Pay-As-You-Go Insurance: Experimental Evidence on Consumer Demand and Behavior*

Raymond Kluender†

December 2022

Abstract

Pay-as-you-go contracts reduce minimum purchase requirements which may increase market participation. We randomize the introduction and price(s) of a novel pay-as-you-go contract to the California auto insurance market where 17 percent of drivers are uninsured. The pay-as-you-go contract increases take-up by 10.8 p.p (89%) and days with coverage by 4.6 days over the three-month experiment (27%). Demand is relatively inelastic and pay-as-you-go increases insurance coverage in part by relaxing liquidity requirements: most drivers' purchasing behavior is consistent with a cost of credit in excess of payday lending rates and 19 percent of drivers have a purchase rejected for insufficient funds.

*I am grateful to Amy Finkelstein, Asim Ijaz Khwaja, Neale Mahoney, Matthew Notowidigdo, James Poterba, Jesse Shapiro, Tavneet Suri, Heidi Williams, Wesley Yin, and seminar participants at MIT, Harvard, the junior household finance seminar, NBER Insurance, and the Chicago Conference on Data and Welfare in Household Finance for helpful comments and Shoshanna Vasserman for an excellent discussion of the paper. I thank my research partners at Hugo Insurance, especially David Bergendahl and Colleen Poynton. The experiment reported in this study is listed in the AEA RCT Registry (#0002537). This work was supported by J-PAL North America and the Harvard Business School Division of Research and Faculty Development. Calvin Jahnke provided exceptional research assistance.

†Entrepreneurial Management Unit, Harvard Business School, 60 N. Harvard St. 217, Boston, MA 02163 (email: rkluender@hbs.edu).

1 Introduction

Despite a universal insurance mandate, 17 percent of drivers in California operate their vehicles without the legally required coverage (Insurance Research Council, 2021). Driving without auto insurance exposes drivers to large financial risks and increases insurance premiums for other drivers, imposing premium externalities of $27 billion per year in the U.S. (Sun and Yannelis, 2016). Enrolling in auto insurance often requires large upfront payments and significant minimum purchase requirements, especially if drivers are purchasing coverage in the nonstandard auto insurance market.[1] Participation in many insurance markets is suboptimally low, and when premiums are charged upfront, liquidity requirements to enroll present a barrier to coverage (Cole et al., 2013; Casaburi and Willis, 2018; Rampini and Viswanathan, 2022).

Many markets, particularly those serving low-income consumers, offer smaller quantities at higher prices to increase market participation (Attanasio and Pastorino, 2020). Pay-as-you-go contracts facilitate purchases of smaller quantities at flexible (typically higher) frequencies than traditional contracts with regular, longer-term billing cycles. These contract structures, which have proliferated across other domains serving low-income consumers including cell phone and utility contracts, relax minimum purchase requirements and allow households to retime insurance purchases to periods of higher liquidity.[2] Pay-as-you-go contracts may also increase coverage by allowing households to buy smaller durations of coverage that they can more easily afford. While pay-as-you-go contracts address commonly cited barriers to insurance market participation, they have never previously been introduced to insurance markets so we know little about their effects on take-up of coverage, at what prices these contracts may be viable, or whether there is demand for smaller quantities at relatively higher prices.

This paper presents the results of a randomized control trial which introduced a novel pay-as-you-go insurance contract to the California auto insurance market. The pay-as-you-go contract I study allows drivers to choose the size and timing of insurance coverage purchases by offering

[1] High-risk drivers must shop in the nonstandard auto insurance market but low-risk drivers who are shopping for minimum liability insurance coverage also comprise a large share of the nonstandard market (Walls, 2015).

[2] Rampini and Viswanathan (2022) note specifically that their theory predicts that InsurTech innovations like pay-as-you-go break the connection between financing and insurance and have the potential to reduce high rates of uninsurance.

the option to buy a flexible number of days of coverage (3, 7, 14, or 30 days, with a 10-day grace period after exhausting their balance). Drivers can deactivate their insurance on days they are not driving to preserve their balance. To evaluate the effects of the pay-as-you-go contract on insurance take-up and persistence, insurance applicants are randomly assigned either a three-month traditional contract or the pay-as-you-go contract. To estimate how demand varies by price, the daily insurance premium is randomly shifted conditional on the risk premium. To evaluate the role liquidity constraints play as a barrier to insurance take-up and to test willingness-to-pay for smaller quantities at relatively higher prices, half of applicants offered the pay-as-you-go contract are offered significant "bundle" discounts for purchasing a larger number of days of insurance (14 or 30) at a time. I supplement the bundle-discount treatment arm with complementary evidence from credit reports, alternative credit data, utilization behavior, and data on transactions rejected for insufficient funds to shed light on the role of liquidity constraints in insurance purchasing decisions.

The pay-as-you-go contract increased insurance take-up by 10.8 percentage points (89 percent) and days with insurance available by 4.6 days (27 percent) over the three-month experiment relative to the traditional contract offer. These intent-to-treat (ITT) estimates include coverage provided by carriers outside the experiment; effects are larger when only considering coverage through the experiment. Drivers take advantage of the feature of the contract which allows them not to pay for insurance on days they are not driving, "turning off" their insurance 32.5 percent of the days for which they have coverage available on average. After accounting for the ability to deactivate coverage, drivers offered the pay-as-you-go contract insure a similar number of days of driving to those offered the traditional contract. While the ITT effect of the pay-as-you-go contract on coverage erodes over time, there is suggestive evidence that the contract is particularly valuable for drivers who have historically struggled to maintain regular coverage.

Demand for the pay-as-you-go contract decreases in price but is strong relative to the traditional contract, even at the highest prices offered. Applicants offered the pay-as-you-go contracts were randomly offered a daily premium at one of three prices: base price (based on their risk, as priced by a backing insurance company, and translated to a daily premium by marking up the cost of a prorated day of insurance coverage by 67 percent to account for the option to deactivate coverage on days not driven), 120% of the base price, or 80% of the base price. Applicants in the lowest price group have larger effects on take-up through the experiment (16.1 percentage points versus between 9.3 and 11.4 percentage points for the other two price groups) and have roughly double the ITT effect on the number of days with access to coverage relative to the other two price groups (9.4 days versus 4.9 days for the base price group and 6.2 days for the high price group).[3] Applicants have an elasticity of demand (days purchased with respect to price) of -0.63 for all applicants and of -0.72 for those who enrolled. The relatively inelastic demand could indicate a preference for the flexibility and lower liquidity requirements features of the pay-as-you-go contract.

The market potential of the pay-as-you-go contract depends on the strength of demand for smaller quantities. I find that demand for smaller quantities is high when prices are the same: 72 percent of days purchased are in bundles of three or seven days when the price is the same across quantities. To assess demand for smaller quantities at relatively higher prices, half of the drivers offered the pay-as-you-go contract are also randomly offered a bundle discount which is designed such that forgoing the discount in favor of repeated purchases of smaller quantities implies a cost of borrowing similar to a payday loan. The bundle discount induces an increase in the share of large-quantity purchases by 12 percentage points, but many drivers continue to opt for smaller quantities even when relative prices are higher. Among those offered the discount, 51 percent of drivers forgo discounts for all of their purchases and 77 percent of drivers forgo them at least once.

Drivers may prefer smaller quantities of coverage even at higher prices because they are liquidity constrained or because they are uncertain about their forecasted demand for driving relative to other consumption priorities. While the payment timing flexibility of the pay-as-you-go helps accommodate demand uncertainty, there is evidence to suggest that liquidity constraints are binding and are significant in driving demand for smaller quantities. The drivers who apply for a pay-as-you-go insurance quote (the plan is marketed to drivers seeking minimum state coverage using standard online marketing strategies) have limited access to formal credit: 78 percent have zero dollars of available credit on their credit report (81 percent are credit constrained when including the 15 percent of applicants who do not have a credit report), compared to 28 percent of a random sample of Californians. 19 percent of drivers who enroll in pay-as-you-go coverage have at least one

[3] Because the price variation is induced only within the pay-as-you-go contract offers, I focus on take-up and coverage outcomes only for the implementing insurer for these outcomes.

purchase rejected for insufficient funds, which may be a more immediate sign of liquidity constraints. For six percent of enrolled drivers, an attempted insurance purchase rejected for insufficient funds is their last observable action before attriting from coverage.

This experiment created a rare opportunity to analyze the introduction of a novel insurance technology to the market and to randomize insurance contract features including the type of the contract, price, and nonlinearity in price with respect to quantity. Furthermore, the experiment targeted uninsured drivers, an understudied and relevant group for policy. Beyond auto insurance, the results shed light on the efficacy of financial and insurance technologies – new and old – which seek to help this segment of consumers smooth their consumption (e.g., technologies enabling pay-as-you-go or buy-now-pay-later structures, brick-and-mortar rent-to-own retailers) and/or income (e.g., technologies enabling earned wage access, brick-and-mortar payday lending) over short periods of time. These technologies are becoming increasingly prevalent, with 56 percent of survey respondents indicating they used a buy-now-pay-later service in a March 2021 survey of 2,000 Americans, up from 38 percent in July 2020,[4] and three-quarters of workers reporting that it is important for their employer to offer earned wage access according to a survey conducted by ADP, Inc.[5] Among uninsured drivers, the flexibility offered by the pay-as-you-go contract increases insurance take-up and coverage which may point to a valuable role for technology in helping lower-income consumers manage their financial lives.

This paper contributes to several areas of research. First, I contribute to the modest literature studying optimal contracts and underinsurance in auto insurance markets. This literature dates back at least to Vickrey (1968), who observed the high-fixed-cost and no-marginal-cost properties of auto insurance contracts generate harmful externalities in the form of excess driving, congestion, and emissions and argued for a usage-based insurance contract. Edlin (1999) and Bordoff and Noel (2008) formalize these insights and estimate that a shift to per-mile premiums would generate large welfare benefits, with the largest benefits for low-income drivers who drive fewer miles on average. This paper studies a contract that partially addresses the "all-you-can-drive" concerns by allowing drivers to deactivate their insurance and save their balance on days they do not drive. Drivers took

[4] https://www.fool.com/the-ascent/research/buy-now-pay-later-statistics/
[5] https://news.bloombergtax.com/payroll/study-shows-interest-in-earned-wage-access-for-workers-employers

advantage of this contract feature on 32.5 percent of days they have coverage available on average. Jin and Vasserman (2021) analyze a modern monitoring technology and find that both benefits and adoption costs are high. I focus on the high-churn minimum liability market where adoption of the on-board diagnostic devices required for monitoring may be less feasible.[6] Sun and Yannelis (2016) find a California program lowering premiums by lowering coverage limits reduces uninsured driving and calculate that the optimal fine (stochastic Pigouvian tax) for uninsured driving should be much higher, but acknowledge that uninsured drivers may be unable to pay. I contribute to this literature by estimating whether, how, and for whom a pay-as-you-go structure can reduce the rate of uninsured driving without reducing coverage limits. The prevalence of credit constraints among the uninsured drivers documented in this experiment also suggests that there they may indeed be limited gains from more severe enforcement, particularly if policymakers and regulators value the benefits of driving for economic mobility.[7]

Second, this paper contributes to our understanding of the role of liquidity constraints for insurance demand. Liquidity constraints have been found to play a role in a number of settings including microlending, subprime auto loans, consumer bankruptcy, health insurance, payday lending, and adoption of energy efficient technologies (Karlan and Zinman, 2008; Adams et al., 2009; Gross et al., 2014; Ericson and Sydnor, 2022; Miller and Soo, 2020; Berkouwer and Dean, 2022). Casaburi and Willis (2018) find retiming premiums to harvest increases take-up of crop insurance in Kenya from five to 72 percent. Their crop insurance intervention, by committing to one-time premium payments at a future period of peak liquidity, presents an extreme case of eliminating liquidity constraints. This paper confirms that liquidity constraints are likely to be a barrier to coverage for some consumers and tests the potential of smaller, periodic purchases to induce and sustain higher levels of coverage for recurring types of insurance. In a related theoretical paper, Rampini and Viswanathan (2022) model insurance as state-contingent savings (because insurance premiums are paid in advance) which implies that, with limited liability, households lacking liquidity are unlikely to participate in insurance markets at all. This paper presents experimental evidence that breaking

[6] An earlier experiment offered by-the-minute insurance coverage. As part of this project, we attempted to incentivize enrolled drivers to install on-board diagnostic devices to monitor their driving but there was minimal interest in taking up this offer.

[7] Baum (2009) finds that lower barriers to driving increase employment and exit from welfare.

the connection between financing and insurance can increase participation in insurance markets for low-resource households.

Finally, this paper extends a small literature studying consumer behavior under pay-as-you-go contracts and a related literature on smaller, more frequent consumption patterns. In two papers studying prepaid electricity metering in South Africa, Jack and Smith (2015) document that poorer customers prefer to make smaller, more frequent electricity purchases which are incompatible with traditional monthly billing cycles and Jack and Smith (2020) find that switching poorer and in-debt customers to prepaid metering generates net revenue gains to the utility. Aker and Mbiti (2010) and Kalba (2008) document the rapid adoption of mobile phones in Africa which has been enabled in part by a pay-as-you-go contract structure.[8] Baker et al. (2020), who find the returns to inventory management are high at low levels of wealth, and Attanasio and Pastorino (2020), who find the availability of smaller quantities – even at higher prices – increases market participation for food in rural Mexico, examine similar consumption decisions. To my knowledge, this is the first paper to study pay-as-you-go contracts of any kind in the United States and the first to study them in the context of insurance markets. In addition to estimating demand for these contracts in relation to standard contracts, I provide evidence on the elasticity of demand and willingness-to-pay for smaller quantities at higher prices using experimentally induced price variation.

2 Setting

Despite regulations which require all drivers to carry auto insurance,[9] 12.6 percent of drivers in the United States operate their vehicles without the mandated insurance coverage; that number is even higher in our setting, California, where millions of people drive without insurance (16.6 percent) (Insurance Research Council, 2021).[10] This paper focuses on uninsured drivers in California shopping for minimum liability insurance coverage. Uninsured drivers are exposed to large

[8]Similar contracts are popular in the developed world but research on them is extremely limited. Chen (2012) describes an industry report which finds 23 percent of wireless customers had a prepaid contract in 2012 and projected that number to grow to 29 percent by 2016.

[9]Two states are exceptions to this rule. Virginia allows drivers to pay a $500 fee with their registration instead of purchasing auto insurance coverage (Virginia Department of Motor Vehicles, 2021). New Hampshire has no law mandating insurance (New Hampshire Department of Motor Vehicles, 2021).

[10]Insurance Research Council (2021) estimates these numbers using the ratio of insurance claims made by individuals injured by uninsured versus insured drivers. See Appendix Table A1 for the share uninsured by state.

financial risks and impose externalities by increasing the financial risk drivers face in the event of an accident. Sun and Yannelis (2016) find a one percentage point increase in the share of drivers in a county who are uninsured increases insurance premiums by 1% and calculate the annual cost of the uninsured driver externality to be \$6 billion in California alone (\$27 billion nationally).

