cost estimate

Notes: This figure plots the distribution of a simulated mean risk pool given our cost estimates.

[81]Our figures use private risk spread among new drivers for illustrative clarity.

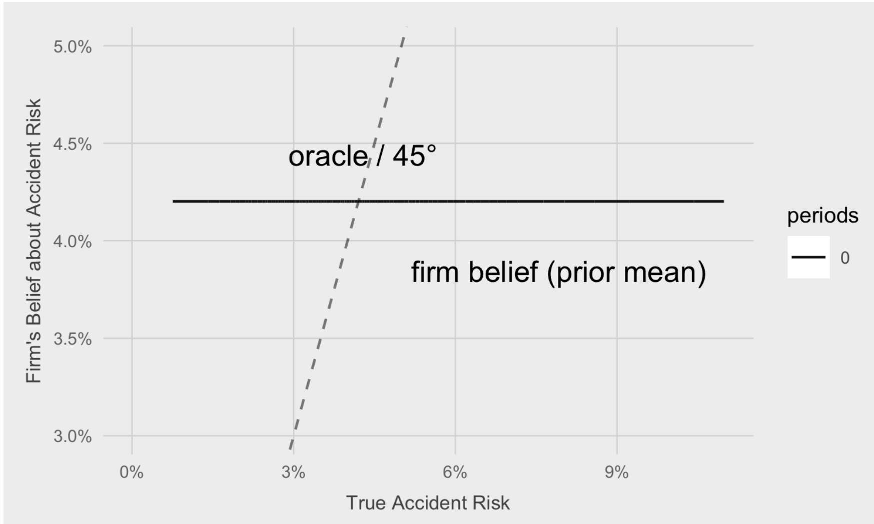

Figure C.2: Firm's prior on simulated risk pool

Notes: This figure plots firm's belief (prior mean / risk rating) for drivers in our simulated pool. In the first period, they are by definition pooled together. Therefore, firm has a flat prior for all drivers in the pool. The dotted line is the 45 degree line, which represents perfect belief.

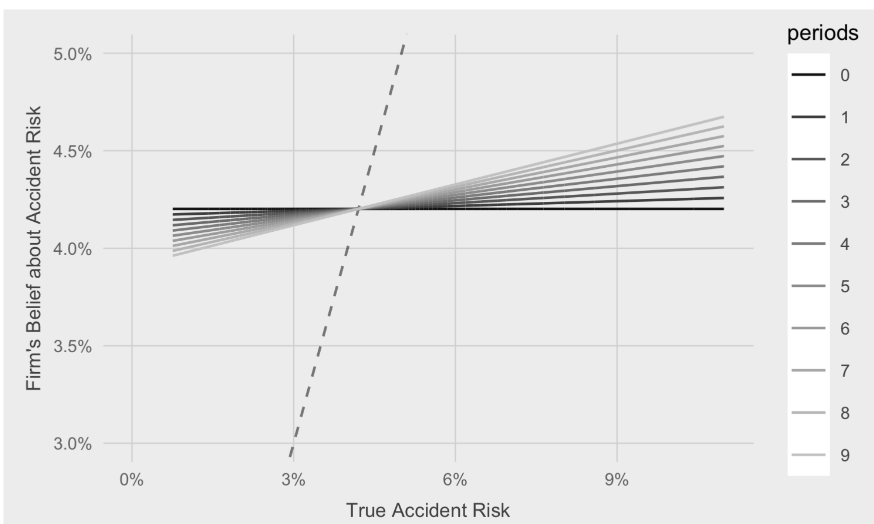

Figure C.3: Firm's posterior updating based on claims

Notes: This figure plots the evolution of firm belief (posterior mean) for drivers in our simulated pool based on liability claims alone. To make the updating analytically feasible, we first fit a gamma distribution on our risk pool by matching the mean and variance. Since gamma distribution is a conjugate prior for poisson updating, we are able to analytically derive the posterior mean.

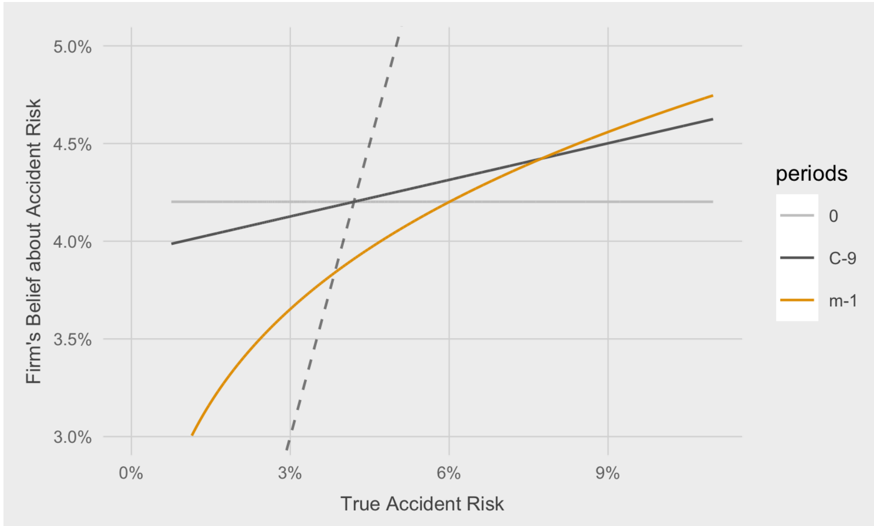

Figure C.4: Firm's posterior updating based on monitoring vs. claims

Notes: This figure plots the evolution of firm belief (posterior mean) for drivers in our simulated pool based on claims versus monitoring. Since lognormal distribution is a conjugate prior for lognormal updating, we are able to analytically derive the posterior mean.

D Additional Robustness Checks

Table D.1: **ESTIMATES FROM MORAL HAZARD REGRESSION**

	dependent variable: claim count (C)					
explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.046^{***}	0.003	0.004	0.046^{***}	0.003	0.004
	(0.000)	(0.005)	(0.005)	(0.000)	(0.005)	(0.005)
post monitoring indicator	-0.001^{**}	-0.003^{***}	-0.003^{***}	-0.001^{**}	-0.003^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
monitoring start indicator (m_{start})	-0.009^{***}	-0.008^{***}	-0.008^{***}	0.025^{***}	0.020^{***}	0.020^{***}
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
monitoring intensity (M)				-0.050^{***}	-0.042^{***}	-0.042^{***}
				(0.004)	(0.004)	(0.004)
interaction ($\mathbf{1}_{post} \times m$)	0.006^{***}	0.006^{***}	0.006^{***}	-0.014^{***}	-0.014^{***}	-0.014^{***}
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
interaction ($\mathbf{1}_{post} \times M$)				0.028^{***}	0.029^{***}	0.029^{***}
				(0.005)	(0.005)	(0.005)
observables controls (x)	N	Y	Y	N	Y	Y
coverage fixed effects	N	N	Y	N	N	Y
implied risk reduction of a full period of monitoring (%)	28.0	29.4	29.5	27.5	29.4	29.6
pre- / post-periods for "first difference"	0 / 1-2					
treatment / control groups "second difference"	all starters / unmonitored					
number of drivers in balanced panel	812,924					

Notes: This table reports results of equation (2), but instead look at all monitored drivers regardless of whether they finish or not. Again, the estimate on the interaction term ($\mathbf{1}_{post} \times m_{start}$ or z) measures the treatment effect of monitoring ending on claim count. We first balance our panel data to include all drivers who stay till the end of the third semester ($t = 3$). This gives us two renewal semesters ($t \in \{1, 2\}$) after the monitoring semester ($t = 0$). We control for a full set of observables, including driver and vehicle characteristics and tiers (past records of violations or claims). It also includes third-order polynomials of calendar year and month. Continuous observable characteristics are normalized. We report estimates with and without these controls.

