The Price of Staying Unmonitored: Strategic Incentivization in U.S. Auto Insurance

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Abstract

Firms increasingly use behavioral data, yet customers often choose whether to provide them. Using a novel dataset from auto insurers' regulatory filings, I study how insurers set prices to encourage customers to share driving data. Auto insurers traditionally set premiums with a limited set of variables, such as age and location, that assess risk only coarsely. Exploiting staggered state approvals of mobile telematics, I find that the transition to mobile monitoring leads insurers to raise the price of remaining unmonitored, particularly for young drivers, with larger increases among young males, and residents of densely populated areas. Repricing is stronger among insurers offering larger enrollment discounts, linking the pricing response to insurers' incentives to obtain data from customers whose risks are difficult to assess.

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1. Introduction

Firms increasingly value data on individual behavior, but such data are not equally informative for every customer. This distinction is particularly important in auto insurance, where insurers are constrained to price customers using state-permitted variables, including a limited set of characteristics such as driver demographics and residential location. These conventional variables classify customers only coarsely, leaving greater residual uncertainty for some groups[1].

Young drivers are one such group because their short driving histories provide fewer signals about their underlying risk. Geographic rating is similarly imprecise in densely populated areas, where many behaviorally different drivers are assigned the same coarse location factor. Individual driving data are therefore particularly valuable for distinguishing risk types within these hard-to-rate groups.

Obtaining this information, however, requires customers to volunteer to be monitored. Insurers must therefore encourage participation among the customers whose driving behavior is most valuable to observe. They commonly offer participation discounts to induce enrollment. This paper studies a complementary pricing channel: raising the standard premium paid by customers who remain unmonitored. Specifically, I test whether insurers selectively increase this price for hard-to-rate groups defined by age, gender, and location, thereby making enrollment in driving-data programs more attractive to those customers. In this paper, I refer to this targeted increase in the price of remaining unmonitored as insurers' strategic incentivization of customer participation.

The technology used to collect driving-behavior data in auto insurance is known as "telematics", a combination of telecommunications and informatics that monitors vehicle movement and records drivers' behavior. These data allow insurers to price policies through usage-based insurance ("UBI"). Using these signals, insurers apply a discount or surcharge on top of the conventional pricing layers.[2] The paper's empirical design centers on a supply-

[1] Big data has spread across insurance markets beyond auto. For example, life and health insurers tie premiums to activity from wearable fitness trackers, homeowners insurers offer discounts for connected smart-home sensors, and crop insurers price policies using satellite and weather data.

[2] According to the J.D. Power 2023 U.S. Auto Insurance Study, approximately 17% of auto insurance customers were enrolled in usage-based programs.

side innovation in this technology: the transition from device-based monitoring to mobile telematics. The mobile application was developed by a telematics company Cambridge Mobile Telematics (henceforth "CMT") and was approved on a staggered schedule across states before auto insurers could incorporate it into their programs. The identification strategy compares changes in insurers' pricing menus in states that approved the technology earlier with those of comparable insurers in neighboring states that approved it later.

Our analysis draws on a novel dataset extracted from auto insurers' product filings, through which state regulators require insurers to disclose their multiplicative pricing models, underwriting rules, and factor-loading tables. The filings thus reveal the pricing menu itself that an insurer would quote for every customer profile it rates. From these filings we extract the age × gender and location factor tables that insurers use to translate these customer characteristics into prices. A factor is the multiplier an insurer assigns to one category of a customer characteristic, such as an age-gender cell or a ZIP Code, and the insurer arrives at a customer's premium by multiplying the base rate by the factors matching her characteristics[3]. The factors in our sample range from 0.52 to 4.55. The product filings are unstructured PDF documents ranging from a few KB to nearly 400 MB in size, and I build an AI-agent-based workflow to process them and extract the data used in this paper.

I match each telematics-adopting insurer in an earlier-approving state with a sibling company or similarly sized peer in a later-approving state and construct a stacked panel around the mobile-telematics approval event. I conduct two complementary analyses. First, difference-in-differences regressions estimate changes in factor levels separately across age and gender groups and across more and less complex locations. Second, a triple-difference design tests whether these changes are significantly larger for the hard-to-rate groups than for other customers within the same pricing menu. The within-menu specification absorbs revision-wide changes that affect all customer groups, isolating whether insurers selectively raise the price of remaining unmonitored for the customers whose driving data are most valuable.

Age is the most important demographic characteristic for predicting driving behavior.

[3] A factor can therefore be read as a price relativity, which measures how the price moves as the customer changes category on one characteristic while all other characteristics stay fixed. A customer in a cell with a factor of 2 pays twice as much as an otherwise identical customer in a cell with a factor of 1.

Young drivers are particularly difficult to assess because their driving profiles are incomplete, with limited driving experience and fewer complementary signals such as credit history.[4] Insurers therefore have strong incentives to encourage both low- and high-risk young drivers to enroll and reveal their underlying risk types. This paper finds that the property damage and collision factors, the two factors most directly related to driving behavior, increase significantly for young customers on treated insurers' menus by 5.4% and 2.9% of the respective group means. I find no comparable increase among middle-aged or senior customers. The stacked DDD analysis further shows that the pricing gap between young and older customers widens significantly, confirming that the additional charges concentrate on the age group whose risk is hardest to assess using conventional information.

Gender provides an additional dimension of heterogeneity in insurers' pricing response.[5] A large literature shows that males are riskier drivers on average, but which gender exhibits greater residual variation in driving behavior remains less clear. I therefore treat gender as an exploratory dimension and estimate the effects separately for male and female factors within each age group. Among young drivers, the property damage factor increases by 6.2% of the group mean for males, compared with 4.6% for females, and the collision factor likewise increases more for males. The larger increase among young males suggests that insurers place greater value on obtaining individual driving data from this group.

Location is another important dimension of driving risk. Insurers may price residential location only at a relatively coarse geographic level, at finest the census block group, even though driving behavior varies substantially within the same area. Residents of the same apartment building, for example, may receive the same location factor despite differing considerably in their underlying risk.

[4] In the United States, chargeable periods for violations and at-fault accidents typically run three to five years, while claims reports cover up to seven years. Cohen and Einav (2007) show that the standard deviation of claim rates is roughly 43% higher among drivers with fewer than ten years of licensing experience, while mean claim rates are similar. Jin and Vasserman (2021) show that new drivers without past claim records exhibit a particularly wide dispersion in private risk. In insurers' filings, years of licensing enters at most as a coarse indicator rather than a detailed schedule, so age serves as the primary rating variable for inexperience.

[5] The use of gender in auto insurance pricing has long been controversial. Insurers and actuaries defend it on actuarial-fairness grounds because gender predicts claim costs, while consumer and civil-rights advocates argue that pricing on an immutable characteristic constitutes unfair discrimination. Six U.S. states currently prohibit gender-based pricing in private auto insurance: California, Hawaii, Massachusetts, Michigan, North Carolina, and Pennsylvania. Montana maintained a similar ban from 1985 until its repeal in 2021. None of the eight states in our sample restricted gender rating during the sample period.

This paper measures how difficult a location is to rate using two ZIP Code-level characteristics: its population-density tier within the state and whether it is located in a metropolitan area. The stacked DiD regressions show that collision factors increase in both more and less complex locations on treated insurers' menus. The within-menu DDD analysis then shows that the increase in property damage factors is significantly larger in more complex locations. The gap widens by 0.013 under the population-density measure and by 0.010 under the metropolitan-area measure, equivalent to approximately 1.3% and 1.0% of the factor mean. These results show that insurers direct the repricing toward locations where conventional geographic factors leave greater uncertainty about individual risk.

I collect the participation discounts offered by each insurer and classify insurers into low- and high-discount groups. Under our hypothesis, the increase in the price of remaining unmonitored and the participation discount are two complementary pricing levers. Insurers offering larger discounts should therefore also raise the unmonitored price more strongly. Consistent with this prediction, the increases in factors charged to young customers and customers in more complex locations are concentrated among high-discount insurers. The magnitude of the repricing thus scales with the strength of the participation incentive, linking the pricing response directly to insurers' motive to encourage enrollment.

A series of robustness tests shows that the repricing is absent where the proposed mechanism should not operate. First, a placebo analysis that assigns the shock to the previous filing revision finds no comparable increase before the mobile transition, indicating that the results do not reflect a pre-existing trend. Second, insurers that had not adopted telematics around the event date show no similar change in their pricing menus. Because these insurers operate under the same state regulations, this result suggests that the repricing follows the technology rather than contemporaneous state-level changes. Finally, we find no comparable increase in comprehensive and medical expense factors. These coverages primarily price exposure to off-road losses, such as theft and weather, and the treatment costs of the insured's own injuries, respectively, and are less directly related to driving behavior. Within adopters' pricing menus, the repricing therefore concentrates in the coverages for which driving data are most informative.

Literature: The primary contribution of this paper is to assess auto insurers' strategy

to acquire data from customers. There is a growing amount of literature of "InsurTech". Specifically studies have documented the application of telematics data in auto insurance, such as the self-selection of safer drivers into monitoring programs and the profit and welfare gains the data generate (Jin and Vasserman (2021)), the diffusion of monitoring programs across states and their effects on competition and accident rates (Reimers and Shiller (2019)), the improvement in driving behavior once customers are monitored (Soleymanian et al. (2019)), and the reversal of the information advantage from the insuree to the insurer once insurers hold the behavioral data (Brunnermeier et al. (2025)). Our contribution is to show that insurers engineer the enrollment itself, repricing their filed menus to raise the charges on hard-to-rate customers and push the most valuable data sources into the program. The paper also contributes to the thread of literature focusing on big data and business strategies surrounding the availability of new information access.

Our paper also relates to the broader literature on big data and business strategy. Data are viewed as valuable assets in the digital economy (Farboodi and Veldkamp (2021)), and firms treat the customer data they accumulate as a competitive advantage that secures their market position(Hagiu and Wright (2023)). Kummer and Schulte (2019) shows that developers offer their apps at lower prices in return for greater access to personal information. Our paper shows that auto insurers likewise use pricing as the instrument for data acquisition, raising the charges on staying unmonitored and aiming the increase precisely at the customers whose information value is the highest. Lastly, we contribute a new source of data by compiling insurers' product filings, which disclose the underwriting models behind their prices. Such data have only recently been incorporated into economic research (Boomhower et al. (2024), Oh et al. (2021)).

Paper Structure. The rest of the paper is structured as follows. Section 2 discusses institutional details of telematics and usage-based insurance. Section 3 discusses the data and the extraction of rating factors from product filings. Section 4 presents the main results from the stacked matched DiD and the within-menu DDD designs, together with the heterogeneity by participation discount size. Section 5 presents the robustness checks, and Section 6 concludes.

2. Institutional Background

2.1. Auto Insurance Pricing and Usage-Based Insurance

Auto insurance pricing is heavily regulated. Insurers are generally required to disclose their pricing models, underwriting rules, and factor-loading tables, except for components approved for confidential treatment as proprietary algorithms.[6] A typical pricing formula takes the following form:

$$\begin{aligned} Price = {} & Base\,Rate \times Characteristics\,Factors \times Coverage\,Factors \\ & \times (UBI\,Participation\,Discount) \times (UBI\,Factor) + Operating\,Costs \end{aligned} \tag{1}$$

where the base rate is a dollar amount that serves as the starting point for the premium calculation. The main categories of customer-characteristic factors include driver demographics, such as age, gender, and marital status; location; driving history, including minor violations, major accidents, and serious offenses such as driving under the influence; credit history; and vehicle characteristics, such as model year, make, model, and horsepower. The premium also increases with the level of coverage selected. Insurers may then add operating fees, including marketing and customer-acquisition charges.

Customers who opt into a usage-based insurance program typically receive a flat participation discount on their premium. The monitoring program then collects driving data over a policy term, usually six months, and assigns a driving score that determines the discount or surcharge applied at the next renewal. This score maps into a usage-based insurance factor ("UBI factor"), which enters the multiplicative pricing formula on top of the conventional pricing layers.[7] For customers who remain outside the program, the participation discount and UBI factor take their default value of one.