While little is known about why individuals drive without insurance, there are several features of the auto insurance market I will highlight as potential contributing factors. First, minimum liability insurance ("15/30/5") in California requires \$15,000 of coverage for bodily injury to a single person (\$30,000 for multiple people) and \$5,000 of coverage for property damage. Liability insurance does not cover any damages to oneself or one's own vehicle and drivers remain liable for costs exceeding these coverage limits. For households with limited assets, they may have limited liability in the event of an accident (either because the other driver and their insurance would not seek a judgment or because they have the option to file for bankruptcy) which could reduce their demand for insurance.

Second, insurers are restricted from pricing on some factors and choose not to price others, which could lead to actuarially unfair pricing along unpriced dimensions. Passed in 1988, Proposition 103 ("The Insurance Rate Reduction and Reform Act") limited the dimensions along which auto insurance premiums could be priced.[11] While annual mileage is nominally one of three primary pricing factors (alongside driving record and experience), in practice the cost of verifying mileage results in mileage going unpriced at the margin. Appendix Figure A1 plots the distribution of priced mileage on rate filings of five insurers against a kernel density estimation of the annual mileage distribution from the 2017 National Household Transportation Survey and shows that the vast majority of drivers are binned into common bins (often 10,000 or 12,000 miles) rather than priced on their individual miles driven. Every minute a driver spends on the road increases accident risk (for themselves and other drivers), congestion, and emissions and pollution. By charging nothing for an additional mile, auto insurance companies induce excess driving and increase insurance premiums.[12]

[11] Specifically, it required auto insurance premiums to be determined by (1) driving record, (2) annual mileage, (3) years of driving experience, and (4) other factors "adopt(ed) by regulation and that have a substantial relationship to the risk of loss." Additionally, it rolled back prices to 20% less than their 1987 levels and temporarily froze them; furthermore, it required that any rate changes be approved by the California Insurance Commissioner. See Appendix A for additional details on auto insurance regulations and premium pricing.

[12] Bordoff and Noel (2008) estimate vehicle miles traveled would be eight percent lower if insurance was priced per mile.

Low-income drivers drive fewer miles on average and therefore subsidize the premiums of higher income drivers under the current pricing regime (Bordoff and Noel, 2008; Consumer Federation of America, 2015), which could push some share of them to drive uninsured.

Third, drivers shopping for minimum liability insurance coverage are also confined to shopping in the "nonstandard" auto insurance market. A distinctive feature of auto insurance markets is that insurers are free to deny coverage for classes of drivers they consider to be high-risk (Value Penguin, 2021). Unlike the health insurance context, there is no regulation requiring insurers to cover those with "pre-existing conditions." Two groups of drivers are commonly relegated to shopping in the nonstandard market: high-risk drivers denied coverage in the standard market and drivers shopping for the minimum insurance coverage required by the state. Walls (2015) describes the nonstandard market as follows:

> Nonstandard auto insurance has been traditionally defined as a market for drivers who have certain risk factors that make it difficult or impossible for them to obtain insurance in a standard or preferred market. These insureds include new or young drivers, drivers with credit problems, drivers with multiple losses or moving violations, people who want only minimum limits coverage and those with an unusual driver's license status.

Pooling credit-constrained drivers shopping for minimum liability coverage with high-risk drivers with multiple losses or moving violations may exacerbate affordability challenges for low-income drivers. Unsurprisingly given these features, the nonstandard market also tends to be more volatile and transaction-heavy than the standard market; one executive reports nonstandard customers typically lapse on their policy within the first three months and re-enroll within 30 days (Walls, 2015). These lapsations incur fees and non-premium fees are a substantial share of nonstandard insurer revenue. Based on public filings, nonstandard carriers charge fees totaling approximately 13% of their net earned premiums.[13] These fees are disproportionately borne by drivers frequently cycling in and out of insurance and may present a barrier to obtaining coverage. In addition to the high share of premiums paid in fees in the nonstandard market, plans typically require

[13] Author's calculation based on the 10-K filings for Infinity Property and Casualty Corporation, Mercury General Corporation, National General Holdings Corporation, First Acceptance Corporation, and Affirmative Insurance Holdings Incorporated. This is based on 2017 10-K filings for the first three, 2016 10-K filing for First Acceptance Corporation, and the 2014 10-K filing for Affirmative Insurance Holdings Incorporated.

a substantial upfront payment.[14] Collectively, the risk pool of drivers insured by nonstandard carriers (high-risk and/or low-resource drivers shopping for minimum coverage), administrative loads and customer acquisition costs posed by high customer churn, and high liquidity requirements to enroll in insurance are likely to push up the cost of insurance coverage for low-income or liquidity-constrained consumers seeking minimum liability coverage.

Uninsured driving has historically been a high-profile policy problem, and California employs several policy instruments in an effort to combat the problem. Insurance is legally mandated and required to register a vehicle. Punishments for uninsured driving include escalating fines (up to \$720 of fines and fees for a first offense, up to \$1,800 for a second offense) and vehicle impoundment at the discretion of the police.[15] In the event of an accident where they are not at fault, "no-pay-no-play" laws prohibit uninsured drivers from collecting damages and compensation. While most of the policies addressing the problem are punitive, California also offers a Low Cost Auto Insurance program which lowers premiums by reducing the minimum insurance requirements from "15/30/5" to "10/20/3" for eligible "good" drivers with incomes below 250% of the Federal Poverty Level and vehicles valued at \$20,000 or less with no outstanding loans. Reducing the minimum required insurance coverage reduced uninsured driving; the program reduced uninsured driving by one to two percentage points off an average of 21% upon implementation in 1999 (Sun and Yannelis, 2016). Citing continued high rates of uninsured driving, eligibility was extended to drivers with fewer than three years of experience and vehicle values up to \$25,000 in 2015 (California Department of Insurance, 2021). While reducing minimum coverage requirements increases take-up on the extensive margin for standard monthly, all-you-can-drive contracts, this comes at the cost of increased liability in the event of an accident. Increasing punitive measures to reduce uninsured driving may also have bounded scope to improve the situation given the limited resources of uninsured drivers. The limited instruments available to policymakers to address the uninsured driving problem highlights the potential value of insurance technology that can expand the contract space and automate many of the administrative loads that drive up the costs of these contracts.

[14] For example, Megna (2021) writes "[v]irtually every car insurance company requires that you pay at least one month ahead on a six-month policy... Drivers with a bad credit history or in need of an SR-22 filing are likely to be required to make a larger down payment or even to pay for the term in full."

[15] https://www.valuepenguin.com/auto-insurance/california/penalties-driving-without-insurance

To summarize, the cost of insurance may be higher than uninsured drivers' willingness-to-pay because: (1) drivers may have limited liability in the event of an accident if they have few resources to protect; (2) insurers offer "all-you-can-drive" contracts with annual mileage underpriced on the margin; (3) drivers shopping for minimum liability insurance coverage are relegated to the nonstandard market with high administrative loads and an unfavorable risk pool leading to high fees and premiums. The pay-as-you-go contract studied in this experiment will more closely tie premiums paid to driving frequency, offer more flexible payment options to eliminate fees for missed payments and reactivation, and reduce the liquidity requirements to enroll in coverage which may collectively address some of the existing barriers to insurance coverage.

3 Experimental Design and Data

3.1 Pay-As-You-Go Insurance and Recruitment

I partner with Hugo Insurance, a California-based insurance technology company offering no-fee and no-obligation minimum liability auto insurance contracts targeted at low-income uninsured drivers. I evaluate the introduction of their novel pay-as-you-go auto insurance contract to the California auto insurance market. Insurance applicants were randomly offered either a traditional contract or the new pay-as-you-go contract. Within the pay-as-you-go contract, applicants were randomly assigned to one of three base price groups (conditional on risk) crossed with the "bundle discount" which lowered the prices for larger quantities of days. The pay-as-you-go contract allows drivers to buy minimum liability auto insurance coverage in quantities of 3, 7, 14, or 30 days and allows drivers to pay for insurance only on days in which they drive. Drivers can "pause" their insurance coverage for periods up to 10 days when they are not driving by texting `PAUSE`.[16] Drivers can reactivate their insurance at any time by texting `COVER`, which immediately initiates coverage for the subsequent 24-hour interval. Pausing coverage stops it from automatically renewing for another day at the end of the 24-hour interval. Drivers who have exhausted their balance of days can continue to insure their driving for a grace period of up to 10 days. Drivers who draw on their reserve balance of grace period days must repay them in addition to the 3, 7, 14, or 30 days when

[16] After 10 days, Hugo will reactivate insurance coverage for drivers with a positive balance of days on their account. Drivers have the option to pause their insurance again following that 24-hour reactivation.

they top up their account.

The California Department of Insurance, given its vested interest in reducing uninsured driving, provided Hugo Insurance with permission to introduce this novel contract structure to the market and to vary features of the contract for the duration of the experiment. This provided a rare opportunity to understand how individuals shopping for insurance respond to contract structure, price, and bundle discounts. The experiment was preregistered with the AEA RCT Registry (Kluender, 2019).

Hugo Insurance acquired customers through standard channels including Google Adwords and purchasing leads through other insurers.[17] Drivers were directed to the Hugo Insurance website (withhugo.com, see Appendix Figure A2 for screenshots) and invited to apply for a quote. Drivers qualified for the experiment if they met the criteria of the underwriting backing insurer.[18] The experiment accepted applicants betwee March 8, 2019 and August 30, 2019 and the duration of the experiment for participants was three months from the time of insurance enrollment. 1,537 participants applied and were offered quotes for insurance coverage through the experiment.

Daily premiums for the pay-as-you-go contract were set by marking up the prorated quote for three months of traditional coverage based on the anticipated share of "exposure" Hugo Insurance is underwriting on a day the drivers activates their pay-as-you-go coverage. The mark-up helps account for the fact that drivers, particularly those who are infrequent drivers, may drive more miles on days their pay-as-you-go coverage is active than if the anticipated mileage was simply prorated daily over the course of the term. The size of the mark-up is estimated using travel diary information from the 2017 National Household Transportation Survey (NHTS) and calculating the share of annual mileage driven on days respondents drive more than five minutes. We estimated the appropriate size of this mark-up using several different comparison groups and assumptions, and Hugo Insurance conservatively set the mark-up at 67 percent over the prorated traditional premium based on this calculation.[19] This mark-up is much higher than Hugo Insurance charged after the

[17] See, for example, this brochure for how one auto insurance advertising platform operates: https://mediaalpha.com/wp-content/uploads/2017/01/MediaAlpha-Direct-to-Quote-Brochure.pdf

[18] 456 applicants (23%) could not be underwritten by the backing insurer. The most common reasons applicants were rejected by the backing insurer were age (drivers younger than 18 were ineligible), driving record, vehicle make, and invalid license, respectively. Roughly a quarter of rejections were for technical failures (e.g., the third-party application programming interface (API) to pull motor vehicle reports was down).

[19] See Appendix A for additional details.

experiment; as of December 2022, the largest mark-up they use in any of the ten states in which they operate is 20 percent. The mark-up on the pay-as-you-go contract used in the experiment will bias downward estimates of the effect of the contract on insurance take-up and coverage and the elasticity of demand estimates for the pay-as-you-go contract should be interpreted relative to this benchmark price (plus or minus 20 percent based on the price treatment group).

3.2 Treatment Arms

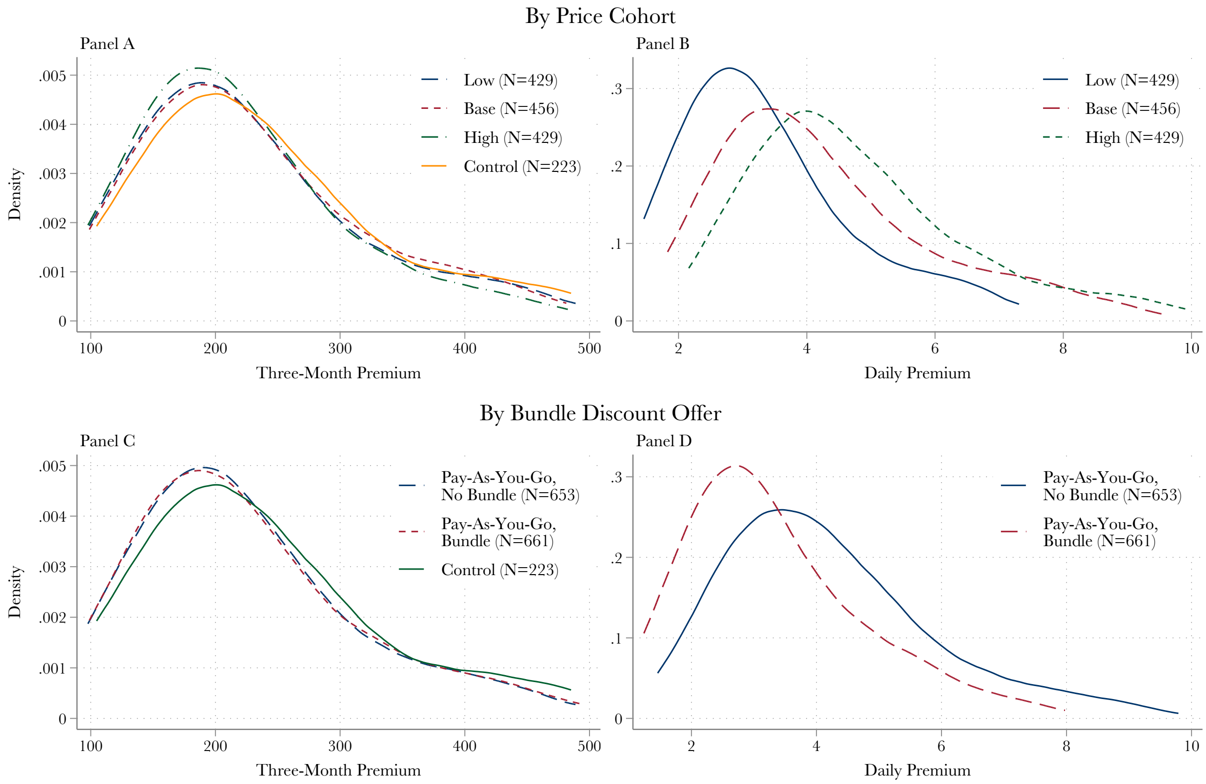
The first hypothesis the experiment tests is whether the pay-as-you-go contract offer increases insurance take-up and coverage relative to a traditional contract. Insurance applicants were randomly assigned to either the control group, which was offered a three-month traditional all-you-can-drive minimum-liability-insurance contract with three months of premiums due at enrollment, or the pay-as-you-go contract. The traditional contract is the contract that would be offered to the applicant by the backing insurance company outside the experiment. The first dimension of the randomization is the type of contract: one-seventh of applicants are offered the traditional contract and the remaining six-sevenths are offered the pay-as-you-go contract. The second and third dimensions of randomization are within the pay-as-you-go contract.

To estimate sensitivity to price, the second dimension of randomization is the price of a day of insurance. We translate an applicant's traditional premium to a daily premium as described above and conditional on the applicant's daily premium, induce additional random variation in the price of a day of insurance. Specifically, applicants offered the pay-as-you-go contract are randomly allocated to one of three pricing treatment groups: 20% up, no adjustment, and 20% down. By conditioning on the risk premium, we induce price variation orthogonal to risk type which would otherwise confound estimates of demand. Figure 1 plots the distribution of the market-rate, three-month premium for the control, low, base, and high price groups in Panel A.[20] Figure 1 Panel B illustrates the pricing variation induced by the experiment.