E Estimation and Simulation Details

Our model includes unobserved state variables (random coefficients) that enter utility non-linearly. Therefore, we use a random coefficient simulated maximum likelihood approach (Train 2009; Handel 2013) to estimate the model.

For each parameter proposal θ, we simulate the model 50 times using Halton draws and compute the likelihood for all observations in the data. We then average over these to get the "simulated log likelihood", denoted as $\hat{\mathcal{L}}_{sim}(\theta)$. The estimator $\theta^\star$ maximizes the log likelihood. Simulated maximum likelihood suffer from simulation bias

Likelihood Function The log likelihood are sample analogs of four types of data likelihoods (denoted as $\mathcal{L}$) - claims, monitoring score, choices (of firm, coverage and monitoring participation), as well as renewal price. Utilities are history-dependent in our model. Therefore, we need to simulate choice sequence for each driver i. For notational simplicity, we suppress firm-dummy random effect ζ as in our baseline specification. The log likelihood function can then be expressed as follows.

$$\mathcal{L}_i \equiv \sum_{t \leq T_i} \int_\lambda \mathcal{L}(\underbrace{R_{it}, s_i, C_{it}, d_{it} | \lambda, \psi, x_{it}, \mathbf{p}_{it}, D_{it}, d_{i,t-1}; \mathbf{\Theta}}_{(A)\text{:obs. stoc outcome}}) \cdot \underbrace{g_\lambda(\lambda | x_{it}; \theta_\lambda, \sigma_\lambda)}_{(B)\text{:latent var.}} \, d\lambda$$

The simulation procedure allows us to numerically integrate over λ given parameter proposals θ_λ and σ_λ. We follow the timing of the model to decompose the likelihood component A as follows.

$$\begin{aligned}(A) = & \ln \Pr(d_{it} | \lambda, \mathbf{x}_{it}, \mathbf{p}_{it}, D_{it}, d_{i,t-1}; a, \psi_0, \psi_1, \theta_\eta, \theta_\xi, \alpha, \theta_\beta) + \\ & + \ln \Pr(C_{it} | \lambda, \mathbf{x}_{it}) + \ln g(\ell_{it} | d_{it}, \mathbf{x}_{it}; \alpha, \theta_\beta) \\ & + \ln g_s(s_i | \lambda, \mathbf{x}_{it}; \theta_s, \sigma_s) + \ln g_R(R_{idt} | C_{it}, s_i, \lambda, \mathbf{x}_{it}, \mathbf{p}_{it}; \theta_{\mathbf{R}}, \theta_{\mathbf{R},\mathbf{m}}, \sigma_R)\end{aligned}$$

Each component of (A) is modeled in the main text and given distributional assumptions.

Choice probability Our choice probability requires integration over all possible C, ℓ, R_0 and s. In our model, we assume away uncertainty in s, and our Poisson-Gamma model gives analytical solutions for expectation over C and ℓ.

For simplicity, in people's expectation, we only consider the possibility of one claim occurrence per term (Cohen and Einav 2007; Barseghyan et al. 2013). We can then capitalize on the attractive analytical property of gamma distributions and avoid numerical integration over C, ℓ, R_0 and s.

F Regulatory Filing Examples

OHIO
VOLUNTARY PRIVATE PASSENGER AUTO
PREMIUM CALCULATION

ROUND AFTER EACH CALCULATION TO THE NEAREST PENNY

STEP #		AA	BB	CC	DD	HH	DNC*^	HNC*^
1	TERRITORIAL BASE RATE (RP-1BR)							
2	RATE ADJUSTMENT FACTOR (PENNY ROUND)	x 1.598	x 1.594	x 1.410	x 1.121	x 1.111	x 1.121	x 1.111
3	INCREASED LIMIT FACTOR/ADDEND (RP-3A)	x	+	x				
4	POLICY GROUP FACTOR (RP-4A-1 through RP-4A-2)	x	x	x	x	x	x	x
5	RATING TIER FACTOR (RP-5A)	x	x	x	x	x	x	x
6	ALLSTATE® YOUR CHOICE AUTO INSURANCE OPTION PACKAGE FACTOR (RP-15A)	x	x	x	x	x	x	x
7	POLICY CLASS FACTOR (RP-7A-1 through RP-7A-4)	x	x	x	x	x	x	x
8	HOUSEHOLD COMPOSITION FACTOR (RP-8A-1 and RP-8A-2)	x	x	x	x	x	x	x
9	SMART STUDENT DISCOUNT FACTOR (RP 10A and RP-11A)	x	x	x	x	x	x	x
10	DEFENSIVE DRIVER DISCOUNT FACTOR (RP-10A and RP-12A)	x	x	x	x	x	x	x
11	MULTIPLE POLICY DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
12	HOMEOWNER DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
13	THE GOOD HANDS PEOPLE® DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
14	RESPONSIBLE PAYER DISCOUNT FACTOR (RP-15A)	x	x	x	x	x	x	x
15	FULLPAY DISCOUNT (RP-15A)	x	x	x	x	x	x	x
16	ALLSTATE EASY PAY PLAN DISCOUNT (RP-15A)	x	x	x	x	x	x	x
17	EARLY SIGNING DISCOUNT (RP-15A)	x	x	x	x	x	x	x
18	ALLSTATE AUTO/LIFE DISCOUNT℠ (RP-15A)	x	x	x	x	x	x	x
19	ALLSTATE eSMART℠ DISCOUNT (RP-15A)	x	x	x	x	x	x	x
20	SAFE DRIVING CLUB (RP-10A and RP-13A through RP-14A)	x	x	x	x	x	x	x
21	PRIOR NON-STANDARD CARRIER SURCHARGE (RP-16A)	x	x	x	x	x	x	x
22	ACCIDENT SURCHARGE FACTOR (RP-17A)	x	x	x	x		x	
23	MAJOR VIOLATION SURCHARGE FACTOR (RP-18A)	x	x		x		x	
24	MINOR VIOLATION SURCHARGE FACTOR (RP-19A)	x	x		x		x	
25	MODEL YEAR FACTOR (RP-20A)				x	x	x	x
26	DEDUCTIBLE BY PGS FACTOR (RP-20A)				x	x	x	x
27	EXPERIENCE GROUP RATING FACTOR (EGR PAGES and RP-21A-24A)	x	x	x	x	x	x	x
28	ALLSTATE DRIVE WISE® ENROLLMENT DISCOUNT (RP-26A)	x	x	x	x	x	x	x
29	ALLSTATE DRIVE WISE® PERFORMANCE RATING (RP-26A)	x	x	x	x	x	x	x
30	ANNUAL VEHICLE MILEAGE FACTOR (RP-16A)	x	x	x	x	x	x	x
31	VEHICLE USAGE FACTOR (RP-16A)	x	x	x	x	x	x	x
32	FARM DISCOUNT FACTOR (RP-16A)	x	x		x		x	
33	ELECTRONIC STABILITY CONTROL DISCOUNT FACTOR (RP-16A)	x	x	x	x		x	
34	PASSIVE RESTRAINT DISCOUNT (RP-16A)			x				
35	ANTILOCK BRAKE DISCOUNT (RP-16A)	x	x		x		x	
36	NEW CAR DISCOUNT FACTOR (RP-16A)	x	x	x	x	x	x	x
37	CERTIFIED RISK SURCHARGE FACTOR (RP-16A)	x	x					
38	CAMPER UNIT ADDITIONAL PREMIUM (RP-25A)				+	+		
39	NEW CAR EXPANDED PROTECTION FACTOR (RP-25A)						x	x
40	RATE TRANSITION FACTOR (Rule 72)	x	x	x	x	x		
41	COMPLEMENTARY GROUP RATING (CGR) FACTOR (RP-9A-1 through RP-9A-13)	x	x	x	x	x	x	x
42	FIXED EXPENSE PREMIUM ^^ (RP-16A)	+						
43	SUB-TOTAL VEHICLE PREMIUM	=	=	=	=	=	=	=