[6] The definition of confidential materials vary greatly across companies' applications and states. In our sample firms and states, the most common information withheld from public disclosure are credit-history-related factors and the UBI models (how behavioral signals are mapped to numerical models).

[7] Progressive (PRGS) was an early pioneer in introducing telematics into private auto insurance, launching its program in 2008. Figure **??** illustrates the current enrollment process for Progressive's telematics product, Snapshot.

2.2. Telematics: From Physical Devices to Mobile Applications

Telematics is a method of monitoring vehicle movement using technologies such as GPS, in-vehicle sensors, and wireless data transmission. The technology collects drivers' behavioral data, such as miles driven, average speed, hard braking, and sharp cornering. In the technology's first developmental stage, a physical device, or tag, had to be plugged into the On-Board Diagnostics (OBD-II) port, a connector standardized in most cars since the mid-1990s. Vendors then returned either raw data or processed metrics to insurers on request, and the insurers performed the statistical, actuarial, and risk modeling themselves. Because the process relied heavily on an insurer's own capital and resources, it was undertaken only by market forerunners.

Modern smartphones are equipped with accelerometers, gyroscopes, GPS, and magnetometers, which together provide precise measures of speed, braking, cornering, and route choice. These sensors capture driving patterns passively and reliably, making mobile devices an efficient tool for telematics-based risk assessment[8]. As early as 2012, Cambridge Mobile Telematics (henceforth "CMT") began patenting and developing mobile sensing technologies, and over the following years it grew into the leading third-party provider of mobile-based telematics data. Beginning in 2018, CMT formally filed its models with state insurance departments for regulatory approval, after which insurers increasingly partnered with the firm and integrated its products into auto insurance pricing[9].

This paper treats CMT's filing with state insurance departments as an exogenous, state-level shock to the industry, denoted $MobileShock_{s,t}$. Before 2018, insurers could not meaningfully price on mobile-sensed data, because the technology was still under development and no approved, ready-to-use model existed. CMT worked with a few insurers during early experimental stages, but a deployable model did not become available until around 2018. Insurers were also barred from applying third-party data before regulatory approval, and in

[8]However, a smartphone may not match the measurement precision of a dedicated in-vehicle device, since its readings can degrade when the GPS signal is weak, when the phone sits in an inconsistent position within the vehicle, or when the tracking app runs in the background.

[9]Anecdotally, CMT has been regarded as the leading firm in mobile-sensing telematics since it began patenting the technology in 2012. We are aware of only two insurers that attempted to develop their own in-app data collection before 2018, namely Progressive and Hartford. Progressive described its effort as still in an experimental stage, while Hartford launched its own product, discontinued it shortly after introduction, and turned to CMT for collaboration.

its initial approval filings CMT clearly stated that no formal cooperation with insurers had occurred beforehand. In other words, insurers' response to the availability of mobile sensing technology is orthogonal to the pass of the adoption. Appendix B.1 discusses the spreadout of the mobile-sensing technology across the states over time.

2.3. Insurance Operating Structure

An auto insurer typically operates not as a single company but as a group of separately licensed insurance companies under common ownership, which we refer to as statutory entities. Each statutory entity is a distinct legal company that bears risk on its own balance sheet, files its own financial statements with state regulators, and files its own rates and rating factors. The parent group, such as State Farm or GEICO, is the brand and ownership umbrella, while the entities beneath it are the units that actually write policies and set prices. A customer's policy is issued by one specific entity, not by the group as a whole, so the objects we study are defined and filed at the entity level. Throughout the paper, we use the term "group" to denote the consolidated insurer and the term "entity"/"firm"/"company" to denote an individual licensed company within it.

There are typically three segments of customers based on their expected claim risk. Preferred layer is the lowest-risk customers who are mature drivers with clean records over several years, having fair credit history and have stable insurance history. The standard layer refers to the average-risk customers who have a decent but imperfect profile. Nonstandard customers are those who the mainstream market doesn't want. This layer of customer may have multiple accidents or violations, driving-under-influence records, very poor credit etc, which takes roughly 20% of the total personal auto premium. In this paper, the sample excludes affiliates that specialize in nonstandard business. The retained entities cover both preferred and standard risks in their product filings, with risk quality entering through tier and factor assignments. Thus, the analysis captures pricing for the mainstream customer spectrum.

3. Data

3.1. Sample Overview

We collect information for eight states, AL, CT, GA, IA, IL, VA[10], SC, and WI[11]. AL, IA, IL, SC, and WI approved the technology in 2018, and CT, GA, and VA serve as the control group of not-yet-approved states, whose insurers are used as the comparison peers. The specific approval dates in these states are reported in Table A.1.

All the sample states operate under an at-fault (tort) system, in which the at-fault party is responsible for the bodily injury and property damage caused in an accident. Insurers pay for the liability its insured incurs to others, while the insured's own losses are covered only if the customer purchases additional first-party coverage. For this reason, Bodily Injury ("BI") and Property Damage ("PD") liability coverages are mandatory in these states. Other coverages, such as Comprehensive ("COMP"), Collision ("COLL"), and Rental ("RENT"), are all optional.

We rank insurance groups by premiums written in the private passenger auto line in each state and keep the top 10 groups. Within every top 10 group in a state, we rank its statutory entities by their share of the group book and keep the largest entities whose shares cumulatively reach 80% of that book. This retains the dominant entity in concentrated groups, both channels in channel groups, and the core entities in fragmented groups, while dropping the small specialty tail[12].

[10]During our sample period 2017–2023, a motorist in Virginia could pay the state an Uninsured Motor Vehicle (UMV) fee (about $500 a year) to the DMV and legally drive uninsured. That fee bought no coverage but just let customers register an uninsured car, leaving the motorist personally liable for any damage caused. Virginia removed this option on July 1, 2024. Our statement therefore refers to customers who choose to be insured, for whom liability coverage is mandatory.

[11]We reviewed state insurance regulation over our sample period and found no enacted law in our sample states that restricted or altered the use of demographic factors (age, gender, and marital status) or territorial factors (ZIP Code or geographic rating) in private passenger auto insurance. We therefore do not expect contemporaneous rating regulation to confound the changes we attribute to the mobile telematics shock.

[12]The selection is applied after we screen out the nonstandard underwriting subsidiaries, so the cumulative 80% covers the mainstream customer book. Appendix B.3 discusses the internal structure of insurance groups and how operating business is distributed across their statutory entities.

3.2. Extract Factors from Product Filings

We access the rate filings for insurers in each of the 8 sample states over the sample years from the System for Electronic Rate and Form Filing ("SERFF"), operated by the National Association of Insurance Commissioners ("NAIC"). The system keeps archive of all auto insurers' rate and form filings since xxx, with the filing-approval timeline of each filings clearly noted. We can see when the product filing was submitted and disposed. These product filings contain rich information from the supply side, including auto insurers' underwriting rules, factor models, factor tables, and acturial materials supporting the filings appended.

The rate filings range from a few KB to nearly 400 MB, and from 5 pages to over 38,000 pages as PDF documents. The rating models differ fundamentally across insurers, and each state adds its own variations in reporting format. To streamline the process and align the data into a consistent format, we build an AI-agent-based workflow for filing processing and data extraction. The workflow consists of four stages: automated searching and file downloading, PDF conversion, factor extraction, and quality check. The details of the workflow and used prompts are discussed in Appendix B.7.

Demographic Factors. We define demographic factors as the rating factors determined by two operator characteristics: age and gender, both of which are present in the rating models of the insurers in our sample. Demographic factors appear in product filings in two formats. Some insurers consolidate the two characteristics into a single factor (e.g., Progressive), while others spread them across multiple factors (e.g., State Farm). In the latter case, we multiply the relevant factors together to obtain one factor that captures the joint demographic adjustment. In all cases, the object of interest is a single aggregate factor that summarizes how age and gender enter the pricing process. We equal-weight all other dimensions that jointly enter the pricing process with age and gender, such as the operator's marital status and vehicle usage purpose.

Territory Factors. Territory factors map a customer's location to the rating factor the insurer charges. Among all firm $\times$ state sample pairs, 70% use a ZIP-based territory definition. In the remaining cases, territories are defined at the county or census block group

level, and a single ZIP Code can fall under more than one territory. We set that ZIP Code's factor to the population-weighted average of the overlapping territories' factors. The weights are each ZIP Code's share of residents in a territory, drawn from the HUD–USPS ZIP Code Crosswalk Files and American Community Survey (ACS) population counts[13]. We keep only ZIP Codes that appear in the ACS ZIP Code universe. The final territory (location) factors are essentially ZIP Code–level factors.

Base Rates. The base rate is the starting dollar premium that an insurer assigns to a coverage before any rating factors are applied. The insurer arrives at a customer's final quote by multiplying the base rate by all the applicable rating factors. The base rate therefore represents the premium for a baseline, or reference, driver, one whose rating factors all equal one, and can be read as the quote for a standard driver in the insurer's customer pool.

We collect base rates, location/territory factors, and demographic factors *whenever* insurers update and file during the sample years[14]. Subsidiaries within the same insurance group typically file their factor tables separately but bundled into a single SERFF filing. Before applying the matching standards for empirical analysis, we have 148 major insurer-state units that disclose demographic factors, territory factors, or base rates in their product filings. Among them, 97 disclose the demographic pricing layer, 133 disclose the territory layer, and 93 disclose base rates. However, we have only 77 insurer-state units for which all three pieces of information have been completely extracted from the original PDF filings.

Telematics Adoption. For all firm-state samples, we go through their product filings and use textual search for (1) whether the firm had adopted the technology as of the first sample year, 2017, and (2) if not, whether it introduced the technology within the sample window. As shown in Figure 1, 67.2% of the units had mentioned adopting the technology before the sample period begins, most of which in the first-stage physical device format. 8.2% of the insurer-state samples had still not introduced any format of telematics by the

[13]See Appendix B.5 for more details. Territories defined at the municipality level cannot be reliably mapped to ZIP Codes, so those samples are dropped. CT is the only state in our sample where State Farm and USAA define some territories at the town or municipality level.

[14]Although insurers are required to file their rating models with state regulators, they may apply to withhold portions of those models on trade-secret grounds. We therefore collect the firm-state pairs for which the factor information is consistently observable in public filings across the sample period, while recognizing that these three dimensions enter every insurer's pricing process whether or not the underlying tables are disclosed.

end of the sample period. We also search for the *explicit* evidence of mobile-app based telematics adoption from insurers' product filings. As shown in Figure 1, the mentioning of mobile phone applications starts to increase in the year of 2018. Once the technology was passed in the operating states, auto insurers begin to actively add the mobile applications to the existing telematics bundle. Before that, a very small portion of auto insurers are experimenting their own developed mobile applications in a limited number of pilot states.

Participation Discounts. We also go through insurers' product filings at each state to collect the magnitudes of participation discounts they offered to customers if they opt in the data collection process. Program discounts were offered at different levels across time, and we take the discount effective at the post-shock event to categorize companies into low- and high-discount companies. The categorization and the discounts each company adopt is reported in the Appendix. Discounts provided nationwide across different states are the same for firms under one parent insurance group.

In the main analysis, we focus on the effect for insurers that had already adopted the technology in the corresponding states before the first-wave shock happened in 2018. We also include insurers who introduced the telematics program right after the mobile shock time but the rollout is more of a national operating decision than related to the mobile shock itself.

3.3. Variables Definition

Factor Loading Value. We study the original factor values from the product filings. A higher factor means a larger surcharge to the customer quoted. Specifically, we study demographic factors at the age $\times$ gender level ($DemoFactor_{a,g,t}$). Some insurers report factor values in risk groups and we "open up" those intervals to get a comprehensive coverage of all age $\times$ gender parameter space. We study the location factors at the ZIP Code level ($ZIPCodeFactor_{z,t}$).