The third and final dimension of the randomization tests demand for smaller quantities of

[20] A Kolmogorov-Smirnov test of distributional equality between the premium distributions of applicants offered the traditional vs. pay-as-you-go contract is not significant (p-value = 0.18). I additionally test the null hypothesis of distributional equality for all two-way pairs of the four groups and between the bundle discount and no bundle discount groups. Only one (Control-High) is statistically significant. Results are robust to the inclusion of controls, including the base premium, and I describe these checks in more detail in Section 4.

Figure 1. Premium Distributions and Experimental Variation



Notes: Panels A and C plot the distributions of market-rate, three-month premiums split by price (Panel A) or bundle discount (Panel C) treatment group assignment. Panels B and D plot the distributions of daily pay-as-you-go premiums split by price (Panel B) and bundle discount (Panel D) treatment group to illustrate the variation in premiums induced by the experiment. Panel D plots the bundle discounted premium distribution assuming a 30-day purchase (30 days for the price of 24, implying a 20 percent discount). The distributions are calculated via kernel density plots with bandwidths of 40 and .6 for the three-month and daily premiums, respectively.

insurance at relatively higher prices by offering discounts for 14 or 30 day purchases. By randomly varying the relative prices for smaller (3 or 7 days) and larger (14 or 30 days) quantities of insurance coverage, I can estimate how often drivers are willing to forgo the bundle discounts in favor of smaller quantities at higher prices. To operationalize this, half of applicants offered the pay-as-you-go contract are offered a discount for buying a larger "bundle" of days of insurance at once. The bundle discount provides no discounts for three or seven-day purchases, but offers 14 days for the price of 12 and 30 days for the price of 24. Figure 1 Panel C plots the market-rate, three-month premium distribution for the control and pay-as-you-go treatment groups split by whether they are offered the bundle discount. Panel D illustrates the variation induced by this arm of the experiment by plotting the daily premium distribution offered to the bundle and no-bundle treatment groups for 30-day purchases.

The cost of borrowing implied when an applicant forgoes the bundle discount to purchase smaller quantities of days of insurance is designed to approximate the cost of a payday loan, which is in the range of a 391 to 600 annual percentage rate (APR).[21] Appendix Table A2 illustrates the cost of borrowing implied by forgoing the bundle, which can be calculated by dividing the foregone savings from the bundle (the "interest") by the difference between price for the bundle purchases (14 or 30 day) and the smaller quantities (3 or 7 days) to determine the size of the loan. To calculate the duration of the loan, I divide the difference in the number of days purchased by the average utilization rate of 67.5 percent (share of days insurance is active among users with a positive balance of days).[22] The APR implied by forgoing the bundle ranges from 261% for drivers who opt for three days relative to the 30-day bundle to 1,409% for drivers who opt for seven days instead of 14-day bundle.

One seventh of applicants were randomized into the control group and one seventh into each of the six pay-as-you-go contract treatment groups, split by price adjustment and whether they were offered a bundle discount (low price-no bundle, low price-bundle, base price-no bundle, base price-bundle, high price-no bundle, high price-bundle). The randomization was pre-specified and blocked for every 49 visitors to the website who began the application process.[23] Appendix Table A3 presents balance on observables by whether an applicant was offered a pay-as-you-go or a traditional contract. As expected, the F-statistic for joint significance of the differences in variables in groups is not statistically significant. To address any residual concerns about differences on observable attributes across the treatment groups, I show robustness to the inclusion of controls as described in more detail in Section 4. Applicants applied for a quote as they would for any typical insurance plan and their randomly assigned plan was presented to them as their quote at the completion of

[21] See, e.g., https://www.stlouisfed.org/open-vault/2019/july/how-payday-loans-work

[22] Appendix Table A2 shows the implied cost of borrowing for each pairwise choice based on the formula Implied APR $= \frac{\text{Foregone discount (“interest”)}}{\text{Borrowing required to access bundle (“principal”)}} * (\frac{365}{T})$. For example, the calculation treats the duration of the loan for a driver who forgoes the 30-day discount to purchase 3 days as 40 days (27 days divided by the utilization rate of 67.5%), the "interest" as 6 days, and the "principal" as 21 days for an implied APR of 261%.

[23] The initial intent was to block every 49 *applicants* as specified in the pre-registration for the experiment; however, this was not feasible for my partner, as technical implementation required assigning the treatment group before pricing an applicant's quote. Therefore, a large number of randomization slots were "used up" with applicants who began but did not complete the quote process (receiving a quote was a requirement for inclusion in the study sample) or who did not meet the underwriting conditions of the backing insurer. Given the block randomization was interrupted by these technical challenges, I do not include strata fixed effects as described in the pre-registration.

their insurance application. Appendix Figure A2 displays the quote screens presented to applicants for the traditional and pay-as-you-go contracts.

3.3 Data and Summary Statistics

Administrative data from Hugo Insurance is my primary data source. These data include insurance application information (age, years of experience, vehicle make, model, and year), a ledger of purchase actions (number of days purchased, amount, and current balance), and a ledger of coverage actions (coverage activations and deactivations) for each applicant. Using the vehicle make, model, and year, I supplement the pricing factors with information on the private resale value of the vehicle based on the CARFAX vehicle valuation tool.[24] Additional data used by Hugo Insurance to administer plans is derived from third-party databases, including motor vehicle reports (driving records) which generate the three-month premium and insurance coverage from other carriers (whether drivers had previous regular insurance and whether they take up other coverage during the experiment). While I cannot access the third-party data sources, Hugo provides relevant derived information including the three-month premium (which embeds information from the driving record), whether the driver has previous regular coverage, and the number of days of the experiment an applicant had coverage from another carrier. For users offered the pay-as-you-go contract, Hugo translates the three-month premium to their daily premium and adjusts it if necessary based on their price treatment group.

I also receive transaction-level data for insurance purchases from Stripe, their payment processor, which I use to validate the administrative data on purchases and to observe failed transactions. Failed transactions include purchase attempts that were rejected due to insufficient funds, which provide one proxy for liquidity constraints.

To further supplement the administrative data from Hugo, I purchased credit report data from Experian and alternative credit reports tracking subprime borrowing from Clarity Services. These data include the standard bevy of credit-report measures including credit score, credit limits, inquiries, borrowing (including credit cards and auto loans), debt past-due, and debt in collections.

[24] I hired three contract workers on Mechanical Turk to use the vehicles' make, model, and year to look up the private, trade-in, and retail values of the vehicles using https://www.carfax.com/value/. After confirming all three completed the task, I take the median private resale value between the three recorded values.

Experian also provides an "Income Insight Score," an estimate of user income derived from a combination of proprietary and verified income data.[25] In the spirit of Miller and Soo (2020), I define users as "credit constrained" if they have outstanding balances equal to or exceeding their available credit or have no available credit (the 15 percent of applicants who do not have a credit report are coded as credit constrained).

Given all applicants apply for a pay-as-you-go insurance quote from Hugo, applicants may be less likely to take up a traditional contract offer even at the market rate (e.g., they may worry that a pay-as-you-go insurer may not provide the best traditional coverage). To address this concern, I obtain an indicator for whether applicants took up insurance through any other carrier (based on data they use for underwriting which they report covers more than 90% of the market) which provides a more comprehensive measure of coverage.

I define four different measures of insurance coverage, separately for coverage from Hugo Insurance (i.e., coverage through the experiment) and from any carrier (including through the experiment): (1) initial take-up; (2) the number of days the driver had coverage available; (3) the number of days insurance was active; and, (4) whether the driver was insured at the end of the three-month study period. To capture behavior over the full course of the pay-as-you-go contract, I consider the date of enrollment with Hugo Insurance as the start date for insurance outcomes within Hugo (purchases, activations, deactivations). Because users who do not take up insurance with Hugo do not have an enrollment date, I use the account creation date (the first time they arrived on the Hugo website) as the start date to align the experimental periods for outcomes that incorporate insurance coverage from other carriers. Take-up through Hugo Insurance is defined as any enrollment in a plan offered through the experiment. Take-up by any insurer is defined as within seven days of their account creation date.

Table 1 presents summary statistics on the sample of applicants. The average three-month premium is $232 which translates to an average daily premium of $4.27. Applicants are around 38 years old on average. Their vehicles are old (mean and median vehicle year of 2004) with low resale value (mean resale value of $1,877, median resale value of just $551). Appendix Table A4 compares summary statistics for the sample of applicants with a random sample of one million

[25] https://www.experian.com/consumer-information/income-insight

Table 1. Applicant Summary Statistics

	Mean	SD	Median
Panel A: Administrative Data Measures			
3-Month Premium	232	94.5	209
Daily Premium	4.27	1.83	3.83
Vehicle Resale Value	1,877	3,293	551
Vehicle Year	2,004	6.65	2,004
Age	37.8	10.4	36.6
N	1,537		
Panel B: Credit Report Measures			
Income Insight Score	37,452	15,625	34,000
Vantage Credit Score	515	127	532
Total Inquiries	5.5	6.82	3
Total Revolving Credit Limit	665	3,402	0
Credit Card Limit	497	2,969	0
Credit Card Balance	404	1,587	0
Is Credit Constrained	80.8	39.4	100
Has Auto Loan	35.5	47.9	0
Auto Loan Amount	1,788	5,866	0
Medical Collections	1,007	5,336	0
Non-Medical Collections	1,432	2,944	284
Non-Missing Credit Report	1,309		
Panel C: Alternative Credit Report Measures			
Clarity Total Inquiries	5.17	19	0
Clarity Credit Limit	84.8	717	0
Clarity Credit Balance	44.5	435	0
Non-Missing Alternative Credit Report	372		

Notes: The table presents the mean, standard deviation (SD), and median of each variable for the experiment sample of 1,537 drivers, split by data source. Measures of credit such as inquiries, limits, and balances are assumed to be zero if missing and summary statistics in Panels B and C include all applicants.

credit reports across the United States and the subset of 122,886 credit reports for individuals located in California. Mean and median Income Insight Scores for the sample of applicants are around $35,000, significantly lower than the mean national Income Insight Score of roughly $85,000. Drivers applying for coverage appear to have limited access to credit, with a mean credit score that is firmly subprime. 80.8 percent of applicants are credit constrained. The large number of inquiries (mean 5.5, median 3) suggests drivers are actively seeking additional sources of credit. Just 35.5 percent of the sample have an outstanding auto loan (with an average outstanding balance of $1,788), which is lower than the California mean of 51.6 and the national mean of 55.3.[26]

4 Results

4.1 The Effect of a Pay-As-You-Go Contract Offer on Insurance Coverage

The first hypothesis I test is whether the pay-as-you-go contract offer increases insurance coverage relative to a traditional contract offer. I regress measures of insurance coverage, y_i, defined above, on an indicator for whether the applicant was offered an pay-as-you-go contract, $\mathbb{1}\{PAYG_i\}$:

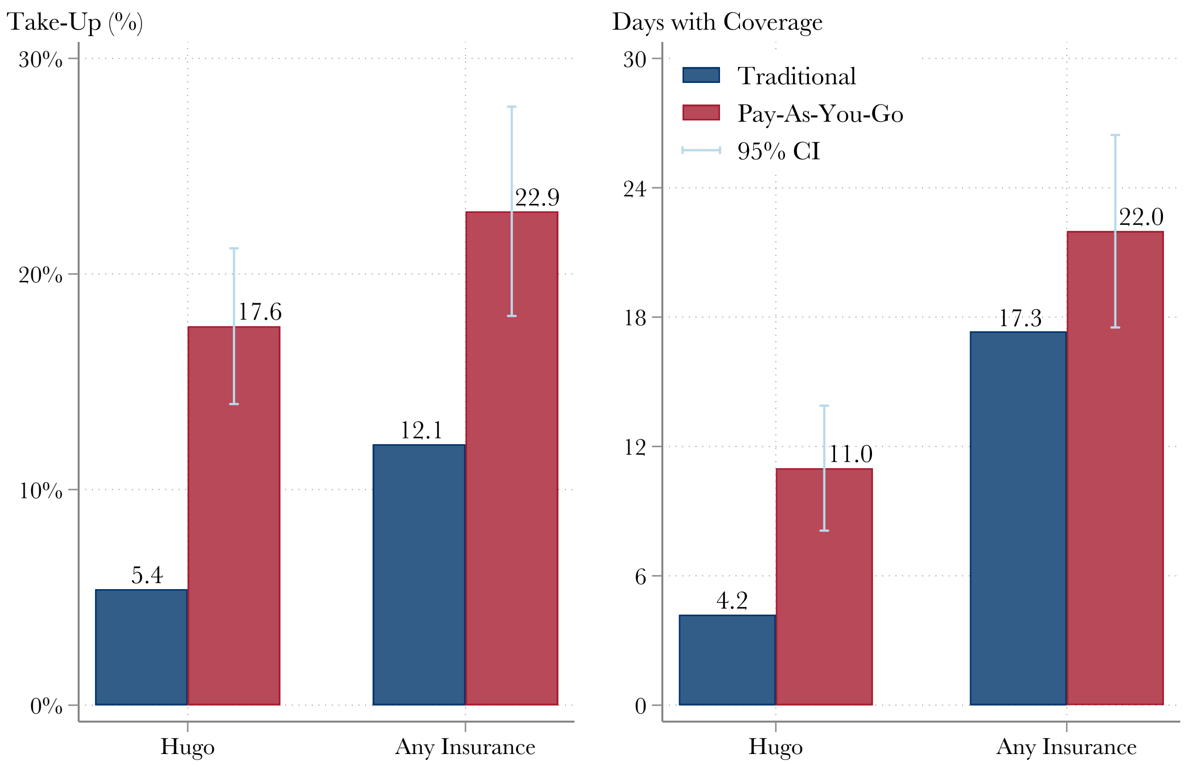
$$y_i = \alpha + \beta \mathbb{1}\{PAYG_i\} + \epsilon_i \tag{1}$$

Figure 2 plots estimates for take-up and days with coverage separately for coverage through the experiment and coverage from any carrier, along with 95 percent confidence intervals for the coefficient β estimated in equation 1. Offering users the pay-as-you-go contract has a large effect on initial take-up of insurance coverage: users offered the pay-as-you-go contract are 12.2 percentage points (227 percent) more likely to take-up insurance coverage from Hugo. ITT effects on take-up remain high when incorporating coverage through Hugo or any other carrier: 22.9 percent of applicants offered the pay-as-you-go plan took up insurance within seven days of their account creation, an 89 percent increase over the traditional contract offer. Patterns remain statistically and economically significant, though more muted, when analyzing the number of days with coverage. Applicants offered the pay-as-you-go plan have 4.6 more days with coverage available (27 percent) in the three months after the account creation date.