	RENTAL REIMBURSEMENT (UU)	
	RENTAL REIMBURSEMENT BASE RATE (RP-52BR)	
	RENTAL REIMBURSEMENT INCREASED LIMIT FACTOR (RP-3A)	x
44	TOTAL RENTAL REIMBURSEMENT COVERAGE PREMIUM	=

	TOWING & LABOR COSTS (JJ) (RP-25A)	
	SOUND SYSTEMS (ZA) (RP-25A)	+
	TAPE (ZZ) (RP-25A)	+
45	TOTAL MISCELLANEOUS COVERAGES	=

	PER AUTO UM/UIM - PROPERTY DAMAGE COVERAGE (SSP)	
46	UM - PROPERTY DAMAGE PREMIUM RATE (RP-3A)	

	POLICY UM/UIM - BODILY INJURY COVERAGE (SS)	
	TERRITORIAL BASE RATE (RP-1BR)	
	RATE ADJUSTMENT FACTOR (PENNY ROUND)	x 0.872
	INCREASED LIMIT FACTOR/ADDEND (RP-3A)	x
	POLICY GROUP FACTOR (RP-4A-1 through RP-4A-2)	x
	RATING TIER FACTOR (RP-5A)	x
	POLICY CLASS FACTOR (RP-7A-1 through RP-7A-4)	x
	HOUSEHOLD COMPOSITION FACTOR (RP-8A-1 through RP-8A-2)	x
	SMART STUDENT DISCOUNT FACTOR (RP 10A and RP-11A)	x
	DEFENSIVE DRIVER DISCOUNT FACTOR (RP-10A and RP-12A)	x
	HOMEOWNER DISCOUNT FACTOR (RP-15A)	x
	RESPONSIBLE PAYER DISCOUNT FACTOR (RP-15A)	x
	FULLPAY DISCOUNT (RP-15A)	x
	SAFE DRIVING CLUB (RP-10A and RP-13A through RP-14A)	x
	ACCIDENT SURCHARGE FACTOR (RP-17A)	x
	MAJOR VIOLATION SURCHARGE FACTOR (RP-18A)	x
	MINOR VIOLATION SURCHARGE FACTOR (RP-19A)	x
	RATE TRANSITION FACTOR (Rule 72)	x
	COMPLEMENTARY GROUP RATING (CGR) FACTOR (RP-9A-1 through RP-9A-13)	x
47	TOTAL UM/UIM - BODILY INJURY COVERAGE	=

48	**TOTAL SEMI-ANNUAL VEHICLE 1 PREMIUM = 43 + 44 + 45 + 46 +47**	+
49	**TOTAL SEMI-ANNUAL VEHICLE 2 PREMIUM = 43 + 44 + 45 + 46 +47**	+
50	**TOTAL SEMI-ANNUAL VEHICLE 3 PREMIUM = 43 + 44 + 45 + 46 +47**	+
51	**TOTAL SEMI-ANNUAL VEHICLE 4 PREMIUM = 43 + 44 + 45 + 46 +47**	+
52	**TOTAL SEMI-ANNUAL POLICY PREMIUM = 48 + 49 + 50 +51**	=

A ALLSTATE FIRE AND CASUALTY INSURANCE COMPANY 04-

Figure F.1: Pricing Algorithm - Insurer 1 OH

Notes: This page is taken from an insurer's Ohio rate filing, which demonstrates their pricing algorithm.

Progressive Direct Insurance Company (DI)
Progressive Specialty Insurance Company (AG)
Ohio Private Passenger Automobile Program
NB Effective Date: 9/05/2014

Exhibit: 11

RATE ORDER OF CALCULATION

The first step of the rate calculation formula is to determine the Household Risk Factor. The Household Risk Factor is the average of the Developed Driver Risk Factors for all eligible to be rated drivers up to the number of vehicles (or at least one in the case of a named operator policy). For policies where there are more drivers than vehicles, the Household Risk Factor is the average of the highest ranked drivers, up to the number of vehicles. The rank is determined by the Developed Driver Risk Factor for BI (higher factor = higher rank). The Developed Driver Risk Factor is determined as follows:

Driver Risk Factor Items	**BI**	**PD**	**COMP**	**COLL**	**LOAN**	**MED**	**RENT**	**ROADSIDE**	**UMPD**
Driver Classification Factor									
Years Licensed Factor	x	x	x	x	x	x	x	x	x
Driving Record Points Factor	+	+	+	+	+	+	+	+	+
Violation Leniency Factor [1]	-	-	-	-	-	-	-	-	-
Subtraction of One	-1	-1	-1	-1	-1	-1	-1	-1	-1
(1 - Distant Student Discount)	x	x	x	x	x	x	x	x	x
(1 - Minor Child Discount)	x	x	x	x	x	x	x	x	x
(1 - Good Student Discount)	x	x	x	x	x	x	x	x	x
(1 - Senior Citizen Discount)	x	x	x	x		x			
Household Member Factor	x	x	x	x	x	x	x	x	x
Driver Age Point Factor	x	x	x	x	x	x	x	x	x
Financial Responsibility by Clean Factor	x	x	x	x	x	x	x	x	x
Developed Driver Risk Factor									

The second step of the rate calculation formula uses the Household Risk Factor and follows