Other Control Variables. We include two firm-state-time level control variables. The first is the insurer's size, measured as the natural logarithm of the premiums written by the firm in the state in the year before the filing ($Log_PremiumsWritten_{j,s,t-1}$). The second is the firm's combined ratio in the state over the same year, the sum of the loss and expense ra-

tios ($CombinedRatio_{j,s,t-1}$), which summarizes underwriting profitability, with values above one indicating that claims and expenses exceed the premiums collected. Both variables are collected from insurers' statutory filings at the firm-state-year level and are lagged by one year, so they reflect the operating conditions the insurer observes when it sets the new factor schedule rather than outcomes realized after the filing. Larger books and weaker underwriting results may both change how aggressively an insurer reprices, so the two controls absorb the size and profitability differences across the matched units.

3.4. Summary Statistics

Table 1 summarizes the data we use in the analysis. There are 28 matched pairs for demographic factors and 17 pairs for territory factors, where both companies in the pair have clean and complete disclosed data in the two-year-period event window. Each pair matches a treated insurer operating in a state that approved the technology in 2018 with a control insurer in a not-yet-approved state. The demographic sample covers filings from February 2016 to September 2021, and the territory sample covers filings from February 2016 to December 2020.

Panels B and C report the factor loadings we use in the paper. The demographic factors range from 0.52 to 4.55 and the territory factors range from 0.52 to 2.71, after winsorizing at the 1st and 99th percentiles. A factor of one represents the reference driver or location, so the most heavily surcharged demographic cells pay more than four times the base premium while the most favorable cells pay roughly half. The medians of both factor families sit close to one, and the demographic factors vary considerably more than the territory factors. The demographic layer moves quotes over a wider range than the location layer.

Panel D reports the balance between the two sides of the matched pairs. Treated insurers are smaller than their matched controls, with average premiums written of \$217 million against \$343 million in the demographic sample and \$349 million against \$476 million in the territory sample. The combined ratios of the two sides are close, 0.72 against 0.73 in the demographic sample and 0.77 against 0.80 in the territory sample, and the differences are not statistically significant. The pairs therefore match insurers of similar underwriting performance.

4. Empirical Method and Results

4.1. Stacked Panel Construction

We conduct an event analysis and match telematics-adopting insurers in the earlier-treated states (AL, IA, IL, SC, WI) to comparable peers in the later-treated states (CT, GA, VA). Insurers revise their models at no regular pace, so the updating frequency is not fixed and our data do not form a traditional fixed-frequency panel. An update takes on average more than one year to be filed and approved by regulators. We therefore narrow the analysis window to the last pre-treatment filing and the first post-treatment filing of adopters in the earlier-treated states. Filings beyond this event window are likely to reflect events unrelated to the technology shock. In addition, COVID-19 paused filing activity and insurers may have delayed their revisions. We therefore allow the first post-shock filing of treated firms to appear within three years of the mobile shock, that is, up to 2021[15].

We first pair states by regional proximity. AL and SC are matched to GA and VA, while IA, IL, and WI are matched to CT, GA, and VA. All insurers that had already adopted telematics before the law are included in the treated sample, as all of them quickly begin adopting the mobile application once it becomes available. We also keep Farmers Insurance ("FARM") and Erie Insurance ("ERAP"), which adopted telematics right after the mobile shock, in 2019 and early 2020, in their states. The telematics rollout at these two firms is a nationwide strategic choice and is not directly linked to the state-level approval of the technology[16]. For these insurers the event date is the telematics introduction date rather than the law date. In other words, $Post_{i,s,t}$ turns to one at the later of the two dates, $\max(law, adoption)$.

[15]Four treated subsidiaries make their first post-event update in the third year. Farmers in Illinois updates in October 2020, Liberty Mutual's Safeco subsidiary updates in June 2020 in Illinois and in September 2021 in Alabama, and Liberty Mutual's First subsidiary in South Carolina updates in November 2020. All other treated insurers that update do so within two years of the event.

[16]Farmers introduced its smartphone telematics program, Signal, in March 2017, initially for policyholders in Arizona. Farmers then expanded Signal state by state over the following years as a national rollout. In our sample states the introduction filings arrive between mid 2018 and mid 2019, in Illinois before June 2018, in Georgia in July 2018, and in Alabama and Wisconsin between May and July 2019. The program's arrival in any given state reflects the company's national expansion schedule rather than a response to that state's law. Erie Insurance introduces its program in Wisconsin in January 2020, seventeen months after the state law of August 2018. Erie files the introduction in Virginia on the same date, which indicates a nationwide rollout rather than a response to any single state law.

We require the matched counterpart to have filing updates both before and after the treatment as well, to ensure that it is an active underwriter. We do not require its update to occur at exactly the same time as the treated insurer's. The update can come earlier or later in terms of the date the new filing is passed. However, the matched counterpart's filings must fall inside the clean window, before the law is passed in its own state.

Then, for each insurer in the treated states, we find its match in the following way. If it is a nationwide insurer with active sibling subsidiaries in the later-treated states, we match it to the subsidiary under the same group that is closest in size. If no such sibling exists or the insurer is a standalone regional company, we match it to the closest peer in size among the later-treated states, where size is measured by total premiums written in the corresponding states. The idea is to control for within-group unobserved characteristics such as company-level strategy and model uniqueness. The match candidates can be either not-yet-treated peers or never-adopters. Matching is done with replacement.

We do the matching separately for the demographic analysis and the territory analysis given the difference in data availability. We obtain 28 and 17 matched insurer-state pairs for demographic and territory analysis respectively[17]. All matched controls in the effective samples eventually adopt telematics. 45 of the 53 controls were already running telematics before the 2018 treatment wave, and the remaining eight introduce their programs between 2019 and 2023. Control adoption timing does not affect identification, since a control contributes to a pair only until its own state law takes effect. In both analyses, the majority of treated insurers are compared with subsidiaries of their own group operating in later-treated states, 61% of the effective pairs in the demographic sample and 77% in the territory sample.

4.2. Screening Alongside Demographics

4.2.1. Stylized Facts

First, we state two observed facts learned from insurers' product filings.

Risk is U-shaped with Age. We take the equal average of the factors quoted at each age across female and male drivers, and the relationship between the average factor and age

[17]The sample is biased to insurers who disclosed their demographic pricing layer. The details are discussed in Appendix B.4

is plotted as the gray dashed line in each coverage panel of Figure 2. We observe U-shapes for all major coverage factors except the comprehensive coverage factor. In general, teenagers are charged the highest factors across all categories. The factors charged decrease with age before customers reach 30 years old and remain relatively flat until the age of 70. Then the factors charged start to increase with age.

This is consistent with common sense that young and senior customers are viewed as riskier than the middle-aged customer group. Young drivers are inexperienced and more prone to risk-taking, and the factors teenagers pay three to four times the base level for the liability coverages. Senior drivers face declining vision, reaction time, and general health. The factors pick this up as well, rising steadily after the mid-sixties and reaching roughly one and a half to two times the base level by age 85. The pricing schedules thus quantify the common intuition that middle-aged customers combine accumulated driving experience with stable driving habits and are charged the least, while the two ends of the age distribution carry visible surcharges. We choose the kinks revealed in the figure - age 30 and 70 - as the age thresholds to identify young versus senior customers. The ages are divided into three groups: young (14-30), middle-age (31-69), and senior (over 70).

The comprehensive factor does not show a U-shape but instead decreases with age. Comprehensive coverage insures losses that occur off the road, such as vandalism, theft, weather, and animal damage, so the insured risk attaches to the vehicle and its surroundings rather than to the customer's driving. These losses depend on where the car is parked and how much it is exposed, and younger customers tend to live in denser areas, rely on street parking, and leave their vehicles more exposed, while older customers are more likely to garage their cars in lower-risk neighborhoods. The decline in the comprehensive factor with age therefore reflects a decline in exposure to non-driving losses.

Male versus female factors. We plot the factors charged on male and female customers as separate lines in each coverage panel of Figure 2. Among the high-risk groups, namely the youngest and the senior customers, males are charged higher factors than females for both liability coverages and the collision coverage. The difference between genders is negligible for middle-aged customers under these coverages. Males are charged relatively higher factors than females at all ages under the comprehensive coverage. This is also consistent with

common sense that males are viewed as more dangerous drivers than females, more likely to cause bodily injury to the other party and property damage to both their own and the other party's vehicles in accidents. Young males in particular are associated with speeding and other risk-taking behaviors, while in middle age accumulated experience narrows the behavioral gap between genders and the two lines nearly coincide. The persistent male surcharge under the comprehensive coverage, which insures losses unrelated to driving, points instead to a difference in exposure, as male customers on average drive more miles and leave their vehicles in riskier settings.

However, for the voluntary medical expense coverage for operators, we observe female factors higher than male factors before the age of 75. Unlike the liability and collision coverages, the medical expense coverage pays for the insured's own treatment, so its factor prices the severity of injury conditional on an accident rather than the likelihood of causing one. Females are viewed as more vulnerable to injury and more likely to incur medical expenses in accidents of a given severity, which is consistent with the higher factors quoted through most of the age range. However, the difference reverses after the age of 75, beyond which males are viewed as more vulnerable, consistent with frailty and slower recovery from injury weighing more heavily on senior males.

4.2.2. Level Change Among Customers of Different Ages

Average treatment effects among each age group. We first run difference-in-differences regressions separately for three age groups that are identified in the Figure 2. The regression specification is:

$$DemoFactor_{jastp} = \beta Treated_{jsp} \times Post_{tp} + \gamma X_{jst} + \alpha_{jasp} + \alpha_{tp} + \epsilon_{jaspt} \tag{2}$$

where $DemoFactor_{jastp}$ is the factor loading that insurer j charges at the age cell a in state s at event time t within pair p. Event time indexes the order of filed revisions around the pair's event, so t takes value -1 or 1, and we compare the last version in force before the event with the first revision after it. $Treated_{jsp}$ turns on for the treated member of each pair and $Post_{tp}$ turns on for both members after the pair's event. X_{jst} contains lagged log

premiums written and the lagged combined ratio. α_{jasp} is the insurer $\times$ age $\times$ state $\times$ pair fixed effect which compares the same insurer's factor at the same age in the same state over event time. Treatment is assigned at the insurer-state level and applies to every age cell on the treated insurer's menu. α_{tp} is the event time $\times$ pair fixed effect controlling for unobserved time effects on the two members of a pair. Standard errors are clustered at the insurer-state level to account for the correlation of factor cells within the same insurer's menu[18].

The regression results are in Panels A to C of Table 2. We find a significant increase of 0.1040 in the mandatory property damage liability coverage ("PD"), equivalent to 5.42% of the young group factor mean. For the optional collision coverage ("COLL"), which covers damage to the customer's own vehicle, the factor increases by 0.0541, equivalent to 2.91% of the group factor mean. The evidence is consistent with the hypothesis that auto insurers raise the pre-enrollment charges on the young group to induce participation.

We do not find comparable increases in the other age groups. There is a drop in the collision factor among the middle-aged group. For ages over 70, property damage factors decrease by 0.026 on average and collision factors by 0.032, equivalent to 1.83% and 2.50% of the group factor means. We interpret the decreases in the other age cells as a menu-balancing strategy, where insurers cut charges on the senior group so that no single revision raises the overall rate level sharply.

We also find heterogeneous effects across coverages. First, we do not find a statistically significant effect in the bodily injury factor among the young group, although BI is the mandatory liability coverage in all sample states and covers the injury cost that customers cause to other parties. Injury severity is a long-tailed outcome driven by litigation and medical development that takes years to resolve. The behavioral signal that telematics prices is therefore heavily diluted for BI. In contrast, conditional on a crash, vehicle damage is bounded, quickly assessed, and settles within weeks. We also observe a stronger effect in the compulsory PD factor than in the optional collision factor among the young driver group. Collision coverage is usually expensive and young drivers are more likely to skip it, so the COLL repricing reaches a smaller share of the young group and the tilt is smaller.