Table 2 adds days insured and whether drivers were insured at the end of the study as outcomes and displays the regression coefficients with robust standard errors in parentheses and p-values in

[26] While the vast majority of subprime auto loans are reported to credit bureaus, auto loans from small finance companies and small buy-here-pay-here dealerships appear on credit reports less than a quarter of the time. These lenders comprise a little under 20 percent of the market but loans made for low-value vehicles and more subprime consumers are less likely to be reported (Clarkberg et al., 2021). The data are consistent with applicants being less likely to have an active auto loan but the share of applicants who own their vehicles outright may be overstated if their auto loans are underreported to credit bureaus.

Figure 2. Effect of Pay-As-You-Go Contract Offer on Insurance Coverage



Notes: The figure presents the mean values of take-up and days with coverage through the experiment and from any carrier, separately for those offered the traditional and pay-as-you-go insurance contract. Error bars represent the 95 percent confidence interval of the treatment effect as estimated in equation 1.

brackets. Relative to days with coverage, days insured will include only days in which insurance was active and puts the pay-as-you-go contract at a particular disadvantage to the traditional contract which provides insurance every day regardless of whether the user drives. Nevertheless, it is informative in providing the actual days the driver is covered and the insurer is exposed to risk. Drivers offered the pay-as-you-go contract insure 0.6 additional days and this difference is not statistically significant. The coverage benefits of the pay-as-you-go contract are smaller by the end of the study, with applicants assigned the pay-as-you-go contract not statistically significantly more likely to be insured on average. Appendix Figure A3 plots the ITT effects by day of the experiment which visualizes this pattern. Drivers are more likely to be insured by Hugo throughout the full three months, but the gap is closed by the end of the experiment after accounting for coverage from other carriers.

Table 2. Effect of Pay-As-You-Go Contract Offer on Insurance Coverage

	Take-Up (1)	Days with Coverage (2)	Days Insured (3)	Insured End of Study (4)
Panel A: Insurance through Experiment				
Pay-As-You-Go	12.20	6.79	2.35	4.19
	(1.84)	(1.48)	(1.37)	(1.59)
	[0.000]	[0.000]	[0.085]	[0.008]
Constant	5.38	4.20	4.20	4.48
	(1.51)	(1.27)	(1.27)	(1.39)
	[0.000]	[0.001]	[0.001]	[0.001]
N	1,537	1,537	1,537	1,537
Mean	15.8	10	6.21	8.07
Panel B: Any Insurance				
Pay-As-You-Go	10.80	4.64	0.60	2.49
	(2.47)	(2.28)	(2.23)	(2.90)
	[0.000]	[0.042]	[0.788]	[0.391]
Constant	12.11	17.34	17.34	19.73
	(2.19)	(2.08)	(2.08)	(2.67)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,537	1,537	1,537	1,537
Mean	21.3	21.3	17.9	21.9

Notes: The table presents estimates from equation 1 of the effect of being offered a pay-as-you-go insurance contract on take-up (defined as accepting the quote at any time for coverage through the experiment and within seven days of receiving their Hugo quote for any insurance), days with coverage (days where users are covered or have nonzero coverage balance), days insured, and whether they were insured at the end of the three-month study period. The coefficients are listed with robust standard errors in parentheses and p-values in square brackets. The number of observations, N, and the mean of the dependent variable are also presented.

In Appendix Table A5, I test whether the ITT effects are robust to controlling for the full set of covariates in Table 1 and selecting covariates via post-double-Lasso (Belloni et al., 2014). The procedure does not find any consistent predictors of take-up other than the pay-as-you-go treatment assignment and the ITT estimates are stable across specifications.

There are several reasons the ITT estimates on insurance coverage may understate the potential benefits of pay-as-you-go contracts. First, the randomized control trial (RCT) coincided with the introduction of pay-as-you-go to the auto insurance market and frictions in this early version of the product – which opted to operate through SMS in order to reach even the lowest-income drivers who may not have smartphones – likely increased the transaction costs of maintaining coverage for drivers. Second, the pay-as-you-go contract bundled the "pause" and financing features of the contract. While both features have desirable properties as described in Section 2, they may differentially appeal to different customer segments and drive larger increases in insurance take-up when unbundled. As of December 2022, Hugo Insurance offers two different plans: one matching the features offered in the experiment and a separate plan that limits the "pause" feature to reduce the costs of the pay-as-you-go plan for frequent drivers. Finally, the prices offered in the RCT are a conservative test of the potential of pay-as-you-go and were marked up to reflect the uncertainty over consumer behavior under the pay-as-you-go contract. The mark-ups in the experiment vary between 33 and 100 percent (depending on price treatment group assignment) on a prorated day of traditional coverage; based consumer behavior in the experiment and in subsequent plans, the maximum mark-up currently charged by Hugo Insurance is 20 percent. An internal company survey found that high prices, especially among frequent drivers, was one of the most commonly cited reason for attrition.[27] As described in the next section, demand is significantly higher at lower prices so estimates of the pay-as-you-go contract at the prices featured in the experiment are likely to underestimate the potential for the contract to reduce uninsured driving.

The next two subsections will leverage the within-pay-as-you-go dimensions of the randomization (price and bundle discounts) to test the mediating role that price plays in demand for these contracts and to test demand for the smaller quantities of coverage offered when relative prices are higher.

4.2 Elasticity of Demand with Respect to the Price of a Day of Insurance

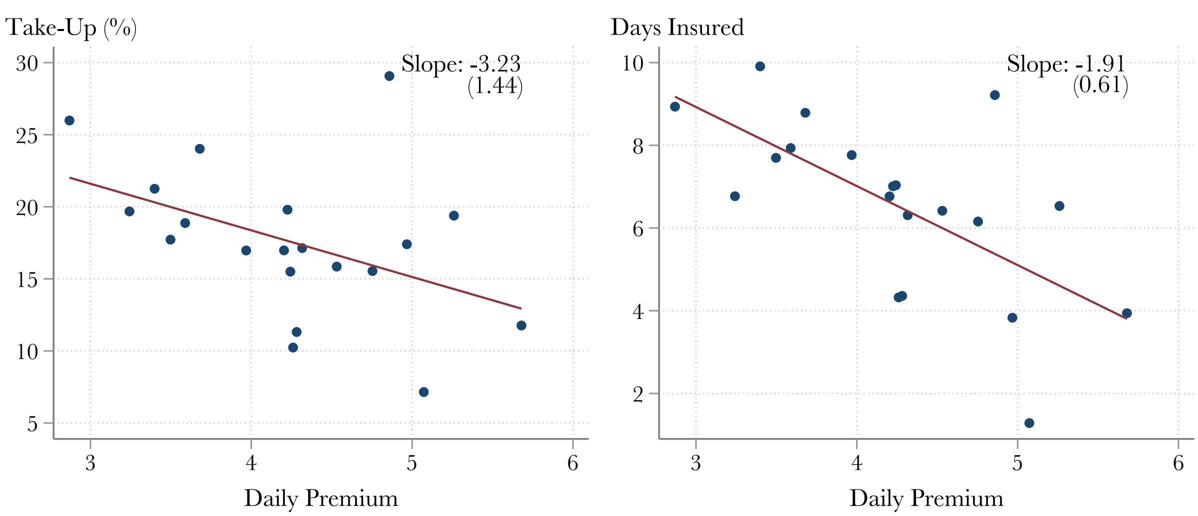
The market potential for the pay-as-you-go contract hinges on drivers' willingness-to-pay for this alternative contract structure. Given the financial situations of many uninsured drivers, the pay-as-you-go contract may be viable at lower prices but not higher prices. In this section, I use randomly induced variation to estimate the price sensitivity of demand for the pay-as-you-go contract.

[27] Hugo Insurance surveyed 36 drivers who churned before three months and categorized mutually exclusively reasons for attrition. 22 percent found cheaper coverage elsewhere, these were often "heavy drivers" who had no interest in deactivating their coverage. 19 percent got rid of their car, 33 percent needed full coverage (the pay-as-you-go contract was only offered as a minimum liability contract), 6 percent only needed insurance for a brief period, 11 percent had underwriting issues with the backing insurer forcing their cancellation, three percent moved to a different state, and the remaining 6 percent cancelled for unknown reasons.

In general, estimating demand for insurance is challenging: higher risk applicants face higher prices. Further, variation uncorrelated with applicant risk is rare and often relies on local discontinuities where it does exist (e.g., Finkelstein et al. (2019)). This experiment offers a rare opportunity to estimate demand using randomly varied prices *conditional on baseline risk premium* which, as displayed in Figure 1, exhibits substantial variation across applicants. The three-month premium is translated to a daily premium as described in Appendix A, then prices are increased by 20% for the high premium group, unchanged for the base group, and lowered by 20% for the low premium group. For this section and the next, I focus on outcomes within the pay-as-you-go contract because that is the level at which the price variation operates. I continue to present results for take-up but substitute days insured instead of days with coverage because that better reflects the effect of price on the decision to "spend" a day of coverage. To begin, I residualize the base premium and estimate the impact of price on these outcomes:

$$y_i = \beta_0 + \underbrace{\beta_1 p_{induced_i}}_{\text{Isolates randomly induced price variation}} + \underbrace{\beta_2 p_{base_i}}_{\text{Controls for risk premium}} + \epsilon_i. \tag{2}$$

Figure 3. Demand for Insurance by Induced Price Variation



Notes: The figure presents bin scatters of take-up rate and days insured over daily premium of the 1,325 drivers offered the pay-as-you-go contract, controlled for whether the user was offered a bundle discount as well as the daily premium faced by the user without experimental variation. The slope of the associated regression is presented in the top right corner with standard error in parentheses.

Both take-up and days insured decrease in price. Figure 3 presents binscatters of take-up and days of paid coverage against the induced variation in price (after residualizing the base premium). β_1 dictates the slope of the lines and is presented in the upper right-hand corner of each of panels. A one-dollar increase in the premium decreases take-up by 3.23 percentage points (19 percent off the pay-as-you-go mean take-up rate of 17.6) and days insured by 1.91 (29 percent off the pay-as-you-go mean days insured of 6.5).

To formalize the degree of price sensitivity and facilitate easy comparisons to other populations and settings, I also estimate the elasticity of demand for days of auto insurance coverage using the induced random variation in price. I analyze the same two outcome variables above with y_i representing the take-up rate of insurance and days insured (both defined using only coverage through Hugo). I take an inverse hyperbolic sine transformation of days insured to accommodate those who do not take up insurance. Appendix Table A6 presents $log(y_i)$ and $log(y_i + 1)$ as alternative transformations with similar results. Elasticity of demand estimates for days insured are presented separately for all applicants and only those who took-up coverage. I estimate

$$y_i = \beta_0 + \beta_1 log(p_{induced_i}) + \beta_2 log(p_{base_i}) + \beta_3 Bundle_i + \epsilon_i. \tag{3}$$

Table 3 presents the elasticity of demand estimates. A ten percent increase in the quoted daily premium for the pay-as-you-go contract decreases take-up of the contract by 1.27 percentage points. The price sensitivity of demand for the uninsured drivers in my sample is more pronounced when looking at how the number of days of insured respond to an increase in price: the elasticity of demand is -0.63 for all applicants and rises to -0.72 for drivers who enroll in the pay-as-you-go contract. Separate ITT regressions by price group, presented in Appendix Figure A5 and Appendix Table A7, show the strongest effects on coverage for the low price group with smaller effects on take-up and days with coverage for the base and high price treatment groups. Elasticity estimates are slightly more inelastic than other estimates of demand for auto insurance. Barone and Bella (2004), for example, find an average elasticity of demand for auto insurance across market segments of -1.1. This relatively inelastic demand could reflect the inaccessibility of alternative insurance contracts, particularly if they are poorly suited to the needs of these uninsured drivers due to large

Table 3. Demand for Insurance with respect to Induced Price Variation

	Take-Up	Take-Up, > 3	asinh(Days Insured)	
	(1)	(2)	(3)	(4)
log(Daily Premium)	-12.66	-13.65	-0.63	-0.72
	(6.61)	(5.32)	(0.27)	(0.34)
	[0.056]	[0.010]	[0.020]	[0.032]
log(Base Daily Premium)	4.99	3.20	0.24	0.17
	(7.18)	(5.71)	(0.29)	(0.35)
	[0.487]	[0.575]	[0.408]	[0.637]
Bundle Discount Offered	-1.23	-0.84	-0.05	-0.03
	(2.10)	(1.68)	(0.09)	(0.11)
	[0.557]	[0.618]	[0.559]	[0.814]
Constant	28.58	25.20	1.26	4.75
	(4.12)	(3.40)	(0.17)	(0.18)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,314	1,314	1,314	231
Sample	All	All	All	Enrolled

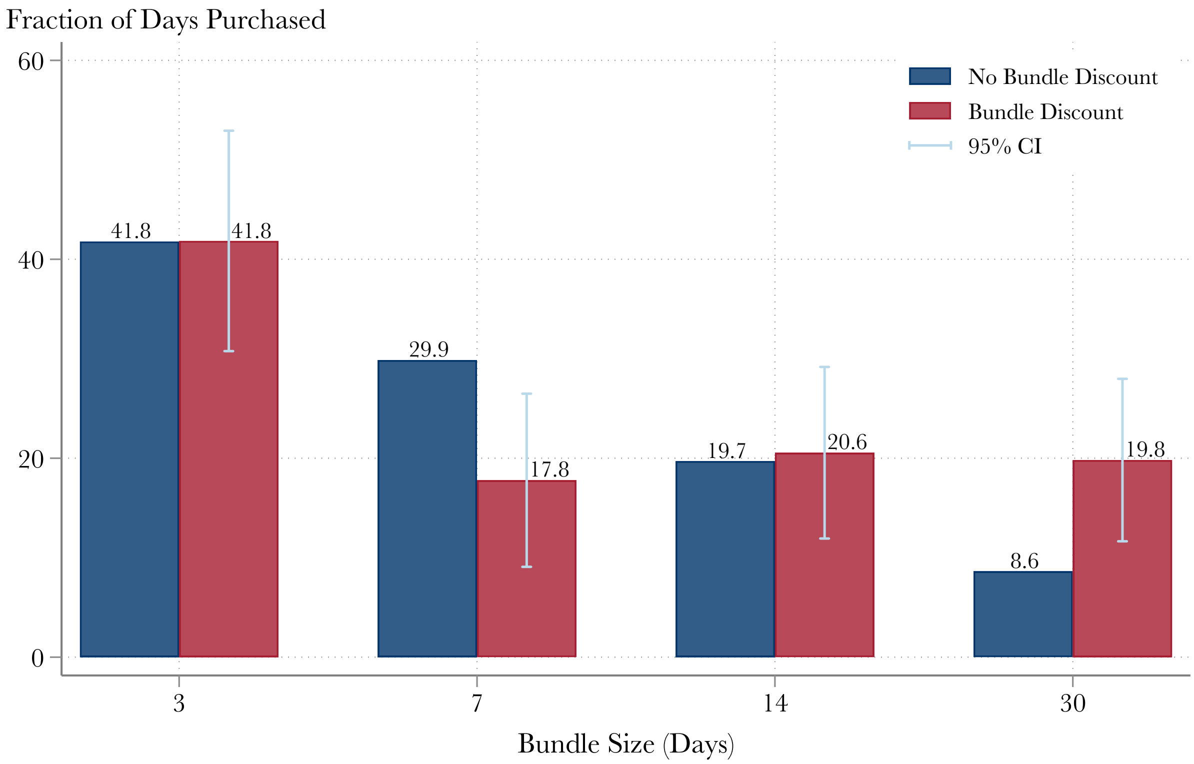
Notes: The table reports estimates of equation 3. The dependent variable in Column (1) is whether the driver took up coverage through the experiment, while Column (2) is whether the driver took up coverage through th experiment and purchased more than 3 days of insurance. Columns (3) and (4) estimate the inverse hyperbolic sine transformation of total days insured. The sample in columns (1) through (3) is restricted to drivers offered the pay-as-you-go contract, while the sample for Column (4) conditional on enrollment in the pay-as-you-go contract. The coefficients are reported along with robust standard errors in parentheses and p-values in square brackets.

minimum purchase amounts and high upfront liquidity requirements. I explore the relative demand for smaller quantities and lower liquidity requirements in the next subsection.