	BI	**PD**	**COMP**	**COLL**	**LOAN**	**MED**	**RENT**	**ROADSIDE**	**UMPD**
Household Risk Factor									
Base Rate	x	x	x	x	x	x	x	x	x
Financial Responsibility Factor	x	x	x	x	x	x	x	x	x
Financial Responsibility by Number of Drivers Factor	x	x	x	x	x	x			x
Deductible Savings Bank Factor	x	x	x	x		x			
Occupation/Education Rating Factor	x	x	x	x	x	x			x
Full Coverage Factor	x	x				x			
Household Structure Factor	x	x	x	x	x	x			x
Residency Rewards Factor	x	x	x	x	x	x	x		x
Luxury Vehicle Factor	x	x	x	x	x	x			x
Tier Factor	x	x	x	x	x	x	x	x	x
Policy Term Factor	x	x	x	x	x	x	x	x	x
Vehicle Age Factor [3]	x	x	x	x	x	x	x	x	x
Excess Vehicle Factor	x	x	x	x	x	x			x
Limit Factor	x	x			x	x	x	x	x
Deductible Factor			x	x					
Vehicle Age by Deductible Factor			x	x					
Vehicle Symbol Factor	x	x	x	x	x	x			x
Value Class Factor (for Vehicle symbols 67 & 68)			x	x	x				x
Vehicle Garaging Location Factor	x	x	x	x	x	x	x	x	x
(1 - Homeowner/Mobile Home/Multi-car Discount)	x	x	x	x		x	x	x	x
(1 - Advance Quote [1]/Three-year Safe Driving/Five-year Accident Free Discount)	x	x	x	x		x			x
(1 - Three-year Safe Driving Bonus) [1]	x	x	x	x		x			x
(1 - Agent Discount) [1]	x	x	x	x		x			x
(1 - Electronic Funds Transfer Discount)	x	x	x	x		x			x
(1 - Paid In Full Discount)	x	x	x	x		x			x
(1 - Online Quote Discount) [2]	x	x	x	x		x			x
(1 - Loyal Customer Discount) [2]	x	x	x	x		x			x
(1 - Paperless Discount)	x	x	x	x	x	x	x	x	x
(1 - Continuous Insurance Discount)	x	x	x	x	x	x	x	x	x
(1 - Multi-policy Discount)	x	x	x	x		x	x	x	x
(1 + Business Use Surcharge)	x	x	x	x		x			x
(1 + Financial Responsibility Filing Surcharge)	x	x	x	x		x			x
Bad Debt Factor	x	x	x	x		x			x
Apply Rate Capping Rule P23 [4]	x	x	x	x	x	x	x	x	x
Usage-based Insurance Factor	x	x	x	x	x	x	x	x	x
(1 - E-signature discount) [2]	x	x	x	x	x	x	x	x	x
Round to the Whole Dollar									
Operations Expense [5]	+		+						
Acquisition Expense [2,6]	+		+						
Developed Premium [8]									

[1] Applies to Progressive Specialty Insurance Company (AG) Only
[2] Applies to Progressive Direct Insurance Company Only (DI)
[3] If coverage is BI, PD, UM/UIM, MED, RENT, or ROADSIDE and Vehicle Symbol = 66, then Vehicle Age Factor = 1.0.
If coverage is COMP, COLL, LOAN, or UMPD and Vehicle Symbol = 66, 67, 68, or 69, then Vehicle Age Factor = 1.0.
[4] Policy level rate changes are capped at +/- 10% as described in Rule P23. The Snapshop Usage Based Insurance Program (UBI) is not taken into consideration when applying the Rate Capping Rule
[5] Operations expense is added to BI if BI is selected; if BI is not selected, then Operations Expense is added to COMP.
[6] Acquisition expense is added to BI if BI is selected; if BI is not selected, then Acquisition Expense is added to COMP.
[7] Average factors are determined by taking the average of Location, Symbol, Vehicle Age factors, and Business Use Surchage for each vehicle, respectively
[8] There is a minimum premium of $5 for each coverage selected for each vehicle.
[9] The trailer coverages will receive the factors associated with COMP and COLL, unless otherwise noted.

NOTES
x means factor is to be used multiplicatively
/ means factor is to be used as a divisor
+ means factor is to be added
- means factor or amount is to be subtracted

Figure F.2: Pricing Algorithm - Insurer 2 OH 1/2

Notes: These pages are taken from a an insurer's rate filing in Ohio, which demonstrate their pricing algorithm.

Progressive Direct Insurance Company (DI)
Progressive Specialty Insurance Company (AG)
Ohio Private Passenger Automobile Program
NB Effective Date: 9/05/2014

Exhibit: 11

	UM/UIM
Base Rate	
Financial Responsibility Factor	x
Financial Responsibility by Number of Drivers Factor	x
Deductible Savings Bank Factor	x
Occupation/Education Rating Factor	x
Full Coverage Factor	x
Household Structure Factor	x
Residency Rewards Factor	x
Driver Count Factor	x
Luxury Vehicle Factor	x
Tier Factor	x
Policy Term Factor	x
Avg. Vehicle Age Factor [3, 7]	x
Excess Vehicle Factor	x
Limit Factor	x
Avg. Vehicle Symbol Factor [7]	x
Avg. Vehicle Garaging Location Factor [7]	x
(1 - Homeowner/Mobile Home/Multi-car Discount)	x
(1 - Advance Quote [1]/Three-year Safe Driving/Five-year Accident Free Discount)	x
(1 - Three-year Safe Driving Bonus) [1]	x
(1 - Agent Discount) [1]	x
(1 - Electronic Funds Transfer Discount)	x
(1 - Paid In Full Discount)	x
(1 - Online Quote Discount) [2]	x
(1 - Loyal Customer Discount) [2]	x
(1 - Paperless Discount)	x
(1 - Continuous Insurance Discount)	x
(1 - Multi-policy Discount)	x
(1 + Avg. Business Use Surcharge [7])	x
(1 + Financial Responsibility Filing Surcharge)	x
Bad Debt Factor	x
Apply Rate Capping Rule P23 [4]	x
(1 - E-signature discount) [2]	x
Round to the Whole Dollar	
Developed Premium [8]	

	ACPE	COMP-TRLR [1,9]	COLL-TRLR [1,9]	CONTENTS [1]	OPERATIONS EXPENSE [5]	ACQUISITION EXPENSE [2,6]
Base Rate				0.015 * Value		
Financial Responsibility Factor		x	x	x		
Deductible Savings Bank Factor		x	x			
Residency Rewards Factor		x	x			
Tier Factor		x	x	x		
Policy Term Factor	x	x	x	x	x	x
Limit Factor	x					
Deductible Factor		x	x			
Vehicle Symbol Factor		x	x			
Value Class Trailer Factor [1]		x	x			
Vehicle Garaging Location Factor	x	x	x			
(1 - Paperless Discount)	x	x	x	x	x	
(1 - Continuous Insurance Discount)		x	x			
(1 - Multi-policy Discount)						x
Operations Expense Factor 1					x	
Operations Expense Factor 2					x	
Operations Expense Factor 3					x	
Acquisition Expense Full Coverage Factor [2]						x
Acquisition Expense Homeowner Factor [2]						x
Acquisition Expense Online Quote Factor [2]						x
Acquisition Expense Prior Insurance Factor [2]						x
Acquisition Expense Vehicle Count Factor [2]						x
Number of Vehicles						/
Apply Rate Capping Rule P23 [4]	x	x	x	x	x	x
Bad Debt Factor		x	x			
Usage-based Insurance Factor	x				x	x
(1 - E-signature discount) [2]	x				x	x
Round to the Whole Dollar						
Developed Premium [8]						