[18]We assume insurers' underwriting models are independent of each other. Clustering at the state level would misstate estimator precision given the small number of states in our sample

4.2.3. Within-Menu Targeting towards Young Group

The previous section shows that the factor levels charged to young and senior customers rise and fall respectively. The comparison was made between customers of the same age who are insured in different states. Although the two groups' factors move in opposite directions, the analysis does not formally test whether the young group is specifically targeted relative to customers of other ages within the same insurer-state. We run one more layer of analysis focusing on within-menu repricing, which shows whether the affected insurers steer their charges towards the young group, compared with any changes in the menus of their matched counterparts.

For this analysis, we divide the customers into only a young group (age ≤ 30) and an older group (age > 30). The specific regression is a triple-difference (DDD) design:

$$DemoFactor_{ajstp} = \beta Treat_{jsp} \times Post_{tp} \times Young_a + \alpha_{ajsp} + \alpha_{jstp} + \alpha_{a(\in k)tp} + \epsilon_{ajstp} \quad (3)$$

where $DemoFactor_{ajstp}$ is the demographic factor loading that auto insurer j charges in state s at event time t for the cell of age a. $Young_a$ equals one if the age cell is at or below 30. We include multiple fixed effects to control for unobserved characteristics at different levels. The insurer-age-state-pair fixed effects absorb time-invariant insurer characteristics that are specific to a state and an age cell, such as pricing priorities and pricing strategies. The insurer-state-event time fixed effects absorb menu-wide changes that move all ages together within an insurer-state unit at each event time. We also include the age group by event time fixed effects to absorb changes common to all cells within the young or the older category at each revision. All fixed effects are interacted with the pair identifier, so the comparison of charging schemes stays within each matched pair.

The results are reported in Panel D of Table 2. The gap between the young and older groups widens by 0.126 for the property damage factor and by 0.080 for the collision factor, equivalent to 6.57% and 4.32% of the young group factor means. The widening is significant among the insurers operating in the states where the mobile-sensing technology became available first, compared with the practice of their matched peers in the other states. This confirms auto insurers' interest in collecting driving data from the young customers, through

raising the pre-enrollment charges on this age group relative to all other ages. The widening gap does not reflect a group-wise adjustment of the risk models, as any adjustment shared with the matched counterpart is absorbed through the counterpart's menu.

4.2.4. Effects among Young Customers by Gender

To compare the changes across genders, we run the specification in Equation 2 for males and females separately. The specification is unchanged, but we keep the male and female factors separate at each age instead of averaging them. The results are reported in Table 3. Among the young customers, the factors charged to males show a larger increase on average than those charged to females. The property damage factors increase by 0.123 among males and 0.084 among females, equivalent to 6.16% and 4.60% of the respective group factor means. The collision factor also increases more for young males than for young females, at 0.070 against 0.036, both statistically significant. This evidence shows that among the young customers, males are viewed as harder to rate than females, and auto insurers raise the pre-enrollment charges on them more to motivate enrollment into the data program.

Among the middle-aged customers the factors barely move, and a small decrease in the female collision factor is the only significant estimate. The senior decreases also mirror the young increases within each gender's menu. The male property damage factor, which rises the most among the young, also receives the deeper senior offset, at 0.032 against 0.021 for females, so each gender's age curve rotates around its own middle. The collision cuts are nearly identical across genders, at 0.032 and 0.033.

4.3. Screening alongside Location

Proxy for Hard-to-Rate Locations. We use two ZIP Code level measures to capture how dense and urban a location is. First, we take population density per square kilometer from the American Community Survey (ACS) five-year files. Each filing is matched to the ACS five-year vintage ending in its filing year. For each ZIP Code we average this density over the sample years 2016-2023, and we set the dummy $HighPopDensity_z$ equal to one when the ZIP Code's density is above the median within its state. The second measure, $Metro_z$, is a dummy equal to one when the ZIP Code falls in a Core-Based Statistical Area

(CBSA) classified as metropolitan.

4.3.1. Change in Metro Areas

First, we use a difference-in-differences (DiD) design to study the change in factor levels in treated complex and non-complex areas, relative to their matched samples in neighboring states that have not yet received the treatment. Similar to our specification for the demographic factor analysis, the fixed effect model is

$$ZIPCodeFactor_{jz(s)tp} = \beta Treated_{jz(s)p} \times Post_{tp} + \gamma X_{jst} + \alpha_{jz(s)p} + \alpha_{tp} + \epsilon_{jz(s)tp} \qquad (4)$$

where $ZIPCodeFactor_{jz(s)tp}$ is the factor loading that insurer j charges at the ZIP Code z (which is in state s) at event time t within pair p, and X_{jst} contains the same lagged log premiums written and lagged combined ratio controls as in the demographic analysis. Event time indexes the order of filed revisions around the pair's event, so t takes value -1 or 1, and we compare the last version in force before the event with the first revision after it. $Treated_{jz(s)p}$ turns on for the treated member of each pair and $Post_{tp}$ turns on for both members after the pair's event. $\alpha_{jz(s)p}$ is the insurer $\times$ ZIP Code $\times$ pair fixed effect which compares the same insurer's factor at the same location over event time. Treatment is assigned at the insurer-state level and applies to every location cell on the treated insurer's menu. α_{tp} is the event time $\times$ pair fixed effect controlling for unobserved time effects on the two members of a pair. Again, standard errors are clustered at the insurer-state level to account for the correlation of factor cells within the same insurer's menu.

We run four sets of such regressions, covering two complex area definitions and two sub-samples. A specific example of the analysis is to compare how auto insurers price location factors in the Atlanta area of Georgia with how their peers price those factors in the Birmingham area of Alabama. The specification controls for each insurer's unobserved invariant characteristics at each location, such as its business emphasis and response to local market competition. The common shocks hitting both members of a pair when they update factors in Atlanta and Birmingham are absorbed by the pair $\times$ event time fixed effects.

The results are reported in Panels A and B of Table 4. In complex areas, both the

property damage and the collision factors increase significantly under each measure. The property damage factor increases by 0.0226 in high population density areas and by 0.0231 in metropolitan areas, about 2.2% and 2.3% of the group factor means, and the collision factor increases by 0.0130 and 0.0154, about 1.3% and 1.5% of the means. At the same time, we also find that the factors also rise in the less complex ZIP Codes, by 0.0130 for property damage under both measures and by 0.0121 and 0.0103 for collision, so part of the increase is shared across the whole menu. The magnitudes of the increase at the more complex areas are larger than those at the less complex areas. The bodily injury factor does not change significantly in either area type.

4.3.2. Widening Gap between More Complex and Less Complex Areas

To formally investigate whether auto insurers raise the charge in more complex areas relative to other areas to incentivize customer enrollment, we use a triple difference-in-differences (DDD) method with the specification:

$$\begin{aligned} ZIPCodeFactor_{jz(s)tp} = \beta\, Treat_{jz(s)p} \times PostMobile_{tp} \times HighPopDensity_z/Metro_z \\ + FE_{jz(s)p} + FE_{jtp} + FE_{z(\in d)tp} + \epsilon_{jz(s)tp} \end{aligned} \tag{5}$$

The specification compares the change in the pricing difference between high- and low-density territories within the treated insurer-state unit with the corresponding change within its matched control unit. As territorial factors are observed at the ZIP code level, the estimate reflects the average differential change across all ZIP codes assigned to each density category, rather than a comparison of only these illustrative cities. Insurer-state-ZIP fixed effects absorb time-invariant differences across individual territories. Insurer-state-by-event-time fixed effects absorb menu-wide changes affecting all territories within an insurer-state unit at a given event time. Density-by-event-time fixed effects absorb changes common to high- or low-density territories across the matched pair. The remaining variation identifies whether the treated unit experiences a differential post-event change in its high-versus-low density pricing gradient relative to the matched control unit.

For example, the specification compares the change in PRGS's pricing gradient between Birmingham-area ZIP codes and Eutaw-area ZIP codes in Alabama (one of the early-treated

states), with its sibiling company's change in pricing gradient between Atlanta-area ZIP codes and Helen-area ZIP codes in Georgia (the comparable control states). We are essentially comparing insurers' within-filing changes, to make sure that the common change at the filing level is absorbed.

The result is reported in Panel C of Table 4. Under the high population density classification, the property damage factor in high-density areas increases by 0.0129 more than that in low-density areas after the early treatment wave, equivalent to 1.3% of the complex-area factor mean. Under the metropolitan area classification, the property damage factor increases by 0.0096 more, equivalent to 1.0% of the factor mean[19]. The bodily injury factor gap also widens marginally under the density classification, by 0.0070, while the collision factor gap does not widen significantly under either classification.

4.4. Heterogeneity by Participation Incentive Amount

Auto insurers differ widely in the size of the incentive discount they attach to enrollment, ranging from no rating discount at all to flat reductions of 10 to 15 percent. Under our strategic incentivization hypothesis, the pre-enrollment charge and the incentive discount work as one scheme. The raised charge makes staying unmonitored the expensive option, and the promised discount is the way out, so the strength of the push depends on how far the insurer moves the two levers together. An insurer that promises a high participation discount is running this scheme at full strength and should raise its pre-enrollment charges more, while an insurer that promises a small discount runs a weaker version of the same scheme and needs only a modest charge behind it. The size of the participation discount therefore predicts not whether the repricing appears but how large it should be. We sort the treated insurers by the discount in force at the filing where we measure the charge and compare the pre-enrollment responses of the high-discount and low-discount insurers.

[19]The level increases in both area types do not contradict the widening gap. The DDD nets out the menu-wide component shared by all ZIP Codes and shows that the property damage increase is larger in the more complex areas, while the collision increase is similar across area types, so its gap does not widen significantly.

5. Robustness Checks

5.1. Placebo Test

The traditional difference-in-differences method tests the parallel trend by examining the dynamic time effects and showing that no trend exists up to N time units before the event time, where N is usually at least two. However, given the uniqueness of our data and the fact that insurers update their rates only every one to two years, which is infrequent compared to financial reporting data at the quarterly or annual frequency, such a test would compare filings across over four years and lead to inaccurate conclusions.

Instead, we conduct a placebo analysis for our major specifications, Equation 2 and Equation 4. We suppose the shock happened between event time $t-2$ and $t-1$. If what we find is truly attributable to the availability of mobile technology, we should not find the effect at event time $t-1$ compared to $t-2$. However, because each pair must have two pre-event filings within our data coverage, the placebo tests recover around half of the sample size of the main analysis.

Panel A in Table A.3 shows that there is no increase among the young customers around the placebo timing but instead a significant decrease in the property damage and collision factors. The treated insurers' young factors were, if anything, drifting down relative to their matched peers before the shock, so the increase we find at the event cannot be the continuation of a pre-existing trend.

For the territory analysis, we find no evident change in the complex areas around the placebo timing. Panel B and C in Table A.3 shows that the estimates there are close to zero and insignificant under both complexity measures, so the parallel trend holds exactly where our main effects are identified. The decreases in location factors are confined to the less complex areas, where the bodily injury and collision factors fall modestly.

5.2. No Change on the Non-Adopter Menu

In the main analysis, we only study the menus of insurers that had already adopted telematics and of adopters that introduced the program right around the mobile shock. There is a group of insurers that had not adopted telematics during our analysis window.

For example, GEICO ("GECC"), a subsidiary of Berkshire Hathaway, is an insurance giant that rolls out the technology nationwide late, and several states receive its telematics program only after the year 2021.

There might be other regulatory changes at the same time that drive insurers' adjustments to pricing factors apart from the technology development, especially if the confounding laws also relate to demographic and territory factors. If such a confounding law exists, it would affect non-adopters as well. We run the same set of regressions among non-adopters and find no significant change in factor loadings in any direction around the mobile law.