4.3 Demand for Smaller Quantities and Evidence of Liquidity Constraints

The pay-as-you-go contract provides consumers the option to smooth their consumption relative to typical payment cycles by purchasing smaller quantities over time. To explore the demand for this contract feature, I analyze the revealed preference for three or seven days relative to 14 or 30 days. I do this first for those offered the pay-as-you-go contract without the bundle discount who face the same price for small and large quantities. Next, I test whether preferences for smaller quantities persist even when applicants are offered a "bundle discount" for purchasing more days of insurance at a time. Drivers who forgo the bundle discounts reveal that they prefer to buy smaller quantities of insurance even when prices are higher, with the size of the bundle discounts designed such that forgoing them implies a lower bound of the cost of borrowing that is similar to a payday loan (see Appendix Table A2).

Figure 4. Quantities of Days Purchased by Bundle Discount Treatment



Notes: The figure plots the mean driver-level share of days purchased by the bundle size of the purchase, split by whether the driver was offered the bundle discount. Error bars represent the 95% confidence interval of the treatment effect of being offered the bundle discount on bundle size fraction.

There is high demand for smaller quantities of days when they are offered at the same price: 71.7 percent of days purchased are in bundles of three or seven days at a time on average among those who are not offered the bundle discount. Demand remains high even as the relative prices of smaller quantities are higher. Figure 4 plots the distribution of purchases in quantities of days by whether the driver was offered the bundle discount. Accompanying regression estimates of the ITT effect of the bundle discount offer are presented in Appendix Table A8. Bundles comprise 28.3 percent of days purchased on average for those offered the pay-as-you-go contract without the bundle discount and the discount increases the share of days purchased via the bundle by 12.0

percentage points. Nearly all of those induced by the discount to purchase the bundle would have counterfactually purchased seven (rather than three) days of coverage at a time: the share of days purchased in three-day quantities is 41.8 percent for *both* the no-discount and discount groups while the share of seven-day quantities purchased falls from 29.9 to 17.8 percent.

Drivers induced by the discount to purchase larger quantities of days are almost entirely drawn from those who would have counterfactually purchased seven (instead of three) days. This is consistent with those selecting three days having stronger demand for smaller quantities. Drivers who "comply" with the bundle discount treatment are more likely to access the largest discounts at 30 days than the 14-day bundle. Demand for the minimum, three-day purchases are remarkably stable and continue to comprise half of purchases even in the presence of the bundle discount.

Drivers may prefer smaller quantities of coverage because they are lower frequency drivers and do not expect to need many days of coverage, have a high degree of demand uncertainty, or because they face binding liquidity constraints. Drivers utilize the option to deactivate their coverage, doing so on 32.5 percent of days on average. Appendix Figure A4 plots daily user activity in the pay-as-you-go plan and regular activation/deactivation behavior is pervasive. Nevertheless, in the absence of liquidity constraints we would still expect to see nearly all drivers opting for the bundle discounts. Few drivers drive so infrequently that the three or seven days would cover their insurance needs over three months and any excess days that are not used are refundable at any moment at the driver's request.

To the extent the demand behavior in response to the bundle discount treatment is driven by liquidity constraints, it can inform the degree to which liquidity constraints may limit participation in auto insurance markets more broadly. Drivers who cannot afford an additional 5 (7 to 12 days), 9 (3 to 12), 17 (7 to 24), or 21 (3 to 24) days of coverage in order to access significant discounts are unlikely to be able to afford traditional insurance plans requiring semi-annual, quarterly, or monthly premium payments. I can use the share of drivers forgoing the bundle discount when it is available to them to provide an upper bound on drivers facing these kind of severe liquidity constraints. 77 percent of drivers with discounts available forgo the discount in at least one purchase, and 51 percent forgo them for all purchases. These can provide reasonable upper bounds on the share of uninsured drivers applying for coverage in my sample who are liquidity constrained, but could overstate the degree of liquidity constraints if drivers have a high degree of demand uncertainty or demand for driving itself is low. Forgoing the bundle discount is also consistent with a model where drivers decide to pursue additional consumption today at the expense of committing to additional insurance coverage in the future. If drivers are hyperbolic discounters, the consumption commitment aspect of traditional contracts could increase coverage despite barriers they present to market participation. I find no evidence that this contract rigidity is beneficial in my sample; drivers offered the traditional contract are slightly less likely to be insured at the end of the three-month experiment.

In addition to inferences from demand behavior, there is complementary evidence that speaks to a central role for binding liquidity constraints. First, it is useful to refer back to the credit report characteristics in Table 1. The mean and median credit scores of 515 and 532 are classified as "poor." Both are firmly in the bottom quintile of borrowers. 80.8 percent of applicants to Hugo have zero dollars of available credit on their reports and the high mean number of inquiries is suggestive of unmet demand for credit. These are strong indications that the uninsured drivers applying for coverage through Hugo are liquidity constrained.

Second, I can examine patterns of purchases by day of the week to see whether a disproportionate share of payments occur on Fridays when drivers are more likely to receive their paychecks. Appendix Figure A6 presents the share of insurance purchases made by day of the week. While this analysis is only suggestive, drivers are 43 percent more likely to make a purchase on a Friday which could suggest limited liquidity before payday.

Finally, I can leverage the Stripe data to observe attempted insurance purchases that failed due to insufficient funds as evidence akin to a "smoking gun" for liquidity constraints. 19 percent of drivers who enroll in a pay-as-you-go insurance plan have at least one attempted purchase fail for insufficient funds. 11.3 percent have an attempted debit transaction fail and 10.4 percent have an attempted purchase using a prepaid card fail. Insufficient funds bounces from a debit account present a clear indicator that they have near-zero dollars available in their bank account. Insufficient funds bounces from prepaid cards may be less of a "smoking gun" for liquidity constraints than failed debit transactions, but may indicate that these drivers are unbanked.

In either case, it is informative to track behavior after the failed transaction. 38 percent of insufficient funds failures are followed by another insufficient funds failure, 48 percent are followed by a successful payment, and 14 percent result in attrition from coverage (they are the user's last observable payment action); users with an insufficient payment notice as their last action make up 12% of those daily users who attrit. Successful payments following an insufficient funds failure occur on average three days after the failed transaction, suggesting that these are binding constraints that take time to alleviate (in contrast to, for example, trying another card immediately afterwards). Six percent of all drivers who enroll in pay-as-you-go coverage attrit following an insufficient funds failure.

4.4 Heterogeneous Effects of the Pay-As-You-Go Contract

Evidence presented so far shows that the pay-as-you-go contract increases market participation, but understanding which types of drivers are most responsive to the pay-as-you-go contract can enhance our understanding of both the mechanisms driving the results and for whom these contracts may be most beneficial. A key potential benefit of the contract is insuring marginal drivers who may not be well-served by traditional auto insurance contracts. Here I test whether these drivers, who do not have a history of regular policy coverage, respond differently to the contract offers than drivers who have regular insurance history.

To explore heterogeneity along this dimension, I interact the ITT regression with an indicator for whether the applicant has no regular policy history at the time of application (an indicator defined by Hugo as the absence of any record of completed insurance coverage of normal policy durations (e.g., multiples of three months)):

$$y_i = \alpha_0 + \beta_0 \mathbb{1}\{PAYG_i\} + \alpha_1 \mathbb{1}\{History_i\} + \beta_1 \mathbb{1}\{PAYG_i\} * \mathbb{1}\{History_i\} + \epsilon_i \tag{4}$$

Table 4 presents regression results for insurance take-up and coverage outcomes through any carrier. 70.2 percent of drivers applying for coverage through the experiment have no regular coverage policy history at the time of application. The results support the notion that these drivers have limited demand for traditional contracts: they are 7.2 percentage points (69 percent) less likely to take up the traditional contract than drivers with prior coverage history. The interaction effects suggest the pay-as-you-go contract effectively closes those baseline differences and differentially increases the take-up and coverage outcomes for drivers without prior coverage history, increasing take-up by an additional 8.2 percentage points and days with coverage by an additional 10.95 days. The interacted ITT regression is under-powered but p-values between 0.05 and 0.08 for these outcomes provides suggestive evidence that the pay-as-you-go contract may hold some promise for increasing insurance coverage among those who have historically struggled the most to stay insured.

Table 4. Effect of Pay-As-You-Go Contract Offer by Prior Coverage History

	Take-Up	Days with Coverage	Days Insured	Insured End of Study
	(1)	(2)	(3)	(4)
Pay-As-You-Go=1	6.43	3.15	-2.17	-2.59
	(4.20)	(5.42)	(3.33)	(4.71)
	[0.125]	[0.562]	[0.514]	[0.581]
No Regular Policy History=1	-7.24	-12.56	-6.08	-11.19
	(4.00)	(5.44)	(3.42)	(4.93)
	[0.070]	[0.021]	[0.076]	[0.023]
Pay-As-You-Go=1 × No Regular Policy History=1	8.24	10.95	6.47	10.35
	(4.60)	(6.02)	(3.58)	(5.33)
	[0.074]	[0.069]	[0.071]	[0.052]
Constant	10.45	20.90	8.45	25.17
	(3.74)	(4.97)	(3.21)	(4.39)
	[0.005]	[0.000]	[0.009]	[0.000]
N	1,537			
No Regular Policy History	70.2			

Notes: The table presents the intent-to-treat effect of being offered a pay-as-you-go insurance contract interacted with whether the driver has no regular policy history (defined as having either no past auto insurance history or exclusively auto insurance contracts that lapsed due to non-payment or early cancellation) per equation 4. The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets.

Given the results on the price sensitivity of demand and binding liquidity constraints, natural additional dimensions of heterogeneity to test are income and credit constraints. Appendix Table A9 presents results interacted with below-median income (defined using the Experian Income Insight Score) and whether the driver is credit constrained (defined as zero dollars of available credit on their credit report or a missing credit report). I find limited evidence of differential treatment effects along these dimensions, but this may reflect limited variation in the interaction variables (e.g., 80.8 percent of drivers are credit constrained) or attenuation bias from measurement error in the income measure.

5 Discussion

In this section, I contextualize the key results of the paper and briefly discuss their implications for pay-as-you-go insurance, the uninsured driver problem, and similar financial products.

The pay-as-you-go insurance contract operationalizes keys insights of recent theoretical work (Ericson and Sydnor, 2022; Rampini and Viswanathan, 2022), breaking the connection between financing and insurance by reducing lower upfront liquidity requirements to enroll in coverage, allowing drivers to retime their insurance premium payments to periods of higher liquidity, and enabling purchases of smaller quantities. The pay-as-you-go contract increases take-up and days with insurance coverage over the duration of the experiment. Coverage benefits of the contract erode over time but the ITT effects are likely to understate the steady-state potential of the contract for several reasons. First, the technology behind the product offered in the experiment was early-stage and required drivers to interact via text message or a website to top up their balance. Second, the contract bundled the pay-as-you-go financing features with the option to deactivate coverage, with concomitant mark-ups which made the contract less competitive for frequent drivers. Finally, pricing in the experiment was high (67 percent mark-up for the base price group, the maximum mark-up charged by Hugo Insurance as of December 2022 is 20 percent) and only offered minimum liability insurance coverage, which would not accommodate drivers interested in "graduating" to comprehensive coverage. As the technology matures, expands its contract offerings, and lowers prices, pay-as-you-go contracts may drive larger and more persistent increases in coverage than those estimated in this experiment.

Nevertheless, it is worth discussing the other factors contributing to the erosion of the ITT effect over time. To avoid attrition from coverage, drivers need to purchase additional days of insurance in the future. To the degree retiming insurance purchases from today to the future exposes drivers to income or expense shocks in the interim, this may limit the coverage benefits even as drivers may be better off by shifting consumption to meet more pressing needs.[28] Auto insurance may not be at the top of households' consumption hierarchy, particularly if they have limited assets to protect in

[28]This potential explanation is similar in spirit to Dobbie and Song (2020), who find that short-run liquidity relief for credit card borrowers (i.e., smaller payments due over a longer period of time) does not improve financial or labor market outcomes.

the event of an accident. Jack and Smith (2015, 2020) offer a complementary setting, pay-as-you-go contracts for utilities in South Africa, where liquidity constrained households also preferred to make frequent, small payments and decrease their electricity consumption, but become more profitable customers for the utility. In the Rampini and Viswanathan (2022) conceptualization of insurance as state-contingent savings, attrition from coverage may be a way of drawing down "savings" to afford other needs and indicate auto insurance is a lower consumption priority than, for example, utility bills.

High rates of uninsured driving have proven to be a difficult problem to solve. The tools used by policymakers to enforce insurance coverage may have limited scope to improve the problem: lowering minimum coverage limits in order to lower premiums (as California does with their Low Cost Auto Insurance program) further exposes drivers to financial risks in the event of a severe accident and steeper penalties for uninsured driving may be counterproductive if drivers are as liquidity constrained as those studied in this experiment. In other insurance markets where willingness-to-pay is lower than the cost of providing coverage (Finkelstein et al., 2019), we subsidize coverage for low-income individuals and this has proven to be more effective at increasing coverage than mandates (Frean et al., 2017).[29] Smith and Wright (1992) argue that auto insurance markets feature multiple equilibria: an efficient full-insurance equilibrium and inefficient high-price equilibrium with many uninsured drivers can simultaneously exist, suggesting there may be large benefits of increasing insurance enrollment if it helps shift to the full-insurance equilibrium. From the insurer's perspective, high costs of customer acquisition and high rates of attrition make providing minimum coverage an expensive business with significant administrative loads which necessitates high fees and upfront liquidity requirements to defray costs. Insurance technology has the potential to automate these processes and the contract offered in this experiment provides one example of how insurers may handle attrition and re-enrollment in the future.

Consumer behavior under the pay-as-you-go contract has implications for similar financial technology products like buy-now-pay-later and earned wage access. Reducing upfront payment requirements (a feature of pay-as-you-go and buy-now-pay-later) increases market participation. As evi-

[29]The optimal level of subsidies is beyond the scope of the paper and would depend on the value of insurance coverage to the insured, the externality on the insured, and any driving externalities (could be positive or negative depending on whether economic benefits of driving offset any increased emissions and congestion).

denced by the larger effects observed by those who have no history of insurance coverage, they may increase participation most among consumers who have not previously participated. The erosion of the increases in coverage over the course of the experiment may suggest that – in the absence of subsidies or policies addressing the financial precarity of uninsured drivers – contract structure alone may not be sufficient to address affordability challenges. More broadly, technologies that enable consumers to smooth consumption can alleviate short-run constraints and increase consumption (in this application, increasing insurance coverage from suboptimally low levels), but may be harmful if they facilitate more discretionary purchases and users are present-biased.[30] Nevertheless, the insurance technology studied here exhibits exciting potential to reduce administrative loads, reduce transaction costs and fees, and better tailor financial contract structures to help drivers, who would otherwise be uninsured, afford coverage.