Total Policy Premium = Sum of Developed Premiums

[1] Applies to Progressive Specialty Insurance Company (AG) Only
[2] Applies to Progressive Direct Insurance Company Only (DI)
[3] If coverage is BI, PD, UM/UIM, MED, RENT, or ROADSIDE and Vehicle Symbol = 66, then Vehicle Age Factor = 1.0.
If coverage is COMP, COLL, LOAN, or UMPD and Vehicle Symbol = 66, 67, 68, or 69, then Vehicle Age Factor = 1.0.
[4] Policy level rate changes are capped at +/- 10% as described in Rule P23. The Snapshop Usage Based Insurance Program (UBI) is not taken into consideration when applying the Rate Capping Rule
[5] Operations expense is added to BI if BI is selected; if BI is not selected, then Operations Expense is added to COMP.
[6] Acquisition expense is added to BI if BI is selected; if BI is not selected, then Acquisition Expense is added to COMP.
[7] Average factors are determined by taking the average of Location, Symbol, Vehicle Age factors, and Business Use Surchage for each vehicle, respectively
[8] There is a minimum premium of $5 for each coverage selected for each vehicle.
[9] The trailer coverages will receive the factors associated with COMP and COLL, unless otherwise noted.

NOTES
x means factor is to be used multiplicatively
/ means factor is to be used as a divisor
+ means factor is to be added
- means factor or amount is to be subtracted

Figure F.3: Pricing Algorithm - Insurer 2 OH 2/2

Notes: These pages are taken from an insurer's rate filing in Ohio, which demonstrate their pricing algorithm.

GEICO Casualty Company - Voluntary Private Passenger Automobile Insurance
Ohio Rate Pages Effective: New Business 10/2/2009 Renewals 10/2/2009 Rate Gen 01
Rate Order of Calculation: Private Passenger

Machine Rated, Exception: Licensed/Registered Dune Buggies rated as PPV are **Manually Rated**

Oper	Step	BI	PD	MED	UM-UND	UMBI	UMPD	COMP	COLL	ERS	RR	MBI
Base Rate												
	Base Rate	x	x	x	x	x	x	x	x	x	x	x
*	Limit Factor	x	x	x	x	x	x			x	x	
*	Deductible Factor							x	x			
*	Term Factor	x	x	x	x	x	x	x	x	x	x	x
*	Upgraded Accident Forgiveness Factor	x	x	x	x	x	x	x	x			
Driver Level Rating Steps- Composite Relativities												
*	Driver Class Factor (Composite Relativity)	x	x	x	x	x	x		x			
	Accident Factor	x	x	x	x	x	x		x			
	* Minor Violation Factor	x	x	x	x	x	x		x			
	* Major Violation Factor	x	x	x	x	x	x		x			
	* Speeding Violation Factor	x	x	x	x	x	x		x			
	* DUI Violation Factor	x	x	x	x	x	x		x			
	* Unverifiable Driving Record Factor	x	x	x	x	x	x		x			
	= Merit Factor	x	x	x	x	x	x		x			
*	Merit Factor (Composite Relativity)	x	x	x	x	x	x		x			
Driver Level Discounts: Composite Relativities												
*	*Good Driver Discount (Composite Relativity)*	x	x	x	x	x	x		x			
*	*Student Away at School Discount (Composite Relativity)*	x	x	x	x	x	x		x			
*	*Driving Experience Discount (Composite Relativity)*	x	x	x	x	x	x		x			
*	*Good Student Discount (Composite Relativity)*	x	x	x	x	x	x		x			
*	*Defensive Driver Discount (Composite Relativity)*	x	x	x	x	x	x		x			
*	*Deployed Driver Discount (Composite Relativity)*	x	x	x	x	x	x		x			
Vehicle Level Rating Steps												
*	Vehicle Type Factor											
*	Annual Mileage/ Vehicle Use Factor	x	x	x	x	x	x	x	x			
*	Vehicle Classification Factor	x	x	x	x	x	x	x	x			
*	Vehicle Cost Factor	x	x	x	x	x	x	x	x			
*	Model Year Factor	x	x	x	x	x	x	x	x			
*	Vehicle Age Factor	x	x	x	x	x	x	x	x	x		
*	MBI Model Year Factor											x
*	MBI Coverage Age											x
Vehicle Level Discounts												
*	*Anti-Theft Discount*							x				
*	*New Vehicle Discount*	x	x	x	x	x	x	x	x			
*	*Extra Vehicle Discount*	x	x	x	x	x	x	x	x			
*	*Anti-Lock Brake Discount*	x	x	x	x	x	x	x	x			
*	*Restraint Discount*			x	x	x						
Policy Level Rating Steps												
*	Household Composite Factor	x	x	x	x	x	x	x	x			
*	Maximum Named Insured Age Factor	x	x	x	x	x	x	x	x			
*	Policy Occurrence Factor	x	x	x	x	x	x	x	x			
*	Risk Tier Factor	x	x	x	x	x	x	x	x	x	x	x
Policy Level Discounts												
*	*Financial Responsibility Discount*	x	x	x	x	x	x	x	x	x	x	x
*	*Seat Belt Discount*			x	x	x						
*	*Multi-Vehicle Discount*	x	x	x	x	x	x	x	x	x	x	x
*	*Continuous Insurance Discount*	x	x	x	x	x	x	x	x			
*	*Military Discount*	x	x	x	x	x	x	x	x			
*	*Multi-Line Discount*	x	x	x	x	x	x	x	x	x	x	x
*	*CDL Discount*											
Policy Level Discounts 2												
*	*Sponsored Marketing Discount*	x	x	x	x	x	x	x	x	x	x	x
*	*Associate Discount*	x	x	x	x	x	x	x	x	x	x	x
*	*E-Banking Discount*	x	x	x	x	x	x	x	x	x	x	x
Expense Constants												
+	Vehicle Expense Load	x	x									
+	Policy Expense Load	x	x									

Figure F.4: Pricing Algorithm - Insurer 3 OH

Notes: These pages are taken from an insurer's rate filing in Ohio, which demonstrate their pricing algorithm.

OHIO
VOLUNTARY PRIVATE PASSENGER AUTO
POLICY CLASS FACTOR

POLICY CLASS FACTOR CALCULATION

Complete the steps below for all applicable coverages. Round to 4 decimals after each step.

Step 1: Based on number of male and female operators on the policy, obtain a value from Value Table 1a and find the corresponding factor from Factor Table 1a.

Step 2: Based on number of single operators, married operators, operators aged <25, and operators aged 25+ on the policy, obtain a value from Value Table 1b and find the corresponding factor from Factor Table 1b.

Step 3: Based on age and gender, obtain a value from Value Table 1c for **each** operator and calculate the geometric average of the corresponding factors from Factor Table 1c to obtain a factor for step 3.