Following the method employed in the main section, we match the non-adopters in the earlier-treated states with their peers in the not-yet-approved states. We limit the event window for the non-adopters to the last revision before the mobile shock and the first revision after the shock but before the company introduces its telematics program, so every post-shock filing we examine comes from an insurer that has not yet adopted the technology. The matched peers in the neighboring states are picked with the same activity requirement as in the main analysis, at least one filing before the shock and at least one revision inside the clean window before their own states approve the technology. Table A.4 shows that the young customers and the customers living in more complex areas do not receive a pre-UBI-enrollment charge on the non-adopter menus. If anything, there is a drop in the factors charged on the young customers, which is opposite in direction to the effect our main hypothesis predicts and our main analysis finds.

5.3. No Effect on Non-Driving-Behavior Related Coverage Items

In this section, we look at two other important coverage factors, the comprehensive ("COMP") factor and the medical expense ("MED") factor. As we discussed before, the comprehensive factor is less related to driving behavior and more to off-road events such as theft, vandalism, weather, and animal damage, so the insured risk attaches to the vehicle and its surroundings rather than to the customer's driving. The medical expense coverage pays the insured's own treatment regardless of fault. The coverage is not fully detached from driving behavior, but the link is nevertheless weaker than that of the liability and collision coverages. The factor prices the severity of injury conditional on an accident, which reflects

physical vulnerability and treatment costs rather than driving conduct, consistent with the gender pattern documented in Figure 2. Therefore, driving data carry limited value for pricing these coverages.

In Table A.5, we show that insurers place no pre-enrollment charge increase on these coverage factors, consistent with the screening motive operating only through the coverages priced on driving behavior. If anything, there is a statistically significant drop in the comprehensive factor charged on the young customers, which runs in the opposite direction of a pre-enrollment charge. We do not find that insurers adjust the medical expense factor in either direction, and there is no significant evidence that either factor changes in the more complex areas.

6. Conclusion

This paper studies how auto insurers use their pricing menus to acquire customers' driving behavior data. Mobile-sensing telematics reached the industry through a staggered sequence of state approvals, and enrollment in the data collection programs stayed optional for customers, sweetened by a participation discount. Reading the pricing menus disclosed in product filings, we compare telematics-adopting insurers in the earlier-approving states with their sibling companies and close peers in the later-approving states around the shock. The treated insurers raise the property damage and collision factors charged to young customers, more for males than for females, and raise their location factors by more in the denser, metropolitan areas. The within-menu comparisons confirm that the increases concentrate on the hardest-to-rate cells of the menu.

The repricing follows the enrollment motive rather than routine risk updating. It scales with the reward behind it, as insurers that attach larger participation discounts to enrollment raise their charges by more. It is absent wherever the motive cannot operate, on the menus of insurers that had not adopted telematics, in the filings before the shock arrived, and in the coverages that driving data cannot help price. Together the evidence supports the strategic incentivization hypothesis, that insurers raise the price of staying unmonitored so that the enrollment discount becomes the way out, and that they aim the raise at the customers

whose data carries the highest information value.

Our findings change how the transition to data-based pricing should be read. The transition is commonly told as a voluntary exchange, in which customers who accept monitoring trade their data for a discount and customers who decline keep the contract they had. The insurer, however, sets the price of that outside option and moves it, so the cost of the data transition falls on the targeted groups themselves, whether or not they enroll. The mechanism is not specific to auto insurance. Life and health insurers price wearable data, homeowners insurers reward smart-home sensors, and lenders value access to transaction records, and in each of these markets the firm that wants the data also prices the option of not sharing it. Wherever monitored contracts spread, the price of the unmonitored option is the margin to watch.

The evidence also carries a lesson for the oversight of pricing in data-rich markets. The revisions we study all cleared their regulators' filing processes on their own actuarial support, and the strategic component surfaces only in relative changes, across cells within a menu, across insurers, and across states. Assembling the filed disclosures at scale is what makes the pattern visible, which suggests that the value of disclosure regimes lies increasingly in the cross-market comparisons they permit rather than in the review of any single filing. As data collection becomes a core input to pricing across consumer markets, the question of who pays for firms' information will only grow in importance.

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Fig. 1. **Telematics Adoption among Sample Firm-States, 2016–2023**

This figure plots the share of firm-states in our sample that have adopted telematics in each calendar year from 2016 to 2023. The solid blue line with circle markers plots the share that have adopted any telematics program, and the solid orange line with square markers plots the share that have adopted mobile-app telematics. Adoption is identified from the subsidiaries' rate filings.

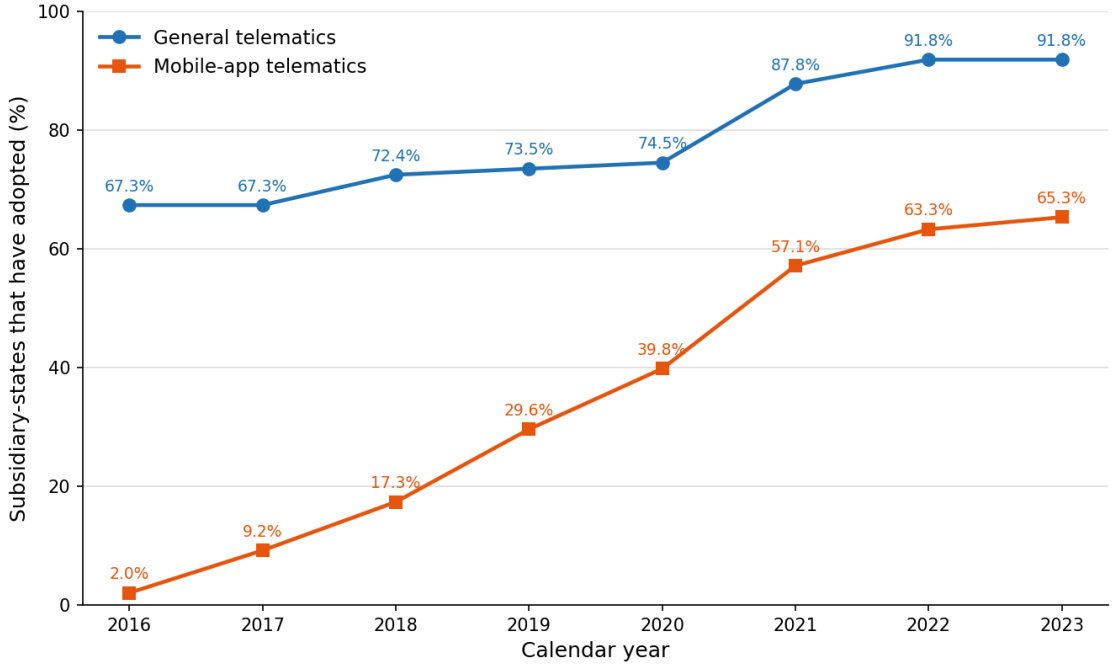


Fig. 2. **Demographic Rating Factors by Age and Gender**

This figure plots the average demographic rating factor by driver age for five coverages, Bodily Injury (BI), Property Damage (PD), Collision (COLL), Medical Expense (MED), and Comprehensive (COMP), pooled across all sample firms, states, and filings. In each panel, the dashed line plots the mean factor across all drivers, the blue line plots the mean factor for male cells, and the orange line plots the mean factor for female cells. The horizontal axis is driver age from 16 to 85, and the vertical axis is the mean factor, with the dotted horizontal line marking a factor of one.

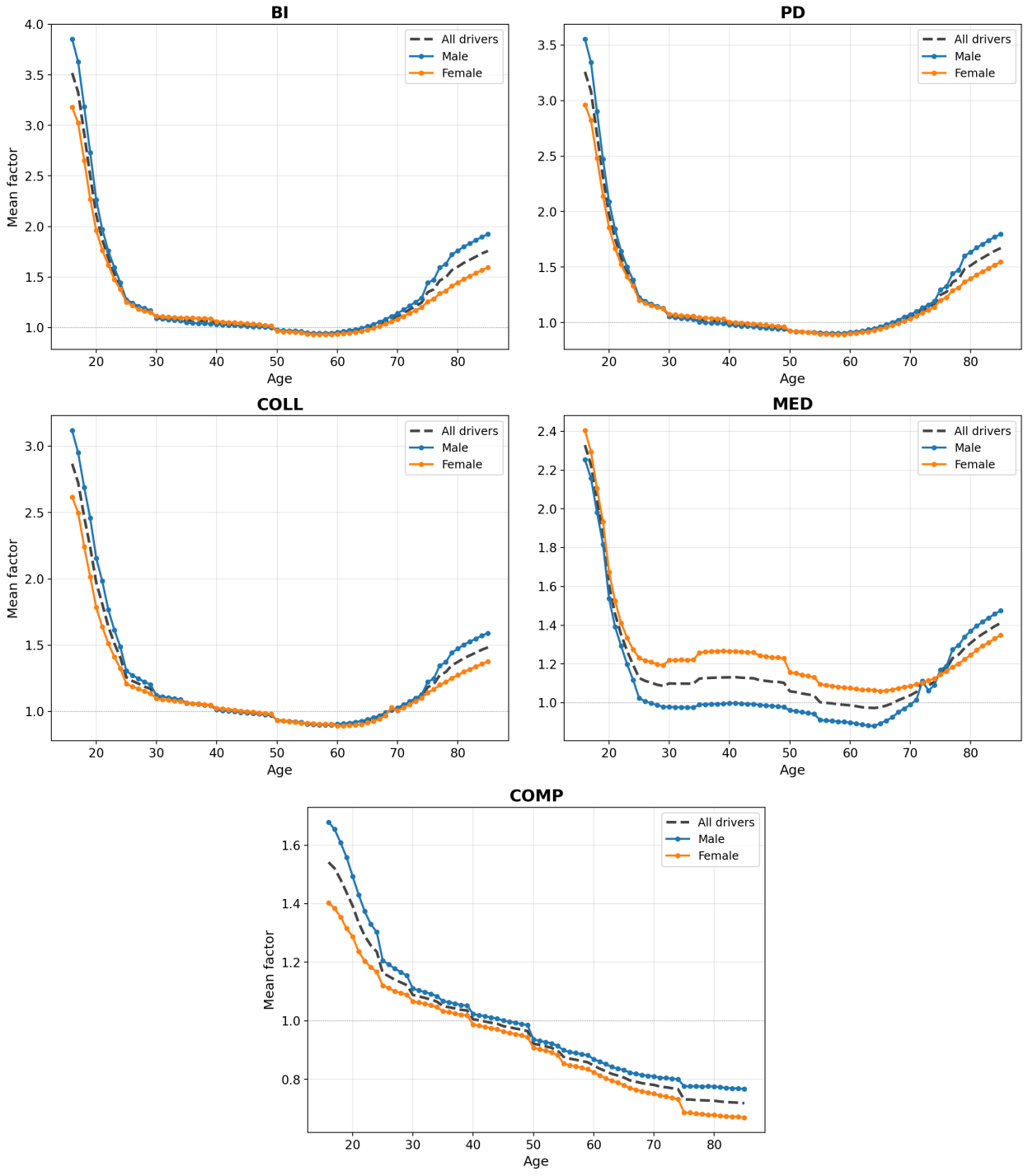


Table 1
Summary Statistics

This table reports summary statistics for the stacked matched samples. Panel A describes the sample structure, the number of matched insurer-state pairs, the number of insurance groups on the treated and the control sides, and the filing period covered, separately for the demographic and the territory analyses. Panels B and C report the distributions of the demographic and the territory factor loadings for the five major coverages, Bodily Injury (BI), Property Damage (PD), Collision (COLL), Comprehensive (COMP), and Medical Payments (MED). The observation unit is an insurer-state-age cell in Panel B and an insurer-state-ZIP Code cell in Panel C, at an event time within the analysis window. Panel D compares the treated and the control members of the matched pairs on premiums written and the combined ratio, with standard deviations in parentheses below the group means and t-statistics in parentheses below the differences. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Panel A: Sample Structure						
	Demographic			Territory		
Matched pairs	28			17		
Treated insurance groups	7			7		
Control insurance groups	4			5		
Sample period	Feb 2016–Sep 2021			Feb 2016–Dec 2020		
Panel B: Demographic Rating Factors						
	N	Mean	SD	Min	Median	Max
Bodily Injury (BI)	7,820	1.363	0.685	0.694	1.188	4.551
Property Damage (PD)	7,820	1.292	0.646	0.627	1.110	4.389
Collision (COLL)	7,820	1.242	0.519	0.739	1.093	3.375
Comprehensive (COMP)	7,820	0.906	0.243	0.518	0.865	1.764
Medical Payments (MED)	7,680	1.211	0.411	0.640	1.181	2.895
Panel C: Territory Rating Factors						
	N	Mean	SD	Min	Median	Max
Bodily Injury (BI)	48,734	0.955	0.179	0.635	0.939	1.508
Property Damage (PD)	48,592	0.912	0.214	0.570	0.866	1.626
Collision (COLL)	48,710	0.987	0.122	0.692	0.975	1.393
Comprehensive (COMP)	48,676	1.203	0.443	0.519	1.106	2.712
Medical Payments (MED)	43,352	1.033	0.184	0.702	1.004	1.720
Panel D: Matched-Pair Balance						
	Demographic			Territory		
	Treated	Control	Diff.	Treated	Control	Diff.
Premiums written ($M)	217.0	342.7	-125.6***	349.4	476.0	-126.7*
	(343.1)	(344.8)	(-3.3906)	(383.5)	(354.4)	(-1.9985)
Combined ratio	0.715	0.728	-0.013	0.770	0.800	-0.030
	(0.140)	(0.140)	(-0.4785)	(0.084)	(0.105)	(-1.6706)