6 Conclusion

I study the introduction of a novel pay-as-you-go insurance contract to the California auto insurance market. Drivers randomly offered the contract increase their insurance take-up by 10.8 percentage points (89 percent) and days insured by 4.6 days (27 percent) relative to a traditional contract, with smaller effects by the end of the three-month experiment. Demand is relatively price inelastic. Applicants for the pay-as-you-go contract are severely credit constrained based on their credit reports, and more than half of drivers exhibit demand behavior consistent with a shadow cost of borrowing at least as high as a payday loan. There is strong demand for quantities of coverage smaller than those available in the market (before the introduction of the pay-as-you-go contract) and this demand persists for most drivers even when relative prices are higher. There is suggestive evidence that the benefits of the pay-as-you-go contract increases take-up and days insured more for drivers who have historically struggled to stay insured, indicating that the smaller minimum payments enabled by pay-as-you-go contracts increase market participation among those who are least well-served by the traditional contracts available.

[30] Di Maggio et al. (2022) argue consumer behavior under buy-now-pay-later products are consistent with a "liquidity flypaper effect" in which the liquidity "sticks where it hits." The results in this paper suggest that encouraging financial product innovation in markets where there is underconsumption relative to optimal levels could be beneficial.

References

Adams, William, Liran Einav, and Jonathan Levin, "Liquidity Constraints and Imperfect Information in Subprime Lending," *American Economic Review*, February 2009, *99* (1), 49–84.

Aker, Jenny C and Isaac M Mbiti, "Mobile Phones and Economic Development in Africa," *Journal of Economic Perspectives*, 2010, *24* (3), 207–32.

Attanasio, Orazio and Elena Pastorino, "Nonlinear Pricing in Village Economies," *Econometrica*, 2020, *88* (1), 207–263.

Baker, Scott, Stephanie Johnson, and Lorenz Kueng, "Financial Returns to Household Inventory Management," Working Paper w27740, National Bureau of Economic Research 2020.

Barone, Guglielmo and Mariano Bella, "Price-Elasticity Based Customer Segmentation in the Italian Auto Insurance Market," *Journal of Targeting, Measurement and Analysis for Marketing*, 2004, *13* (1), 21–31.

Baum, Charles L, "The Effects of Vehicle Ownership on Employment," *Journal of Urban Economics*, 2009, *66* (3), 151–163.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen, "Inference on treatment effects after selection among high-dimensional controls," *The Review of Economic Studies*, 2014, *81* (2), 608–650.

Berkouwer, Susanna B and Joshua T Dean, "Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households," *American Economic Review*, 2022, *112* (10), 3291–3330.

Bordoff, Jason E and Pascal J Noel, "Pay-As-You-Drive Auto Insurance: A Simple Way to Reduce Driving-Related Harms and Increase Equity," *Brookings Institution Discussion Paper*, July 2008, p. 58.

California Department of Insurance, "California's Low Cost Auto Insurance Program," 2021. http://www.insurance.ca.gov/01-consumers/105-type/95-guides/01-auto/lca/, last accessed September 22, 2021.

Casaburi, Lorenzo and Jack Willis, "Time versus State in Insurance: Experimental Evidence from Contract Farming in Kenya," *American Economic Review*, December 2018, *108* (12), 3778–3813.

Chen, Brian X., "Prepaid Cellphones Are Cheaper. Why Aren't They Popular?," *New York Times*, August 2012.

Clarkberg, Jasper, Jack Gardner, and David Low, "Data Point: Subprime Auto Loan Outcomes by Lender Type," Data Point No. 2021-10, Consumer Financial Protection Bureau September 2021.

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery, "Barriers to Household Risk Management: Evidence from India," *American Economic Journal: Applied Economics*, January 2013, *5* (1), 104–135.

Consumer Federation of America, "Auto Insurers Fail to Reward Low Mileage Drivers," 2015. https://consumerfed.org/press_release/auto-insurers-fail-to-reward-low-mileage-drivers/, last accessed September 21, 2021.

Di Maggio, Marco, Justin Katz, and Emily Williams, "Buy Now, Pay Later Credit: User Characteristics and Effects on Spending Patterns," Working Paper w30508, National Bureau of Economic Research September 2022.

Dobbie, Will and Jae Song, "Targeted Debt Relief and the Origins of Financial Distress: Experimental Evidence from Distressed Credit Card Borrowers," *American Economic Review*, April 2020, *110* (4), 984–1018.

Edlin, Aaron S, "Per-Mile Premiums for Auto Insurance," Working Paper w6934, National Bureau of Economic Research February 1999.

Ericson, Keith Marzilli and Justin Sydnor, "Liquidity Constraints and the Value of Insurance," Working Paper w24993, National Bureau of Economic Research December 2022.

Finkelstein, Amy, Nathaniel Hendren, and Mark Shepard, "Subsidizing Health Insurance for Low-Income Adults: Evidence from Massachusetts," *American Economic Review*, April 2019, *109* (4), 1530–1567.

Frean, Molly, Jonathan Gruber, and Benjamin D Sommers, "Premium Subsidies, the Mandate, and Medicaid Expansion: Coverage Effects of the Affordable Care Act," *Journal of Health Economics*, 2017, *53*, 72–86.

Gross, Tal, Matthew J Notowidigdo, and Jialan Wang, "Liquidity Constraints and Consumer Bankruptcy: Evidence from Tax Rebates," *Review of Economics and Statistics*, 2014, *96* (3), 431–443.

Insurance Research Council, "The Potential Effects of No Pay, No Play Laws," *Industry Report*, 2012.

—, "One in Eight Drivers Uninsured," *News Release*, 2021. https://www.insurance-research.org/sites/default/files/downloads/UM%20NR%20032221.pdf, last accessed September 20, 2021.

Jack, Kelsey and Grant Smith, "Pay as You Go: Prepaid Metering and Electricity Expenditures in South Africa," *American Economic Review: Papers and Proceedings*, May 2015, *105* (5), 237–241.

— **and** —, "Charging Ahead: Prepaid Metering, Electricity Use, and Utility Revenue," *American Economic Journal: Applied Economics*, 2020, *12* (2), 134–68.

Jin, Yizhou and Shoshana Vasserman, "Buying Data from Consumers: The Impact of Monitoring Programs in U.S. Auto Insurance," Working Paper w29096, National Bureau of Economic Research 2021.

Kalba, Kas, "The Adoption of Mobile Phones in Emerging Markets: Global Diffusion and the Rural Challenge," *International Journal of Communication*, 2008, *2*, 31.

Karlan, Dean S and Jonathan Zinman, "Credit Elasticities in Less-Developed Economies: Implications for Microfinance," *American Economic Review*, May 2008, *98* (3), 1040–1068.

Kluender, Raymond, "Prepaid Auto Insurance Contracts and Willingness-to-Pay for Lower Liquidity Requirements.," AEA RCT Registry #002537 July 2019.

Megna, Michelle, "Do You Need a Car Insurance Down Payment?," 2021. https://www.insurance.com/auto-insurance/auto-insurance-basics/car-insurance-down-payment.html#Is_there_no_down_payment_car_insurance, last accessed May 6, 2022.

Miller, Sarah and Cindy K Soo, "Does Increasing Access to Formal Credit Reduce Payday Borrowing?," Working Paper w27783, National Bureau of Economic Research September 2020.

New Hampshire Department of Motor Vehicles, "Insurance Requirements/SR-22," 2021. https://www.nh.gov/safety/divisions/dmv/financial-responsibility/insurance.htm, last accessed September 21, 2021.

Rampini, Adriano A. and S. Viswanathan, "Financing Insurance," Working Paper July 2022.

Smith, Eric and Randall Wright, "Why is Automobile Insurance in Philadelphia So Damn Expensive?," *The American Economic Review*, 1992, *82* (4), 756–772.

Sun, Stephen (Teng) and Constantine Yannelis, "Quantifying the Premium Externality of the Uninsured," *Journal of the European Economic Association*, April 2016, *14* (2), 405–437.

Value Penguin, "What to Do if You're Denied Auto Insurance (And Why You Were Denied)," 2021. https://www.valuepenguin.com/denied-auto-insurance-reasons-what-to-do, last accessed September 21, 2021.

Vickrey, William, "Automobile Accidents, Tort Law, Externalities, and Insurance: An Economist's Critique," *Law and Contemporary Problems*, 1968, *33*, 464–487.

Virginia Department of Motor Vehicles, "Insurance Requirements," 2021. https://www.dmv.virginia.gov/vehicles/#insurance.asp, last accessed August 16, 2021.

Walls, Andrea, "Nonstandard Auto Insurance Market Is Not For Everybody," 2015. https://www.insurancejournal.com/news/national/2015/04/13/364065.htm, last accessed February 28, 2018.

A Insurance Premium Regulations and Pay-As-You-Go Pricing

A.1 Insurance Regulations

All drivers in the experiment apply for minimum liability insurance coverage. In California, this requires $15,000 of coverage for bodily injury to a single person, $30,000 for multiple people, and $5,000 of coverage for property damage. Premium pricing is heavily regulated and insurers are required to have their rate filings approved by the Department of Insurance. As dictated by Proposition 103, auto insurance in California must be priced primarily on three mandatory rating factors, with a number of additional optional rating factors also affecting premiums. The three mandatory rating factors are driver safety record, annual mileage, and years of driving experience. Driver safety record is a mapping of minor violations, major violations, and at-fault accidents to negative points with an associated pricing premium over a driver with a clean record. In practice, because it is difficult to verify, annual mileage is rarely priced and insurance carriers typically default drivers into a single rating bin until they can verify their mileage.

A.2 Experiment Premium Pricing

All insurance applicants are priced by the backing insurance company. Applicants assigned to the control group are offered the three-month market-rate minimum-liability-coverage contract.

Applicants assigned to one of the pay-as-you-go treatment groups had their three-month premium translated to a daily premium. In order to set the pay-as-you-go premium for a single day, Hugo estimates how the exposure that is underwritten for longer-term risk (e.g., 3, 6, or 12 months) is distributed across the days which drivers choose to insure using information from, for example, the 2017 National Household Transportation Survey (NHTS). The NHTS includes demographic and household information about drivers, as well as a "travel diary" for a specified day in which individuals log all of their transportation trips throughout the day. Taking into account the share of miles respondents report driving on days they report driving as a share of their reported annual mileage among other factors, the daily premium is set at roughly 1.85 percent of the three-month premium to reflect estimated risk exposure. This results in a daily premium 1.67 times the prorated traditional premium. For example, a three-month premium of $176.72 is translated to a daily premium of $3.26.

Another way to consider the mark-up on the daily pay-as-you-go insurance premium is that it incorporates some of the fee revenues that are collected by traditional non-standard auto insurance carriers and embeds them in a salient way into the premium offered to the consumer. These carriers charge fees equivalent to 13 percent of their net earned premium revenue in large part to cover the costs associated with servicing these transaction-heavy consumers. The mark-ups on the pay-as-you-go contract can also be thought of as reflecting the way it embeds activation, deactivation, and temporary cancellations into the structure of the contract.

A.3 Notification of Coverage Expiration

Regulation requires insurers to notify drivers when their contract is 30 days from expiration. Notifying drivers that their coverage is expiring and not presenting them with the option to renew (because the experiment was limited to three months) may drive some early attrition, which would lead to an underestimate of the effect of the pay-as-you-go contract on insurance coverage. Appendix Table A10 shows the results for the first two months. ITT estimates on days with coverage defined over two months are larger (proportionally) and more significant–those offered the pay-as-you-go contract have 5.4 more days with coverage through Hugo (190 percent) and 4.3 more days with coverage overall (41 percent)–but there is no effect on coverage at two months after factoring in coverage from other carriers. While the three-month outcomes may be somewhat biased downward due to the notification that coverage was expiring, I present the full three-month outcomes as the primary results because I cannot detect whether attrition was driven by the notification or other causes and it seems unlikely the notification is the primary driver of attrition.

B Appendix Tables

Table A1. Uninsured Driving Rate by State

State	Share Uninsured	State	Share Uninsured
Alabama	19.5%	Montana	8.5%
Alaska	16.1%	Nebraska	9.3%
Arizona	11.8%	Nevada	10.4%
Arkansas	19.3%	New Hampshire	6.1%
California	16.6%	New Jersey	3.1%
Colorado	16.3%	New Mexico	21.8%
Connecticut	6.3%	New York	4.1%
Delaware	8.5%	North Carolina	7.4%
Florida	20.4%	North Dakota	13.0%
Georgia	12.4%	Ohio	13.0%
Hawaii	9.3%	Oklahoma	13.4%
Idaho	13.2%	Oregon	10.7%
Illinois	11.8%	Pennsylvania	6.0%
Indiana	15.8%	Rhode Island	16.5%
Iowa	11.3%	South Carolina	10.9%
Kansas	10.9%	South Dakota	7.4%
Kentucky	13.9%	Tennessee	23.7%
Louisiana	11.7%	Texas	8.3%
Maine	4.9%	Utah	6.5%
Maryland	14.1%	Vermont	8.8%
Massachusetts	3.5%	Virginia	10.5%
Michigan	25.5%	Washington	21.7%
Minnesota	9.9%	West Virginia	9.2%
Missippi	29.4%	Wisconsin	13.3%
Missouri	16.4%	Wyoming	5.8%
United States	12.6%		

Notes: The table presents the estimated share of uninsured drivers by state according to Insurance Research Council (2012).

Table A2. Cost of Borrowing Implied by Forgoing Bundle

	Days Purchased			
	3	7	14	30
APR Implied by Forgoing 14-Day Bundle (%)	498	1,409	0	0
APR Implied by Forgoing 30-Day Bundle (%)	261	378	514	0

Notes: The table presents the lower bound on the cost of credit implied by forgoing the bundle discount when purchasing the number of days indicated by each column. The calculation assumes the size of the loan is the difference in the amount required to purchase 14 or 30 days versus the smaller quantity, the implied interest is the foregone savings, and the duration is the difference in the number of days purchased divided by the average utilization rate of 67.5% (defined as the share of days with nonzero reserve balance that insurance is active).