Step 4: Multiply steps 1, 2, and 3 together to obtain the policy class factor to be applied to all vehicles on the policy.

See **RP-6A** for instructions on how to calculate the geometric average.

VALUE TABLE 1a - GENDER

Continuous Prior Insurance	# of Males	# of Females 0	1	2	3+
Yes	**0**	-	1	2	3
Yes	**1**	10	11	12	13
Yes	**2**	20	21	22	23
Yes	**3+**	30	31	32	33
No	**0**	-	4	5	6
No	**1**	14	15	16	17
No	**2**	24	25	26	27
No	**3+**	34	35	36	37

VALUE TABLE 1b - MARITAL STATUS AND AGE

Continuous Prior Insurance (Y/N)	# age >= 25	# age < 25	Marital Status # Married: 0	0	0	1	1	1	1	2	2	2	2	3+	3+	3+	3+
		# Single	1	2	3+	0	1	2	3+	0	1	2	3+	0	1	2	3+
Yes	0	1	1			16											
Yes	0	2		3			18			33							
Yes	0	3+			6			21	25		36	40	45	52	62	70	77
Yes	1	0	2			17											
Yes	1	1		4			19			34							
Yes	1	2			7			22			37			53			
Yes	1	3+			8				26			41	46	54	63	71	78
Yes	2	0		5			20			35							
Yes	2	1			9			23			38			55			
Yes	2	2			10				27			42		56	64		
Yes	2	3+			11				28				47	57	65	72	79
Yes	3+	0			12			24	29		39	43	48	58	66	73	80
Yes	3+	1			13				30			44	49	59	67	74	81
Yes	3+	2			14				31				50	60	68	75	82
Yes	3+	3+			15				32				51	61	69	76	83
No	0	1	84			99											
No	0	2		86			101			116							
No	0	3+			89			104	108		119	123	128	135	145	153	160
No	1	0	85			100											
No	1	1		87			102			117							
No	1	2			90			105			120			136			
No	1	3+			91				109			124	129	137	146	154	161
No	2	0		88			103			118							
No	2	1			92			106			121			138			
No	2	2			93				110			125		139	147		
No	2	3+			94				111				130	140	148	155	162
No	3+	0			95			107	112		122	126	131	141	149	156	163
No	3+	1			96				113			127	132	142	150	157	164
No	3+	2			97				114				133	143	151	158	165
No	3+	3+			98				115				134	144	152	159	166

VALUE TABLE 1c - AGE AND GENDER

Age	Male	Female
16 and Under	1	20
17	2	21
18	3	22
19	4	23
20	5	24
21	6	25
22	7	26
23	8	27
24	9	28
25-29	10	29
30-49	11	30
50-54	12	31
55-59	13	32
60-64	14	33
65-70	15	34
71-75	16	35
76-80	17	36
81-84	18	37
85+	19	38

RP-7A-1 ALLSTATE FIRE AND CASUALTY INSURANCE COMPANY 04-01-2014

Figure F.5: Variable Definition and Interactions

Notes: This is an excerpt from an insurer's rate filing on how observable information is used and interacted.

GEICO Casualty Company - Voluntary Private Passenger Automobile Insurance
Ohio Rate Pages Effective: New Business 06/07/2013 Renewals 07/22/2013 Rate Gen 12
Driver Class Factors

** Risk Group: B = B10, B20, and B30; C = C10, C20, C30; D = D10, D20, D30
** Z in Risk Tier represents all Risk Tiers
** Driver Age 999 = 80 and older
** RV Factor = 1.0

Risk Group	Risk Tier	Rated Vehicle Type	Coverage	Named Insured Indicator	Gender	Marital Status	Driver Age	Factor
B	Z	PP	BI	N	F	S	24	1.1660
B	Z	PP	BI	Y	M	M	24	0.9460
B	Z	PP	BI	N	M	M	24	1.1976
B	Z	PP	BI	Y	M	S	24	0.9361
B	Z	PP	BI	N	M	S	24	1.1387
B	Z	PP	BI	Y	F	M	25	0.7939
B	Z	PP	BI	N	F	M	25	0.8392
B	Z	PP	BI	Y	F	S	25	0.9649
B	Z	PP	BI	N	F	S	25	1.1458
B	Z	PP	BI	Y	M	M	25	0.9460
B	Z	PP	BI	N	M	M	25	1.1633
B	Z	PP	BI	Y	M	S	25	0.9361
B	Z	PP	BI	N	M	S	25	1.1178
B	Z	PP	BI	Y	F	M	26	0.8060
B	Z	PP	BI	N	F	M	26	0.8520
B	Z	PP	BI	Y	F	S	26	0.9649
B	Z	PP	BI	N	F	S	26	1.0819
B	Z	PP	BI	Y	M	M	26	0.9460
B	Z	PP	BI	N	M	M	26	1.1360
B	Z	PP	BI	Y	M	S	26	0.9361
B	Z	PP	BI	N	M	S	26	1.0359
B	Z	PP	BI	Y	F	M	27	0.8060
B	Z	PP	BI	N	F	M	27	0.8520
B	Z	PP	BI	Y	F	S	27	0.9649
B	Z	PP	BI	N	F	S	27	1.0525
B	Z	PP	BI	Y	M	M	27	0.9460
B	Z	PP	BI	N	M	M	27	1.0460
B	Z	PP	BI	Y	M	S	27	0.9361
B	Z	PP	BI	N	M	S	27	1.0251
B	Z	PP	BI	Y	F	M	28	0.8060
B	Z	PP	BI	N	F	M	28	0.8520
B	Z	PP	BI	Y	F	S	28	0.9649
B	Z	PP	BI	N	F	S	28	1.0398
B	Z	PP	BI	Y	M	M	28	0.9460
B	Z	PP	BI	N	M	M	28	1.0260
B	Z	PP	BI	Y	M	S	28	0.9361
B	Z	PP	BI	N	M	S	28	1.0172
B	Z	PP	BI	Y	F	M	29	0.8060
B	Z	PP	BI	N	F	M	29	0.8530
B	Z	PP	BI	Y	F	S	29	0.9649
B	Z	PP	BI	N	F	S	29	1.0118
B	Z	PP	BI	Y	M	M	29	0.9460
B	Z	PP	BI	N	M	M	29	1.0110
B	Z	PP	BI	Y	M	S	29	0.9361
B	Z	PP	BI	N	M	S	29	0.9821
B	Z	PP	BI	Y	F	M	30	0.8060
B	Z	PP	BI	N	F	M	30	0.8440
B	Z	PP	BI	Y	F	S	30	0.9649
B	Z	PP	BI	N	F	S	30	1.0100
B	Z	PP	BI	Y	M	M	30	0.9460
B	Z	PP	BI	N	M	M	30	0.9900
B	Z	PP	BI	Y	M	S	30	0.9361
B	Z	PP	BI	N	M	S	30	0.9800
B	Z	PP	BI	Y	F	M	31	0.8060
B	Z	PP	BI	N	F	M	31	0.8360
B	Z	PP	BI	Y	F	S	31	0.9648
B	Z	PP	BI	N	F	S	31	1.0010
B	Z	PP	BI	Y	M	M	31	0.9415
B	Z	PP	BI	N	M	M	31	0.9760
B	Z	PP	BI	Y	M	S	31	0.9360
B	Z	PP	BI	N	M	S	31	0.9710
B	Z	PP	BI	Y	F	M	32	0.8060
B	Z	PP	BI	N	F	M	32	0.8270
B	Z	PP	BI	Y	F	S	32	0.9648
B	Z	PP	BI	N	F	S	32	0.9900
B	Z	PP	BI	Y	M	M	32	0.9421
B	Z	PP	BI	N	M	M	32	0.9670

Figure F.6: Rating Factors based on Observables

Notes: This is an excerpt from an insurer's rate filing on how observable information is translated into pricing factors.