Table 2
The Effect of Mobile Telematics Availability on Demographic Rating Factors

This table reports the effect of the mobile telematics shock on demographic rating factors. Panels A to C show the stacked DiD estimates of Equation 2 within each age group, and Panel D shows the DDD estimate of the change in the gap between the young (age ≤ 30) and the older cells. The sample consists of telematics-adopting insurers in the earlier-treated states and their matched peers in the later-treated states, and the dependent variables are the factor loadings for Bodily Injury (BI), Property Damage (PD), and Collision (COLL). Event time takes the value -1 or $+1$, comparing the last filed version before the pair's event with the first revision after it. Controls, the insurer's lagged log premiums written and lagged combined ratio, are included in Panels A to C and are absorbed by the firm-by-event-time fixed effects in Panel D. Coefficient / Group Mean scales each estimate by the group's mean factor, the young group's mean in Panel D. The observation unit is an insurer-state-age cell at an event time. t-statistics are in parentheses, and standard errors are clustered at the insurer-state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	BI	PD	COLL
Panel A: DiD, Young (Age 15-30)			
Treat × Post	0.0448	0.1040***	0.0541***
	(1.6642)	(3.4874)	(3.4566)
Obs.	1,664	1,664	1,664
Adj. R2 (within)	0.0344	0.0802	0.1069
Pair × Firm FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Coefficient / Group Mean	0.0220	0.0542	0.0291
Panel B: DiD, Middle Age (Age 31-69)			
Treat × Post	0.0122	-0.0124	-0.0220**
	(1.2370)	(-1.2763)	(-2.4297)
Obs.	4,368	4,368	4,368
Adj. R2 (within)	0.0214	0.0318	0.1364
Pair × Firm FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Coefficient / Group Mean	0.0117	-0.0125	-0.0223
Panel C: DiD, Senior (Age 70-85)			
Treat × Post	-0.0043	-0.0263*	-0.0324***
	(-0.3108)	(-1.8178)	(-3.2198)
Obs.	1,788	1,788	1,788
Adj. R2 (within)	0.0036	0.0649	0.1004
Pair × Firm FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Coefficient / Group Mean	-0.0028	-0.0183	-0.0250
Panel D: DDD, Young (Age≤30) vs. Older			
Treat × Post × Age≤30	0.0326	0.1260***	0.0803***
	(1.0613)	(3.5094)	(4.1200)
Obs.	7,820	7,820	7,820
Adj. R2 (within)	0.0052	0.0645	0.1046
Pair × Firm × Age FE	Yes	Yes	Yes
Pair × Firm × Event-Time FE	Yes	Yes	Yes
Pair × Age Group × Event-Time FE	Yes	Yes	Yes
Coefficient / Group Mean	0.0160	0.0657	0.0432

Table 3
The Effect of Mobile Telematics Availability on Demographic Rating Factors by Age Group and Gender

This table shows the stacked difference-in-differences estimates of the change in demographic rating factors around the mobile telematics shock, estimated separately for male and female cells within each age group. The sample and specification follow Panels A to C of Table 2, including the controls, the insurer's lagged log premiums written and lagged combined ratio. The dependent variables are the demographic factor loadings for Bodily Injury (BI), Property Damage (PD), and Collision (COLL). Columns (1) to (3) focus on male cells and columns (4) to (6) focus on female cells. Panel A focuses on the young group (age 15–30), Panel B on the middle-age group (age 31–69), and Panel C on the senior group (age 70–85). Treat × Post is the interaction between the treated-member indicator and the post-event indicator. The row Coefficient / Group Mean scales the estimate by the mean factor of the corresponding gender-age group. t-statistics are reported in parentheses, and standard errors are clustered at the insurer-state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	Male			Female		
	BI	PD	COLL	BI	PD	COLL
Panel A: Young (Age 15-30)						
Treat × Post	0.0456	0.1226***	0.0695**	0.0440*	0.0837***	0.0361***
	(1.6132)	(3.0522)	(2.6773)	(1.6889)	(3.7518)	(2.9731)
Obs.	1,664	1,664	1,664	1,664	1,664	1,664
Adj. R2 (within)	0.0423	0.0898	0.1241	0.0284	0.0639	0.0603
Pair × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	0.0214	0.0616	0.0348	0.0230	0.0460	0.0210
Panel B: Middle Age (Age 31-69)						
Treat × Post	0.0140	-0.0041	-0.0123	0.0105	-0.0208	-0.0319**
	(1.3594)	(-0.4777)	(-1.6565)	(1.0806)	(-1.5651)	(-2.4157)
Obs.	4,368	4,368	4,368	4,368	4,368	4,368
Adj. R2 (within)	0.0239	0.0015	0.0395	0.0192	0.0755	0.1945
Pair × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	0.0134	-0.0041	-0.0124	0.0101	-0.0208	-0.0325
Panel C: Senior (Age 70-85)						
Treat × Post	-0.0056	-0.0317*	-0.0316**	-0.0029	-0.0212*	-0.0331***
	(-0.3149)	(-1.6884)	(-2.0578)	(-0.2401)	(-1.7125)	(-3.1559)
Obs.	1,788	1,788	1,788	1,788	1,788	1,788
Adj. R2 (within)	-0.0001	0.0491	0.0419	0.0327	0.0754	0.1786
Pair × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	-0.0033	-0.0204	-0.0227	-0.0021	-0.0161	-0.0276

Table 4
The Effect of Mobile Telematics Availability on Location Rating Factors

This table reports the effect of the mobile telematics shock on location rating factors. Panels A and B show the stacked DiD estimates of Equation 4 separately for the more and the less complex ZIP Codes, defining a more complex area by population density above the within-state median in Panel A and by metropolitan Core-Based Statistical Area status in Panel B. Panel C shows the DDD estimates of the change in the gap between the two area types under each definition. The sample consists of telematics-adopting insurers in the earlier-treated states and their matched peers in the later-treated states, and the dependent variables are the ZIP Code factor loadings for Bodily Injury (BI), Property Damage (PD), and Collision (COLL). Event time takes the value -1 or $+1$, comparing the last filed version before the pair's event with the first revision after it. Controls, the insurer's lagged log premiums written and lagged combined ratio, are included in Panels A and B and are absorbed by the unit-by-event-time fixed effects in Panel C. The row Coefficient / Group Mean scales each estimate by the mean factor of the corresponding estimation sample, the more complex areas' mean in Panel C. The observation unit is an insurer-state-ZIP Code cell at an event time. t-statistics are in parentheses, and standard errors are clustered at the insurer-state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	More complex ZIPs			Less complex ZIPs		
	BI	PD	COLL	BI	PD	COLL
Panel A: DiD, More Complex Area = High-density Area						
Post × Treat	0.0097	0.0226**	0.0130***	0.0043	0.0130**	0.0121**
	(1.3065)	(2.7194)	(3.0113)	(0.5349)	(2.7146)	(2.5962)
Obs.	24,104	24,054	24,088	24,630	24,538	24,622
Adj. R2 (within)	0.0423	0.0931	0.0782	0.0400	0.0352	0.1133
Pair × Firm × ZIP FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	0.0096	0.0222	0.0130	0.0048	0.0161	0.0125
Panel B: DiD, More Complex Area = Metropolitan Area						
Post × Treat	0.0089	0.0231**	0.0154***	0.0074	0.0130***	0.0103**
	(1.0864)	(2.6778)	(3.5832)	(1.0139)	(2.9383)	(2.3864)
Obs.	27,932	27,866	27,908	21,068	20,992	21,068
Adj. R2 (within)	0.0329	0.0736	0.0799	0.0475	0.0569	0.1075
Pair × Firm × ZIP FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	0.0088	0.0230	0.0153	0.0083	0.0166	0.0107
Panel C: DDD, More vs. Less Complex Areas						
	High density			Metropolitan		
	BI	PD	COLL	BI	PD	COLL
Treat × Post × Urban	0.0070*	0.0129*	0.0040	0.0023	0.0096*	0.0048
	(1.7774)	(2.0046)	(0.6710)	(0.9053)	(1.9508)	(1.1446)
Obs.	48,734	48,592	48,710	49,000	48,858	48,976
Adj. R2 (within)	0.0008	0.0053	0.0007	0.0000	0.0028	0.0010
Pair × Firm × ZIP FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Unit × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Density × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	0.0069	0.0126	0.0040	0.0023	0.0096	0.0047

Table 5
Heterogeneity by Participation Discount Size

This table compares the repricing of the high-discount and the low-discount insurers around the mobile telematics shock. Panel A reports the stacked DiD estimates for the young customers' demographic factors, and Panels B and C report the estimates for the location factors in the more complex ZIP Codes, defined by within-state population density in Panel B and by metropolitan status in Panel C. Insurers are categorized by the participation discount in force at the post-shock filing, as reported in Table A.2. The dependent variables are the factor loadings for Bodily Injury (BI), Property Damage (PD), and Collision (COLL). Controls are the insurer's lagged log premiums written and lagged combined ratio. The row Coefficient / Group Mean scales each estimate by the mean factor of the corresponding subsample. t-statistics are in parentheses, and standard errors are clustered at the insurer-state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	High discount			Low discount		
	BI	PD	COLL	BI	PD	COLL
Panel A: Young Customers (Age 15-30)						
Treat × Post	-0.1112	0.4071***	0.1549***	0.0313	0.0219*	0.0237**
	(-1.7476)	(3.1893)	(4.1845)	(1.4152)	(2.0360)	(2.1696)
Obs.	480	480	480	1,184	1,184	1,184
Adj. R2 (within)	0.0930	0.1862	0.2909	0.0571	0.1390	0.0925
Pair × Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	-0.0593	0.2380	0.0896	0.0149	0.0109	0.0124
Panel B: More Complex Areas, High-density						
Treat × Post	0.0348***	0.0451***	0.0117**	0.0006	0.0013*	0.0003
	(3.4236)	(3.4823)	(2.9874)	(0.0935)	(2.1577)	(0.0451)
Obs.	11,972	11,922	11,956	10,734	10,734	10,734
Adj. R2 (within)	0.1743	0.2096	0.1800	0.0230	0.0000	0.0536
Pair × Firm × ZIP FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	0.0341	0.0434	0.0115	0.0006	0.0013	0.0003
Panel C: More Complex Areas, Metropolitan						
Treat × Post	0.0360***	0.0471***	0.0120***	0.0011	0.0024**	0.0030
	(3.2296)	(3.2383)	(3.5449)	(0.1536)	(2.8882)	(0.4563)
Obs.	13,714	13,648	13,690	12,566	12,566	12,566
Adj. R2 (within)	0.1508	0.1730	0.1367	0.0257	0.0006	0.0847
Pair × Firm × ZIP FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient / Group Mean	0.0352	0.0458	0.0117	0.0011	0.0025	0.0030

Appendix A. Appendix Figures and Tables

Fig. A.1. **Enrollment and Rating Process of a Telematics Program**

This figure shows the enrollment and rating process of Progressive's Snapshot program, presented from Progressive's 2022 Q4 Investor Relations presentation (The Progressive Corporation, 2023). The process has four steps. The customer receives a participation discount for signing up during the quote, registers the mobile app or plugs in the device within 45 days, has the collected driving data used to determine the rate at the next renewal, and continues to be monitored with the rate adjusted at each subsequent renewal based on the new data.