Table A3. Balance Table: Pay-As-You-Go vs. Traditional

	Pay-As-You-Go		Traditional		
	Mean/SD	N	Mean/SD	N	Diff/SE
3-Month Premium	230	1,314	238	223	7.54
	(94.9)		(91.8)		(6.84)
Daily Premium	4.24	1,314	4.39	223	.15
	(1.85)		(1.7)		(.13)
Vehicle Resale Value	1,940	1,278	1,507	216	-432
	(3,419)		(2,382)		(242)
Vehicle Year	2,004	1,314	2,004	223	-.231
	(6.68)		(6.48)		(.48)
Age	37.7	1,314	37.8	223	.079
	(10.4)		(10.9)		(.76)
Income Insight Score	37,414	1,081	37,665	194	251
	(15,766)		(14,853)		(1,219)
Vantage Credit Score	514	1,112	522	197	8.49
	(129)		(113)		(9.82)
Total Inquiries	5.55	1,314	5.24	223	-.307
	(6.83)		(6.76)		(.49)
Total Revolving Credit Limit	808	1,112	629	197	-179
	(3,841)		(2,539)		(284)
Credit Card Limit	625	1,112	350	197	-275
	(3,422)		(1,516)		(248)
Credit Card Balance	464	1,112	532	197	67.9
	(1,647)		(2,038)		(132)
Is Credit Constrained	81	1,314	79.8	223	-1.15
	(39.3)		(40.2)		(2.85)
Has Auto Loan	42	1,112	40.1	197	-1.9
	(49.4)		(49.1)		(3.81)
Auto Loan Amount	2,090	1,112	2,156	197	66.9
	(6,065)		(7,538)		(488)
Medical Collections	1,158	1,112	1,319	197	160
	(5,498)		(7,095)		(446)
Non-Medical Collections	1,720	1,112	1,465	197	-254
	(3,242)		(2,349)		(242)
Omnibus F-Statistic					1.4
p-value					0.132

Notes: The balance table presents mean, standard deviation, and sample size for each variable split by whether drivers were offered the pay-as-you-go or traditional contract. The final column presents differences in means and standard errors. The F-statistic tests for joint significance of differences in the variables between groups.

Table A4. Credit Summary Statistics

	Hugo		CA Sample		US Sample	
	Mean/SD	N	Mean/SD	N	Mean/SD	N
Panel A: Experian						
Income Insight Score	37,452	1,275	93,980	120,717	84,442	986,011
	(15,625)		(85,896)		(67,602)	
Vantage Credit Score	515	1,309	679	122,886	674	1,000,000
	(127)		(143)		(138)	
Total Inquiries	6.46	1,309	2.39	122,886	2.09	1,000,000
	(6.95)		(3.34)		(3.05)	
Total Revolving Credit Limit	781	1,309	22,490	122,886	19,582	1,000,000
	(3,675)		(56,745)		(42,616)	
Credit Card Limit	584	1,309	15,288	122,886	13,475	1,000,000
	(3,210)		(26,663)		(23,879)	
Credit Card Balance	475	1,309	3,683	122,886	3,511	1,000,000
	(1,711)		(8,313)		(7,950)	
No Available Credit	77.5	1,309	28.1	122,886	31	1,000,000
	(41.8)		(44.9)		(46.3)	
Has Auto Loan	41.7	1,309	51.6	122,886	55.3	1,000,000
	(49.3)		(50)		(49.7)	
Auto Loan Amount	2,100	1,309	5,706	122,886	6,184	1,000,000
	(6,305)		(12,415)		(12,896)	
Medical Collections	1,183	1,309	294	122,886	388	1,000,000
	(5,764)		(3,116)		(2,967)	
Non-Medical Collections	1,681	1,309	348	122,886	374	1,000,000
	(3,124)		(2,223)		(1,819)	
Reports		1,309		122,886		1,000,000
Panel B: Clarity						
Clarity Total Inquiries	5.7	1,309	.77	122,886	.84	1,000,000
	(19.7)		(5.68)		(6.16)	
Clarity Credit Limit	97.2	1,309	72.9	122,886	88.3	1,000,000
	(775)		(886)		(1,051)	
Clarity Credit Balance	49.8	1,309	34.8	122,886	48.8	1,000,000
	(467)		(574)		(708)	
Reports		348		12,816		112,092

Notes: The table presents mean, standard deviation, and sample size for the credit variables for the 1,309 drivers in the experiment with a non-missing credit report and a random sample of 1,000,000 credit reports. The California sample of 122,886 credit reports is a subset of the random sample. Measures of credit such as inquiries, limits, and balances are assumed to be zero if missing for the Clarity variables and summary statistics in Panel B include the full sample from Panel A.

Table A5. Intent-to-Treat Effects: Robustness to Controls

	(1)	(2)	(3)
Panel A: Take-Up through Experiment			
Pay-As-You-Go	12.20	12.82	12.44
	(1.84)	(2.08)	(2.02)
	[0.000]	[0.000]	[0.000]
N	1,537	1,239	1,239
Controls Method	None	All	Plug-in LASSO
Selected Controls			1
Panel B: Take-Up Any Insurance			
Pay-As-You-Go	10.80	10.09	10.30
	(2.47)	(2.85)	(2.80)
	[0.000]	[0.000]	[0.000]
N	1,537	1,239	1,239
Controls Method	None	All	Plug-in LASSO
Selected Controls			0
Panel C: Days with Coverage through Experiment			
Pay-As-You-Go	6.79	7.40	7.38
	(1.48)	(1.72)	(1.67)
	[0.000]	[0.000]	[0.000]
N	1,537	1,239	1,239
Controls Method	None	All	Plug-in LASSO
Selected Controls			0
Panel D: Days with Any Coverage			
Pay-As-You-Go	4.64	4.77	4.37
	(2.28)	(2.61)	(2.56)
	[0.042]	[0.068]	[0.087]
N	1,537	1,239	1,239
Controls Method	None	All	Plug-in LASSO
Selected Controls			0

Notes: The table presents ITT estimates with each column presenting a different approach to controls; the constant is not presented. Column (1) presents the estimate with no controls (as presented in Table 2), Column (2) presents the estimate including all variables presented in Table 1 (excluding daily premium), and Column (3) presents the output of a double-selection LASSO using 'Plug-in' selection of the penalization coefficient. The LASSO selection process selects variables independently in each regression; the number of control variables selected is presented. The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets.

Table A6. Elasticity of Demand: Robustness to Alternative Transforms

	log(Days Insured)			asinh(Days Insured)		log(Days Insured + 1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Daily Premium)	-0.65						
	(0.37)						
	[0.083]						
log(Base Daily Premium)	0.12						
	(0.37)						
	[0.745]						
asinh(Daily Premium)		-0.69		-0.77	-0.66		
		(0.39)		(0.35)	(0.28)		
		[0.079]		[0.031]	[0.019]		
asinh(Base Daily Premium)		0.14		0.19	0.25		
		(0.39)		(0.37)	(0.30)		
		[0.721]		[0.616]	[0.405]		
log(Daily Premium + 1)			-0.87			-0.93	-0.70
			(0.48)			(0.40)	(0.29)
			[0.071]			[0.022]	[0.015]
log(Base Daily Premium + 1)			0.19			0.24	0.28
			(0.47)			(0.42)	(0.31)
			[0.686]			[0.568]	[0.370]
Bundle Discount Offered	-0.05	-0.05	-0.05	-0.03	-0.05	-0.02	-0.04
	(0.12)	(0.12)	(0.12)	(0.11)	(0.09)	(0.10)	(0.07)
	[0.692]	[0.692]	[0.698]	[0.814]	[0.561]	[0.866]	[0.577]
Constant	4.02	4.45	4.38	5.19	1.57	4.44	1.29
	(0.20)	(0.31)	(0.29)	(0.28)	(0.25)	(0.24)	(0.20)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	231	231	231	231	1,314	231	1,314

Notes: The table reports estimates of equation 3. Columns (1)-(3) report estimates using the natural log, Columns (4) and (5) report estimates using the inverse hyperbolic sine transform, and Columns (6) and (7) report estimates using a log(x + 1) transform. The same transforms are applied to the dependent variables in each Column. Columns (5) and (7) estimate elasticities for all drivers offered the pay-as-you-go contract. Columns (4) and (6) estimate elasticities for drivers who enrolled in the pay-as-you-go contract. The coefficients are reported along with robust standard errors in parentheses and p-values in square brackets.

Table A7. Intent-to-Treat Effects by Price Treatment Group

	Take-Up (1)	Days with Coverage (2)	Days Insured (3)	Insured End of Study (4)
Panel A: Insurance through Experiment				
PAYG, Low Price	16.06	9.43	4.40	6.24
	(2.50)	(1.92)	(1.61)	(2.04)
	[0.000]	[0.000]	[0.006]	[0.002]
PAYG, Base Price	9.31	4.86	1.55	2.75
	(2.25)	(1.72)	(1.50)	(1.84)
	[0.000]	[0.005]	[0.302]	[0.136]
PAYG, High Price	11.40	6.21	1.15	3.67
	(2.36)	(1.81)	(1.48)	(1.92)
	[0.000]	[0.001]	[0.437]	[0.056]
Constant	5.38	4.20	4.20	4.48
	(1.51)	(1.28)	(1.28)	(1.39)
	[0.000]	[0.001]	[0.001]	[0.001]
N	1,537	1,537	1,537	1,537
Panel B: Any Insurance				
PAYG, Low Price	14.00	6.96	2.41	4.51
	(3.05)	(2.68)	(2.54)	(3.38)
	[0.000]	[0.009]	[0.342]	[0.182]
PAYG, Base Price	6.75	2.14	-0.95	0.88
	(2.85)	(2.56)	(2.45)	(3.27)
	[0.018]	[0.404]	[0.699]	[0.787]
PAYG, High Price	11.90	4.99	0.43	2.18
	(3.01)	(2.65)	(2.51)	(3.33)
	[0.000]	[0.060]	[0.864]	[0.513]
Constant	12.11	17.34	17.34	19.73
	(2.19)	(2.08)	(2.08)	(2.67)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,537	1,537	1,537	1,537

Notes: The table presents estimates of the effect of being offered a pay-as-you-go insurance contract on take-up (defined as accepting the quote at any time for coverage through the experiment and within seven days of receiving their Hugo quote for any insurance), days with coverage (days where users are covered or have nonzero coverage balance), days insured, and whether they were insured at the end of the three-month study period. Here, the indicator for treatment from equation 1 is replaced with separate indicators for being offered the pay-as-you-go contract at each price level (Low, Base, or High). The coefficients are listed with robust standard errors in parentheses and p-values in square brackets.

Table A8. ITT Effect of Bundle Discount Treatment on Quantities of Days Purchased

	3-Day (1)	7-Day (2)	14-Day (3)	30-Day (4)	Either Bundle (5)
Panel A: All Purchases					
Bundle Discount	0.06	-12.08	0.84	11.18	12.02
	(5.62)	(4.42)	(4.38)	(4.14)	(5.45)
	[0.992]	[0.007]	[0.848]	[0.007]	[0.028]
Constant	41.79	29.87	19.71	8.63	28.34
	(3.81)	(3.39)	(2.94)	(2.35)	(3.52)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Users	231	231	231	231	231
Mean Share	41.82	24.01	20.12	14.05	34.17
Days Purchased	5,973	5,973	5,973	5,973	5,973
Panel B: First Purchase					
Bundle Discount	0.68	-8.72	-3.20	11.24	8.04
	(6.47)	(5.87)	(5.13)	(4.55)	(6.18)
	[0.916]	[0.139]	[0.533]	[0.014]	[0.195]
Constant	39.50	31.93	20.17	8.40	28.57
	(4.50)	(4.29)	(3.69)	(2.55)	(4.16)
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
Users	231	231	231	231	231
Mean Share	39.83	27.71	18.61	13.85	32.47
Days Purchased	2,286	2,286	2,286	2,286	2,286
Panel C: Follow-On Purchases					
Bundle Discount	-5.77	-10.33	7.80	8.30	16.10
	(7.20)	(4.96)	(5.86)	(4.46)	(6.67)
	[0.424]	[0.039]	[0.185]	[0.065]	[0.017]
Constant	52.35	24.53	17.15	5.97	23.12
	(4.81)	(3.81)	(3.72)	(2.39)	(4.20)
	[0.000]	[0.000]	[0.000]	[0.013]	[0.000]
Users	151	151	151	151	151
Mean Share	49.71	19.82	20.72	9.76	30.48
Days Purchased	3,687	3,687	3,687	3,687	3,687

Notes: The table reports the ITT effect of offering the bundle discount on the fraction of days purchased through each bundle size (Columns (1) through (4)) and whether the purchase is a bundle (Column (5)), separately by all purchases (Panel A), first purchases (Panel B), and follow-on purchases (Panel C). The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets. The bottom of each panel contains the number of users in the estimate, mean of the dependent variable, and the total days purchased.

Table A9. Effect of Pay-As-You-Go Contract Offer by Income and Credit Constraints

	Take-Up (1)	Days with Coverage (2)	Days Insured (3)	Insured End of Study (4)
Panel A: Income Insight Score				
Pay-As-You-Go=1	16.10	12.05	4.49	2.11
	(2.38)	(3.74)	(1.76)	(3.60)
	[0.000]	[0.001]	[0.011]	[0.558]
Below Median Income Insight Score=1	4.34	1.56	3.10	-4.59
	(3.19)	(4.82)	(2.79)	(4.54)
	[0.174]	[0.746]	[0.266]	[0.312]
Pay-As-You-Go=1 × Below Median Income Insight Score=1	-6.87	-3.40	-4.23	4.55
	(3.95)	(5.47)	(3.00)	(5.00)
	[0.083]	[0.534]	[0.159]	[0.363]
Constant	3.03	12.12	2.76	20.75
	(1.73)	(3.29)	(1.57)	(3.29)
	[0.079]	[0.000]	[0.079]	[0.000]
N	1,275			
Median Income Insight Score	34,000			
Panel B: Credit Constrained				
Pay-As-You-Go=1	14.53	14.27	0.68	5.07
	(4.53)	(5.81)	(3.65)	(5.38)
	[0.001]	[0.014]	[0.853]	[0.346]
Credit Constrained=1	-1.61	-1.54	-2.53	-0.95
	(4.07)	(5.62)	(3.72)	(5.42)
	[0.692]	[0.785]	[0.496]	[0.861]
Pay-As-You-Go=1 × Credit Constrained=1	-2.86	-4.26	2.10	-0.52
	(4.96)	(6.42)	(3.93)	(5.94)
	[0.564]	[0.507]	[0.592]	[0.930]
Constant	6.67	13.33	6.22	18.10
	(3.72)	(5.07)	(3.47)	(4.91)
	[0.074]	[0.009]	[0.074]	[0.000]
N	1,537			
Credit Constrained	80.8			

Notes: The table presents the intent-to-treat effect of being offered a pay-as-you-go insurance contract interacted with whether the driver has a below-median income insight score (Panel A) or whether the driver is credit constrained (Panel B, defined as having credit balances at or above credit limits or having no credit limit) per equation 4. The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets.