Progressive Direct Insurance Company
State of Ohio
New Business Effective: January 23, 2015
Renewals Effective: February 20, 2015

D06-Driving Violation Descriptions

The following chart lists the violation codes and their associated descriptions:

Violation Code	Violation Description
AAF	At Fault Accident
AFM	Accident found on MVR only at renewal - Not Chargeable
ANC	Waived Claim – Closed
ANO	Waived Claim – Open
ASW	Accident Surcharge Waived
CML	Commercial Vehicle Violation
CMP	Comprehensive Claim
CMU	Comprehensive Claim Less Than $1000
CRD	Careless or Improper Operation
DEV	Traffic Device/Sign
DR	Drag Racing
DWI	Drive Under Influence
FDL	Foreign Drivers Lic
FEL	Auto Theft/Felony Motor Vehicle
FFR	Failure to File Required Report
FLE	Fleeing from Police
FTC	Following Too Close
FTY	Failure to Yield
HOM	Vehicular Homicide
IP	Improper Passing
IT	Improper Turn
LDL	Operating Without Owner's Consent
LIC	License/Credentials Violation
LTS	Leaving the Scene
MAJ	Other Serious Violation
MMV	Minor Moving Violation
NAF	Not At Fault Accident
NFX	Waived Not At Fault Accident
PUA	Permissive Use At Fault Accident
PUN	Permissive Use Not At Fault Accident
RKD	Reckless Driving
SLV	Serious License Violations
SPD	Speeding
SUS	Driving Under Suspension
TMP	Dispute - At Fault Accident
UDR	Unverifiable Record
WSR	Wrong Way on a One Way Street

Figure F.7: Violation Captured in OH

Notes: This is an excerpt from an insurer's rate filing on the kinds of violations recorded in tier rating in Ohio.

GEICO Casualty Company - Voluntary Private Passenger Automobile Insurance
Ohio Rate Pages Effective: New Business 06/07/2013 Renewals 07/22/2013 Rate Gen 12
Accident Factors

** Risk Group: B = B10, B20, and B30; C = C10, C20, C30; D = D10, D20, D30
** Z in Risk Tier represents all Risk Tiers
** For Coverages BI,PD, COLL, COLL PP, and COLL TL Driver Age 18 = 18 and younger; 999 = 80 and older. All other Coverages Driver Age 18 = 18 and you

Risk Group	Risk Tier	Rated Vehicle Type	Coverage	Driver Age	Number of Chargeable Occurrences	Months Since First Occurrence	Months Since Second Occurrence	Factor
B	Z	PP	BI	31	4	23	35	3.3112
B	Z	PP	BI	31	4	35	35	3.0748
B	Z	PP	BI	31	99	11	11	4.9426
B	Z	PP	BI	31	99	11	23	4.5307
B	Z	PP	BI	31	99	11	35	4.3248
B	Z	PP	BI	31	99	23	23	3.9644
B	Z	PP	BI	31	99	23	35	3.7842
B	Z	PP	BI	31	99	35	35	3.5140
B	Z	PP	BI	32	0	0	0	1.0000
B	Z	PP	BI	32	1	11	0	1.6375
B	Z	PP	BI	32	1	23	0	1.3267
B	Z	PP	BI	32	1	35	0	1.2320
B	Z	PP	BI	32	2	11	11	2.2925
B	Z	PP	BI	32	2	11	23	2.1014
B	Z	PP	BI	32	2	11	35	2.0059
B	Z	PP	BI	32	2	23	23	1.6550
B	Z	PP	BI	32	2	23	35	1.5797
B	Z	PP	BI	32	2	35	35	1.4669
B	Z	PP	BI	32	3	11	11	3.5525
B	Z	PP	BI	32	3	11	23	3.2565
B	Z	PP	BI	32	3	11	35	3.1083
B	Z	PP	BI	32	3	23	23	2.8493
B	Z	PP	BI	32	3	23	35	2.7199
B	Z	PP	BI	32	3	35	35	2.5256
B	Z	PP	BI	32	4	11	11	4.3248
B	Z	PP	BI	32	4	11	23	3.9644
B	Z	PP	BI	32	4	11	35	3.7842
B	Z	PP	BI	32	4	23	23	3.4689
B	Z	PP	BI	32	4	23	35	3.3112
B	Z	PP	BI	32	4	35	35	3.0748
B	Z	PP	BI	32	99	11	11	4.9426
B	Z	PP	BI	32	99	11	23	4.5307
B	Z	PP	BI	32	99	11	35	4.3248
B	Z	PP	BI	32	99	23	23	3.9644
B	Z	PP	BI	32	99	23	35	3.7842
B	Z	PP	BI	32	99	35	35	3.5140
B	Z	PP	BI	33	0	0	0	1.0000
B	Z	PP	BI	33	1	11	0	1.6375
B	Z	PP	BI	33	1	23	0	1.3267
B	Z	PP	BI	33	1	35	0	1.2320
B	Z	PP	BI	33	2	11	11	2.2925
B	Z	PP	BI	33	2	11	23	2.1014
B	Z	PP	BI	33	2	11	35	2.0059
B	Z	PP	BI	33	2	23	23	1.6550
B	Z	PP	BI	33	2	23	35	1.5797
B	Z	PP	BI	33	2	35	35	1.4669
B	Z	PP	BI	33	3	11	11	3.5525
B	Z	PP	BI	33	3	11	23	3.2565
B	Z	PP	BI	33	3	11	35	3.1083
B	Z	PP	BI	33	3	23	23	2.8493
B	Z	PP	BI	33	3	23	35	2.7199
B	Z	PP	BI	33	3	35	35	2.5256
B	Z	PP	BI	33	4	11	11	4.3248
B	Z	PP	BI	33	4	11	23	3.9644
B	Z	PP	BI	33	4	11	35	3.7842

Figure F.8: Tier Factors

Notes: This is an excerpt from an insurer's rate filing on how tier information is rated.