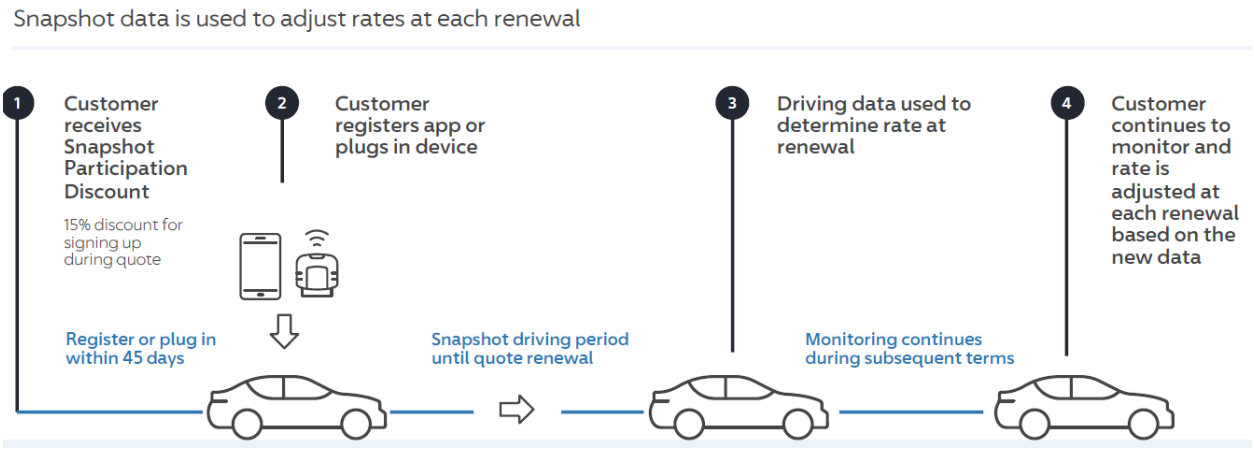


Table A.1
Mobile Telematics Approval Dates in the Sample States

This table reports the date on which the mobile telematics model from Cambridge Telematics Technology ("CMT") was approved in each sample state. Each row lists the state, the SERFF tracking number of the rate filing that introduces the technology, and the approval date. The filing introducing the technology in Alabama was not directly found in our search but was mentioned in a later product filing from CMT in this state.

State	SERFF Tracking No.	Pass Date
AL	–	11/01/2018
CT	FRCS-132344713	06/08/2020
GA	FRCS-132127243	11/02/2020
IA	FRCS-131500025	06/01/2018
IL	FRCS-131501667	06/01/2018
SC	FRCS-131602528	09/06/2018
VA	FRCS-132797546	05/05/2021
WI	FRCS-131563848	08/01/2018

Table A.2
Participation Discounts of Telematics Programs

This table reports the participation discount each insurer offers to customers who opt into telematics data collection, collected from the insurers' product filings in the sample states. The discount shown is the level effective at the post-shock event, or at the program introduction for insurers that adopted after the shock; later changes are shown in parentheses. Companies are categorized as high-discount (10 percent or more) or low-discount (5 percent or less). Insurers whose programs reward participation outside the rating plan (Allstate, Erie), apply a purely score-based schedule (Amica), or file a schedule varying with policy characteristics (Travelers) do not have a flat participation discount and are labeled accordingly. For GEICO, American Family, and states where Liberty Mutual does not restate the discount in the filed manual, the level is corroborated with the insurer's public program materials. Discounts are set at the parent-group level and are generally uniform across states, although the effective dates of discount updates differ across states.

Company (Abbreviation)	Program	Participation Discount	Categorization
Panel A: Flat participation discount			
GEICO (GECC)	DriveEasy	10%	High
Liberty Mutual (LBPM)	RightTrack	10%	High
Nationwide (NWPC)	SmartRide	10%	High
USAA (USAA)	SafePilot	10%	High
American Family (AMFC)	KnowYourDrive	10%	High
COUNTRY Financial (CFPC)	DriverIQ	10%	High
State Farm (SFMA)	Drive Safe & Save	5%	Low
Farmers (FARM)	Signal	5%	Low
Panel B: No flat participation discount			
Progressive (PRGS)	Snapshot	1–10% by class	High
MetLife (FAIG)	My Journey	8–10% by category	High
Travelers (TRVA)	IntelliDrive	schedule, up to 10%	Low
Amica (AMMA)	StreetSmart	score-based, 6–20%	Score-based
Allstate (ALSE)	Drivewise	rewards outside the rating plan	Rewards
Erie (ERAP)	YourTurn	rewards outside the rating plan	Rewards
Panel C: No telematics program in the sample states			
Alfa (ALFA)	–	–	n.a.
Auto-Owners (AOIC)	–	–	n.a.
Georgia Farm Bureau (GFBR)	–	–	n.a.
Grinnell Mutual (GRNX)	–	–	n.a.

Table A.3
Placebo Tests of the Main Specifications

This table shows the placebo estimates for the main demographic and territory specifications, assuming the shock happened between event times $t-2$ and $t-1$. The regressions compare each pair's two pre-event filings, so no true treatment occurs inside the placebo window and the sample recovers around half of the main analysis. The dependent variables are the factor loadings for Bodily Injury (BI), Property Damage (PD), and Collision (COLL). Panel A focuses on the demographic factors of the young group (age 15–30). Panels B and C focus on the location factors of the more complex ZIP Codes, defined by population density above the within-state median in Panel B and by metropolitan Core-Based Statistical Areas in Panel C. Treat × Post is the interaction between the treated-member indicator and the placebo post indicator. Fixed effects are included as reported in each panel. The row Coefficient / Group Mean scales the estimate by the group's mean factor. t-statistics are reported in parentheses, and standard errors are clustered at the insurer-state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	BI	PD	COLL
Panel A: Demographic Factors, Young Group (Age 15-30)			
Treat × Post	-0.0346	-0.1166**	-0.0494***
	(-1.5796)	(-2.5518)	(-3.4550)
Obs.	1,124	1,124	1,124
Adj. R2 (within)	0.0179	0.0920	0.0324
Pair × Firm FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Coefficient / Group Mean	-0.0190	-0.0662	-0.0274
Panel B: Territory Factors, More Complex ZIP Codes (High Density)			
Treat × Post	-0.0049	-0.0000	-0.0001
	(-1.1051)	(-0.0052)	(-0.0159)
Obs.	8,150	8,150	8,150
Adj. R2 (within)	0.0022	-0.0002	-0.0002
Pair × Firm × ZIP FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Coefficient / Group Mean	-0.0048	-0.0000	-0.0001
Panel C: Territory Factors, More Complex ZIP Codes (Metropolitan)			
Treat × Post	-0.0044	0.0001	-0.0009
	(-1.0533)	(0.0693)	(-0.2262)
Obs.	10,236	10,236	10,236
Adj. R2 (within)	0.0022	-0.0002	-0.0001
Pair × Firm × ZIP FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Coefficient / Group Mean	-0.0043	0.0001	-0.0009

Table A.4
The Effect of Mobile Telematics Availability on Non-Adopter Menus

This table shows the difference-in-differences estimates of the main demographic and territory specifications on the menus of insurers that had not adopted telematics. Non-adopters in the earlier-treated states are matched to their peers in the later-treated states following the method of the main analysis. The event window keeps each non-adopter's last revision before the mobile shock and its first revision after the shock but before the company introduces its own telematics program. The dependent variables are the factor loadings for Bodily Injury (BI), Property Damage (PD), and Collision (COLL). Panel A focuses on the demographic factors of the young group (age 15–30). Panels B and C focus on the location factors of the more complex ZIP Codes, defined by population density above the within-state median in Panel B and by metropolitan Core-Based Statistical Areas in Panel C. Treat × Post is the interaction between the treated-member indicator and the post-event indicator. Fixed effects are included as reported in each panel. The row Coefficient / Group Mean scales the estimate by the group's mean factor. t-statistics are reported in parentheses, and standard errors are clustered at the insurer-state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	BI	PD	COLL
Panel A: Demographic Factors, Young Group (Age 15-30)			
Treat × Post	-0.0245**	-0.0376**	-0.0583
	(-2.2074)	(-2.3844)	(-1.4473)
Obs.	510	540	600
Adj. R2 (within)	0.1107	0.1404	0.0568
Pair × Firm FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Coefficient / Group Mean	-0.0151	-0.0235	-0.0359
Panel B: Territory Factors, More Complex ZIP Codes (High Density)			
Treat × Post	0.0049	0.0092	0.0093
	(0.8393)	(1.2147)	(1.3738)
Obs.	14,357	14,357	14,357
Adj. R2 (within)	0.0034	0.0149	0.0049
Pair × Firm × ZIP FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Coefficient / Group Mean	0.0050	0.0094	0.0096
Panel C: Territory Factors, More Complex ZIP Codes (Metropolitan)			
Treat × Post	0.0060	0.0067	0.0103
	(1.0345)	(1.1961)	(1.6987)
Obs.	16,775	16,775	16,775
Adj. R2 (within)	0.0051	0.0081	0.0046
Pair × Firm × ZIP FE	Yes	Yes	Yes
Pair × Event-Time FE	Yes	Yes	Yes
Coefficient / Group Mean	0.0063	0.0069	0.0107

Table A.5
The Effect of Mobile Telematics Availability on Coverages Less Related to Driving Behavior

This table shows the difference-in-differences estimates of the main demographic and territory specifications for the two coverages less related to driving behavior. The dependent variables are the factor loadings for Comprehensive (COMP) and Medical Expense (MED). The sample consists of telematics-adopting insurers in the earlier-treated states and their matched peers in the later-treated states. Panel A focuses on the demographic factors of the young group (age 15–30). Panels B and C focus on the location factors of the more complex ZIP Codes, defined by population density above the within-state median in Panel B and by metropolitan Core-Based Statistical Areas in Panel C. Treat × Post is the interaction between the treated-member indicator and the post-event indicator. Fixed effects are included as reported in each panel. The row Coefficient / Group Mean scales the estimate by the group's mean factor. t-statistics are reported in parentheses, and standard errors are clustered at the insurer-state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	COMP	MED
Panel A: Demographic Factors, Young Group (Age 15-30)		
Treat × Post	-0.0528**	0.0050
	(-2.2222)	(0.2217)
Obs.	1,784	1,724
Adj. R2 (within)	0.0759	-0.0010
Pair × Firm FE	Yes	Yes
Pair × Event-Time FE	Yes	Yes
Coefficient / Group Mean	-0.0438	0.0032
Panel B: Territory Factors, More Complex ZIP Codes (High Density)		
Treat × Post	-0.0008	0.0078
	(-0.0845)	(0.9286)
Obs.	28,336	25,706
Adj. R2 (within)	-0.0001	0.0020
Pair × Firm × ZIP FE	Yes	Yes
Pair × Event-Time FE	Yes	Yes
Coefficient / Group Mean	-0.0008	0.0076
Panel C: Territory Factors, More Complex ZIP Codes (Metropolitan)		
Treat × Post	-0.0090	0.0010
	(-1.4626)	(0.1091)
Obs.	32,922	29,594
Adj. R2 (within)	0.0012	-0.0000
Pair × Firm × ZIP FE	Yes	Yes
Pair × Event-Time FE	Yes	Yes
Coefficient / Group Mean	-0.0084	0.0009