Progressive Direct Insurance Company (DI)
Progressive Specialty Insurance Company (AG)
Ohio Private Passenger Automobile Program
Effective Date: January 23, 2015

Usage-based Insurance Factor Table - Initial Discount (DI Experience) Exhibit: 9C

UBI SCORE	BI/PD	COLL	COMP	LOAN	MED	RENT	ROADSIDE	UMPD	ACPE	OPERATIONS EXPENSE	ACQUISITION EXPENSE
0	0.56	0.56	0.96	0.96	0.56	0.56	0.96	0.56	0.96	1.00	1.00
1	0.61	0.61	0.96	0.96	0.61	0.61	0.96	0.61	0.96	1.00	1.00
2	0.65	0.65	0.97	0.97	0.65	0.65	0.97	0.65	0.97	1.00	1.00
3	0.75	0.74	0.97	0.97	0.75	0.74	0.97	0.75	0.97	1.00	1.00
4	0.79	0.79	0.97	0.97	0.79	0.79	0.97	0.79	0.97	1.00	1.00
5	0.83	0.83	0.97	0.97	0.83	0.83	0.97	0.83	0.97	1.00	1.00
6	0.86	0.87	0.97	0.97	0.86	0.87	0.97	0.86	0.97	1.00	1.00
7	0.89	0.89	0.97	0.97	0.89	0.89	0.97	0.89	0.97	1.00	1.00
8	0.89	0.90	0.97	0.97	0.89	0.90	0.97	0.89	0.97	1.00	1.00
9	0.89	0.91	0.97	0.97	0.89	0.91	0.97	0.89	0.97	1.00	1.00
10	0.90	0.90	0.97	0.97	0.90	0.90	0.97	0.90	0.97	1.00	1.00
11	0.90	0.90	0.97	0.97	0.90	0.90	0.97	0.90	0.97	1.00	1.00
12	0.90	0.90	0.98	0.98	0.90	0.90	0.98	0.90	0.98	1.00	1.00
13	0.91	0.89	0.98	0.98	0.91	0.89	0.98	0.91	0.98	1.00	1.00
14	0.91	0.88	0.98	0.98	0.91	0.88	0.98	0.91	0.98	1.00	1.00
15	0.91	0.90	0.98	0.98	0.91	0.90	0.98	0.91	0.98	1.00	1.00
16	0.92	0.90	0.98	0.98	0.92	0.90	0.98	0.92	0.98	1.00	1.00
17	0.92	0.91	0.98	0.98	0.92	0.91	0.98	0.92	0.98	1.00	1.00
18	0.92	0.91	0.98	0.98	0.92	0.91	0.98	0.92	0.98	1.00	1.00
19	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
20	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
21	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
22	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
23	0.92	0.92	0.98	0.98	0.92	0.92	0.98	0.92	0.98	1.00	1.00
24	0.93	0.93	0.98	0.98	0.93	0.93	0.98	0.93	0.98	1.00	1.00
25	0.93	0.93	0.98	0.98	0.93	0.93	0.98	0.93	0.98	1.00	1.00
26	0.93	0.93	0.98	0.98	0.93	0.93	0.98	0.93	0.98	1.00	1.00
27	0.93	0.93	0.99	0.99	0.93	0.93	0.99	0.93	0.99	1.00	1.00
28	0.93	0.94	0.99	0.99	0.93	0.94	0.99	0.93	0.99	1.00	1.00
29	0.93	0.94	0.99	0.99	0.93	0.94	0.99	0.93	0.99	1.00	1.00
30	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
31	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
32	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
33	0.94	0.94	0.99	0.99	0.94	0.94	0.99	0.94	0.99	1.00	1.00
34	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
35	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
36	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
37	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
38	0.95	0.95	0.99	0.99	0.95	0.95	0.99	0.95	0.99	1.00	1.00
39	0.95	0.96	0.99	0.99	0.95	0.96	0.99	0.95	0.99	1.00	1.00

Note:
-The premium-weighted average factor for the vehicle is calculated and applied to all coverages for the vehicle as indicated in the Rate Order of Calculation. This factor cannot be lower than 0.70 or greater than 1.0.

-If a vehicle does not participate in the Usage-based Insurance program it is assigned a 1.0 factor.

Figure F.9: Violation Captured in OH

Notes: This is an excerpt from an insurer's rate filing on how monitoring pricing is filed.

Progressive Direct Insurance Company (DI) & Progressive Specialty Insurance Company (AG)
Private Passenger Automobile Program
Supporting Exhibits for the State of Ohio
Effective Date: September 5, 2014
Coverage: BI **Exhibit 10Y**

Limit Factor

Experience	Has Prior Insurance	Limit	Incurred Loss Capped	Indicated Factor	Proposed Factor	Current Factor	Percent Change
AG	N	$25,000/$50,000	243,943,611	1.00	1.00	1.00	0.0%
AG	N	$50,000/$100,000	102,950,757	1.16	1.08	1.08	0.0%
AG	N	$100,000 CSL	1,444,950	1.24	1.11	1.11	0.0%
AG	N	$100,000/$300,000	70,326,408	1.54	1.29	1.29	0.0%
AG	N	$300,000 CSL	3,758,408	2.04	1.50	1.50	0.0%
AG	N	$250,000/$500,000	9,874,286	2.15	1.68	1.68	0.0%
AG	N	$500,000 CSL	5,350,267	2.25	1.80	1.80	0.0%
AG	Y	$25,000/$50,000	302,253,249	1.00	1.00	1.00	0.0%
AG	Y	$50,000/$100,000	256,452,902	1.21	1.13	1.12	0.9%
AG	Y	$100,000 CSL	7,102,129	1.26	1.19	1.16	2.6%
AG	Y	$100,000/$300,000	388,729,047	1.53	1.37	1.33	3.0%
AG	Y	$300,000 CSL	25,394,374	1.85	1.45	1.46	-0.7%
AG	Y	$250,000/$500,000	85,216,412	2.10	1.69	1.80	-6.1%
AG	Y	$500,000 CSL	45,591,859	2.15	1.93	1.95	-1.0%
DI	N	$25,000/$50,000	94,310,074	1.00	0.95	0.95	0.0%
DI	N	$50,000/$100,000	71,807,198	1.16	1.00	1.00	0.0%
DI	N	$100,000 CSL	81,354	1.27	1.11	1.11	0.0%
DI	N	$100,000/$300,000	45,810,439	1.54	1.28	1.28	0.0%
DI	N	$300,000 CSL	254,864	1.56	1.41	1.41	0.0%
DI	N	$250,000/$500,000	10,296,001	2.00	1.49	1.49	0.0%
DI	N	$500,000 CSL	440,458	2.16	1.59	1.59	0.0%
DI	Y	$25,000/$50,000	182,880,315	1.00	1.00	1.00	0.0%
DI	Y	$50,000/$100,000	199,882,577	1.15	1.05	1.05	0.0%
DI	Y	$100,000 CSL	1,287,766	1.22	1.17	1.17	0.0%
DI	Y	$100,000/$300,000	286,763,971	1.40	1.33	1.33	0.0%
DI	Y	$300,000 CSL	4,867,338	1.74	1.39	1.39	0.0%
DI	Y	$250,000/$500,000	53,447,656	1.82	1.47	1.47	0.0%
DI	Y	$500,000 CSL	5,998,809	2.13	1.60	1.60	0.0%

Figure F.10: Tier Factors

Notes: This is an excerpt from an insurer's rate filing on how limit choices influence pricing.