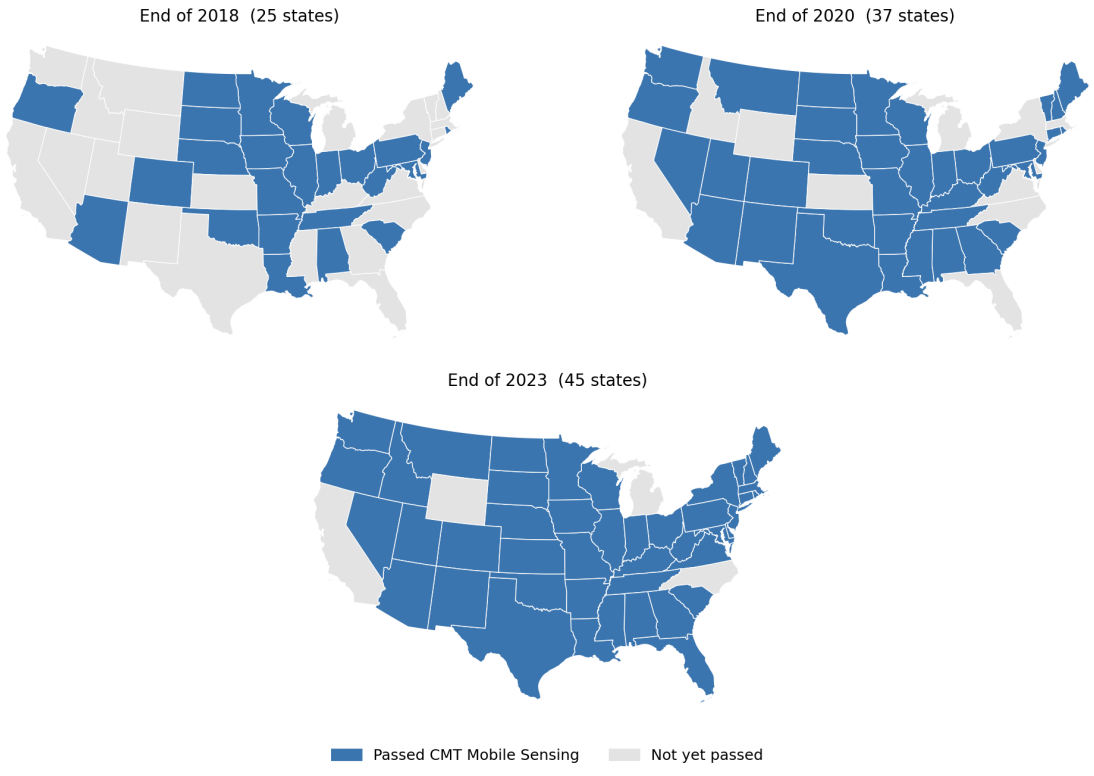
Appendix B. Data Appendix

B.1. Staggered Approval of the Mobile-Sensing Technology Across States

CMT's filings and approvals are staggered across states, and we collect them state by state from its product-filing records in SERFF. Alaska, Hawaii, Puerto Rico, and Guam are excluded from the sample. Figure B.1 shows the staggered approval of CMT's mobile-sensing technology across calendar years.

The first wave of approvals arrives in 2018, and coverage then spreads nearly nationwide over the following years. The 2018 wave concentrates in mid-sized, operationally simple markets with homogeneous books of business (OH, IN, IL, WI, MO, NE, and the Dakotas). Three states never approved the technology: California, where telematics-based rating beyond verified mileage is effectively prohibited under Proposition 103; North Carolina, whose rate-bureau system denied the filing; and Michigan, where CMT filed in early 2020 but the model was ultimately rejected. As far as we can track, CMT never filed in Wyoming.

Fig. B.1. **The Spread of the CMT Technology Across States, 2018–2023**



B.2. Heterogeneity in Regulatory Procedure Stringency

States differ in the procedures insurers must follow to update their pricing menus. The most common types are "file-and-use" and "use-and-file". Under the former, insurers must file new rates with the regulator before applying them, and the rates take effect without formal approval unless the regulator objects. Under the latter, insurers may apply new rates first and file within a specified window afterward, and they can keep using the rates as long as the regulator does not deny the new schedule ex post. The most stringent format, "prior approval", requires explicit regulatory approval before the new rates can be used.

Our sample states feature heterogeneity in regulatory stringency. Table B.1 ranks the states from the least to the most stringent. Despite this heterogeneity, we observe neither retroactive denials of filings in the use-and-file states nor frequent back-and-forth revisions of rate manuals in the file-and-use and prior-approval states.

Table B.1
Rate Filing Methods for Personal Auto in the Sample States

State	Filing Method for Personal Auto	Stringency
IL	Use and file within 10 days after use	Permissive
WI	File and use with a 30-day waiting period	Permissive
CT	File and use in a competitive market, 30-day waiting period otherwise	Permissive
VA	File and use in a competitive market	Permissive
IA	Prior approval with a 30-day deemer	Intermediate
GA	File and use with a 45-day waiting period, 60-day deemer above minimum limits	Intermediate
SC	Prior approval by default, file and use where the market is deemed competitive	Intermediate
AL	Prior approval for personal lines	Stringent

B.3. Statutory Entity Selection

The concentration of operating business across the statutory entities under a single insurance group is a strategic choice of the company. We observe three broad scenarios. In the dominant case, one flagship entity writes almost the entire group book such as with State Farm, whose lead one automobile entity accounts for more than 90% of the group's state premiums. Single-charter regional insurers and farm bureau groups behave the same way. In

the channel case, a group splits its book across a few comparable entities that serve distinct distribution channels, such as Progressive's separate agency and direct companies, each filing its own rates. In the fragmented case, a group spreads its book across many entities that price different risk tiers from preferred to nonstandard, so no single entity dominates and a long tail of small specialty companies appears, as with GEICO and USAA.

Given this structure, we select entities by each group's internal composition. Within every top 10 group in a state, we rank its statutory entities by their share of the group book and keep the largest entities whose shares cumulatively reach 80% of that book. This retains the dominant entity in concentrated groups, both channels in channel groups, and the core entities in fragmented groups, while dropping the small specialty tail.

B.4. Bias Towards Product Filings with Demographic Factors Disclosure

The observability of explicit demographic pricing layers reflects insurers' disclosure architecture rather than differences in pricing technology. There are mainly two rating architectures. The first is "factor-table insurers" such as PRGS, SFMA, and USAA. Their rating plan is a chain of multiplicative filed tables, so repricing a risk segment requires amending the relevant table and every move is visible in the filings. The other is "tier insurers" which wrap the core of their pricing in a proprietary tier in which the mapping from customers profiles to price is not. For tier insurers, the filings show continuous revision of the surrounding model machinery, but whether and how demographic relativities move inside that machinery is not publicly observable. The signature insurers in this category are ALSE and TRVA.

There is no dominant disclosure format, and an insurer's choice between the factor-table style and the trade-secret tier model is sticky. Keeping the factor model as a trade secret is less about hiding information from competitors during our sample period than a tradition of historical practice. Leaders such as Progressive, which drove the granular segmentation wave of the 1980s and 1990s, grew rapidly on the strength of their modeling and have kept the factor-table disclosure style since then. The trade-secret tier model is a later invention that arrived with credit-based insurance scores. For example, ALSE and TRVA adopted it in the 2000s and have kept it since. Also conditional on the regulatory environments we observe, the disclosure format is a firm choice which is invariant to state regulation.

B.5. Rating Factors

Imputing base rates and territory factors. Some insurers file base rates at the territory level, where each territory's filed value equals $BaseRate \times TerritoryFactor$. We decompose this value into a base rate and a territory factor: we take the average across all territories as the firm's standard base rate, then divide each territory's filed value by this imputed base rate to recover its territory factor. We cannot observe the exact reference product underlying the base rate, but any such benchmark level is absorbed by firm fixed effects and therefore does not affect our analysis.

Population-weighted territory/ZIP Code factors. When a ZIP Code falls under more than one territory, we set its factor to the population-weighted average of the overlapping territories' factors. If ZIP Code z overlaps K territories, its imputed factor is

$$Factor_z = \sum_{k=1}^{K} \frac{Population_{z \cap k}}{Population_z} \times TerritoryFactor_k, \tag{B.1}$$

where $Population_{z \cap k}$ is the population living in the overlap of ZIP Code z and territory k, and $Population_z$ is the total population of ZIP Code z. The weight is therefore the share of the ZIP Code's residents that fall in each territory. For county-defined territories we obtain these shares from the HUD USPS ZIP Code Crosswalk Files, which record the residential addresses each county contributes to a ZIP Code (a proxy for population). For block-group-defined territories — which HUD's crosswalk does not resolve — we use census block-group population from the ACS, allocated to ZIP Codes through the HUD tract-to-ZIP crosswalk.

B.6. Identifying telematics adoption

For each insurer subsidiary in each sample state, we determine whether the firm offers a telematics (usage-based) auto insurance program, and if so, when it introduced that program. We therefore searched each unit's rate filings — both the filing text and the rating-factor tables — for evidence of a telematics program. The search covered general terms such as telematics, usage-based insurance, pay-as-you-drive, and mileage-based pricing, together with the brand names insurers use for these programs (for example, Progressive's Snapshot, Allstate's Drivewise, and GEICO's DriveEasy), which we confirmed and extended through

public sources.

A telematics rating factor appearing as its own table or column is the strongest evidence of adoption, so we treated such factors, along with explicit references to a named program, as confirmation that the program is in use. We separated genuine product launches from routine mentions of an existing program: only filings with explicit launch language (for example, "we introduce" or "new program") were read as introductions, and the earliest such filing dates the firm's entry in that state. Where a program appears only as a recurring factor with no launch language, we infer that the firm adopted it before our filing record begins and record the earliest observed mention as a lower bound.

B.7. AI Workflow

This appendix section describes the key steps the AI agents performed at the data collection stage to complete the project.

Automated Searching and Downloading of Filings from the Public Internet. From the selection standard, we obtain the list of state-firm pairs for which we need product filings. The AI agent then builds a document-searching and auto-downloading pipeline that draws from the public state-level SERFF systems.

PDF Conversion. The product filings are all in PDF format and range widely in size, from less than one megabyte to more than 350 megabytes. AI agents pre-process these PDFs into markdown files, which are easier to reference and to extract information from repeatedly in later use.

Factors Extraction. We write factor extraction prompts that direct AI agents to pull the necessary information from the markdown files. Exemplar original wordings from the prompts include the following:

- *Base rates: "... extract the base rates, the dollar amounts per coverage, sometimes territory-dependent, from each firm's rate manual filings, in long format with one row per entity, coverage, limit, and territory ..."*
- *Demographic factors: "... trace how demographic characteristics enter the firm's rating plan, then extract the multiplicative factors related to age, gender, and marital status that adjust the base rate for policyholder characteristics ..."*

- *Territory factors: "... extract the geographic rating factors, that is, any rating input keyed to geography such as ZIP Code, county, city, or rating territory number, from the converted filings ..."*

Telematics Adoption. We write telematics adoption detection prompts that direct an AI agent to search the product filings for evidence of a firm's telematics adoption and its timing. Exemplar original wordings from the prompt include: *"... for each insurer subsidiary in each state, search the unit's product filings to decide whether the firm introduced a telematics, behavior-based, or usage-based pricing program in that state, and when it first appears ...".*

Quality check. We build verification into the extraction workflow rather than trusting the AI output directly. Each firm follows a three-phase, human-approved procedure. The AI first reports the format of a firm's filings, then extracts a single trial filing and stops, and only after we approve that trial does it process the rest in a batch. This gate catches format misreads before they spread. Before any batch, we confirm extracted values against the source PDF, paying particular attention to the largest and most complex filings. We also record, for every firm-state, which filings yielded data and which did not, so that gaps are documented rather than silent.