Table A10. Effect of Pay-As-You-Go Contract Offer: Outcomes Defined at Two Months

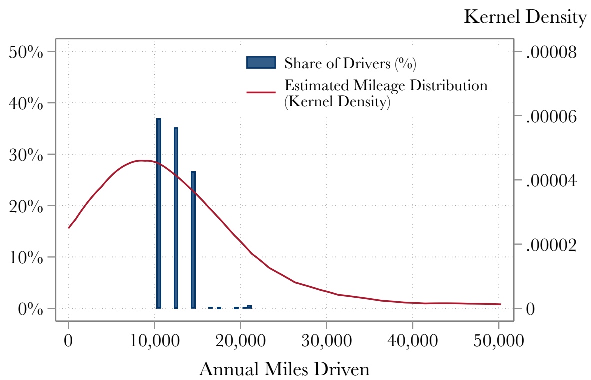
	Take-Up (1)	Days with Coverage (2)	Days Insured (3)	Insured End of Study (4)
	Panel A: Insurance through Experiment			
Pay-As-You-Go	12.20	5.36	2.45	5.33
	(1.84)	(1.00)	(0.93)	(1.61)
	[0.000]	[0.000]	[0.008]	[0.001]
Constant	5.38	2.82	2.82	4.48
	(1.51)	(0.85)	(0.85)	(1.39)
	[0.000]	[0.001]	[0.001]	[0.001]
N	1,537	1,537	1,537	1,537
	Panel B: Any Insurance			
Pay-As-You-Go	10.80	4.30	1.71	3.51
	(2.47)	(1.53)	(1.49)	(3.00)
	[0.000]	[0.005]	[0.252]	[0.242]
Constant	12.11	10.61	10.61	21.52
	(2.19)	(1.38)	(1.38)	(2.75)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,537	1,537	1,537	1,537

Notes: The table presents estimates from equation 1 of the effect of being offered a pay-as-you-go insurance contract on outcomes measured within two months of the study start; that is, two months from when the driver signed up for their contract for coverage through the experiment and two months from when the driver received their quote for the any insurance measures. The outcomes are take-up (defined as any time after receiving their Hugo quote for Hugo insurance and within seven days of receiving their Hugo quote for any insurance), days with coverage (days where users are covered *or* have nonzero coverage balance), days insured, and whether they were insured at the end of *two months* for both Hugo (Panel A) and Any Insurance (Panel B) outcomes. The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets. The number of observations, N, is also presented.

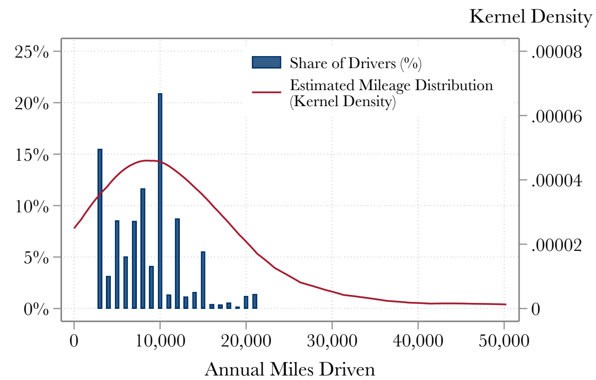
C Appendix Figures

Figure A1. Policies Written by Mileage against NHTS Mileage Distribution

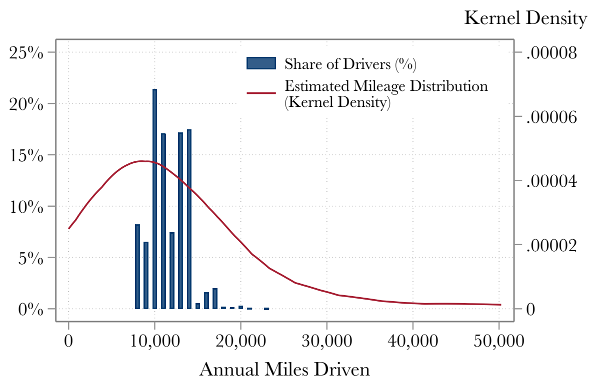
(a) Aspire



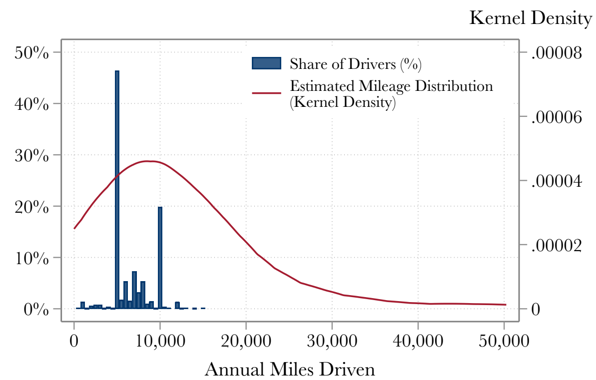
(b) Mercury



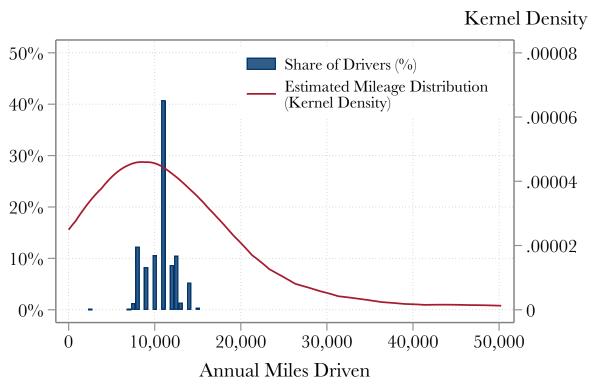
(c) Sterling



(d) Viking

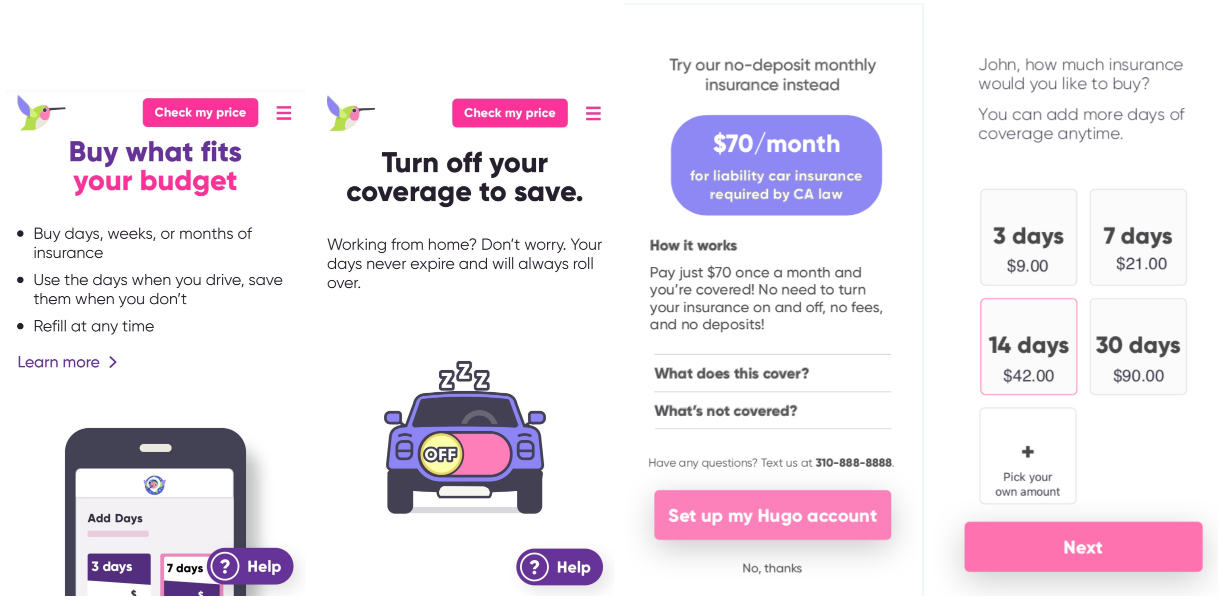


(e) Western



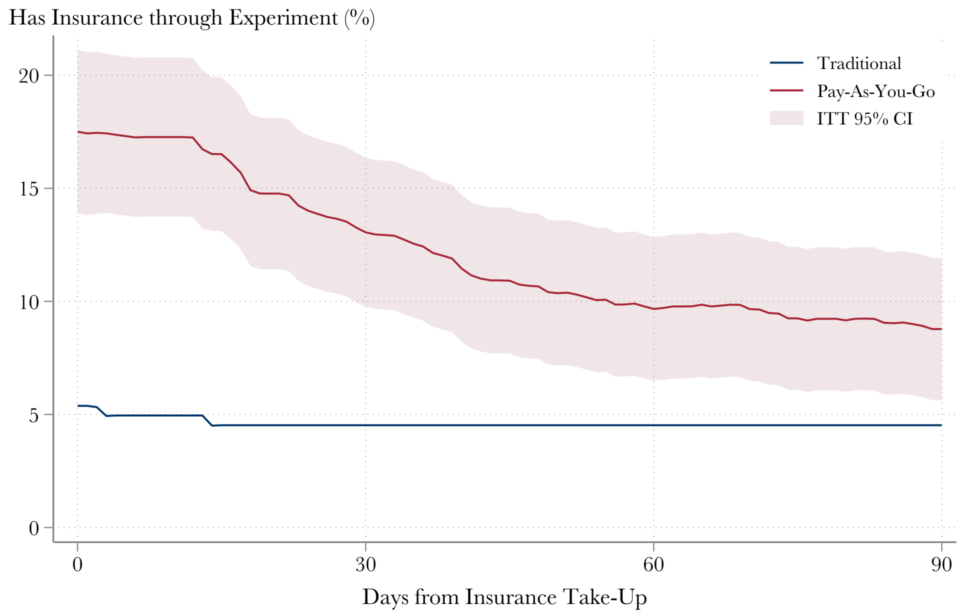
Notes: Each figure displays bars indicating the share of drivers in each mileage bin according to rate filings for five different insurance companies: Aspire (Panel A), Mercury (Panel B), Sterling (Panel C), Viking (Panel D), and Western (Panel E). The overlaid line shows a kernel density estimation of the distribution of annual mileage according to the 2017 National Household Travel Survey.

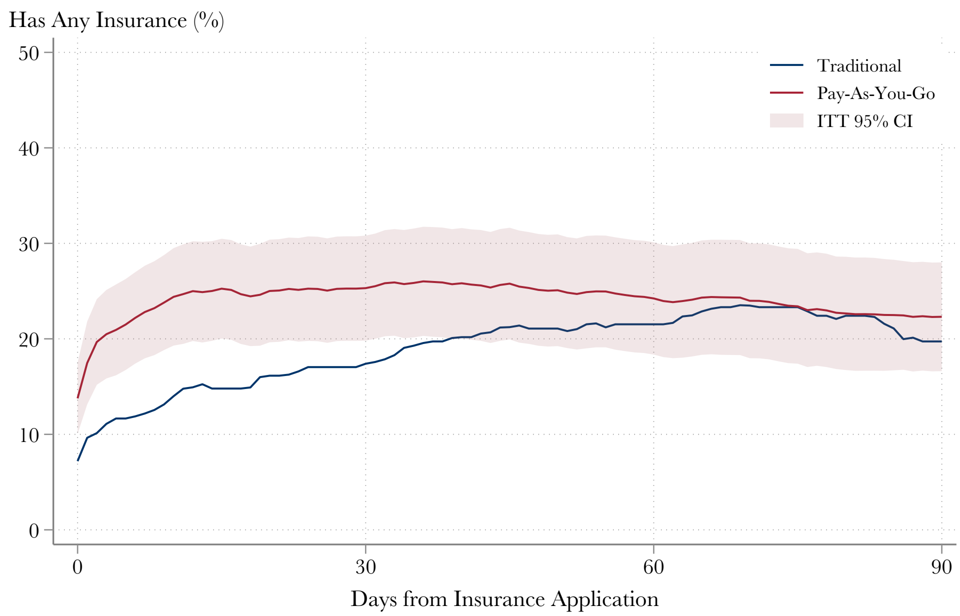
Figure A2. Screenshots of Pay-As-You-Go Quote Application



Notes: Screenshots from the quote application and pay-as-you-go contract explanation pages used in the experiment.

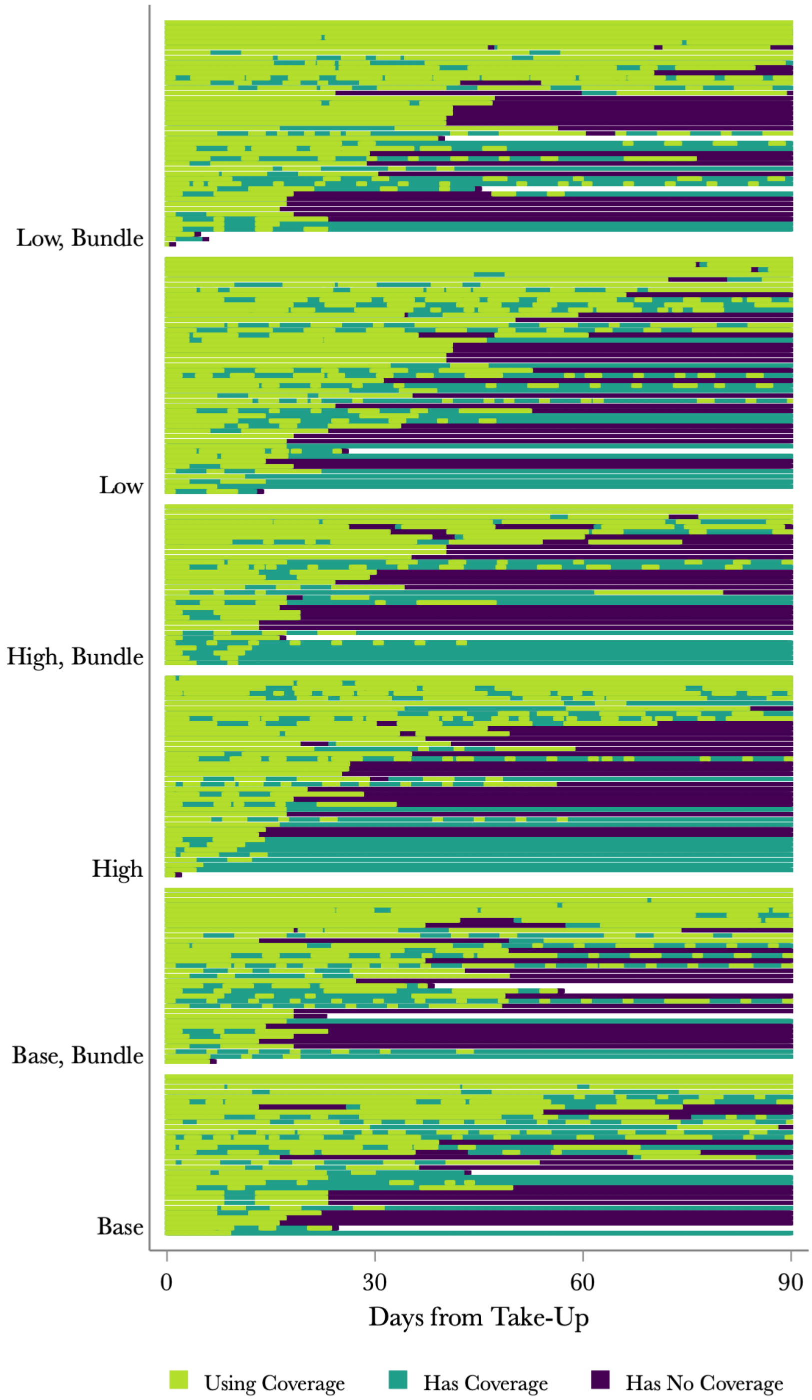
Figure A3. Intent-to-Treat Effect of Pay-As-You-Go Contract over Time





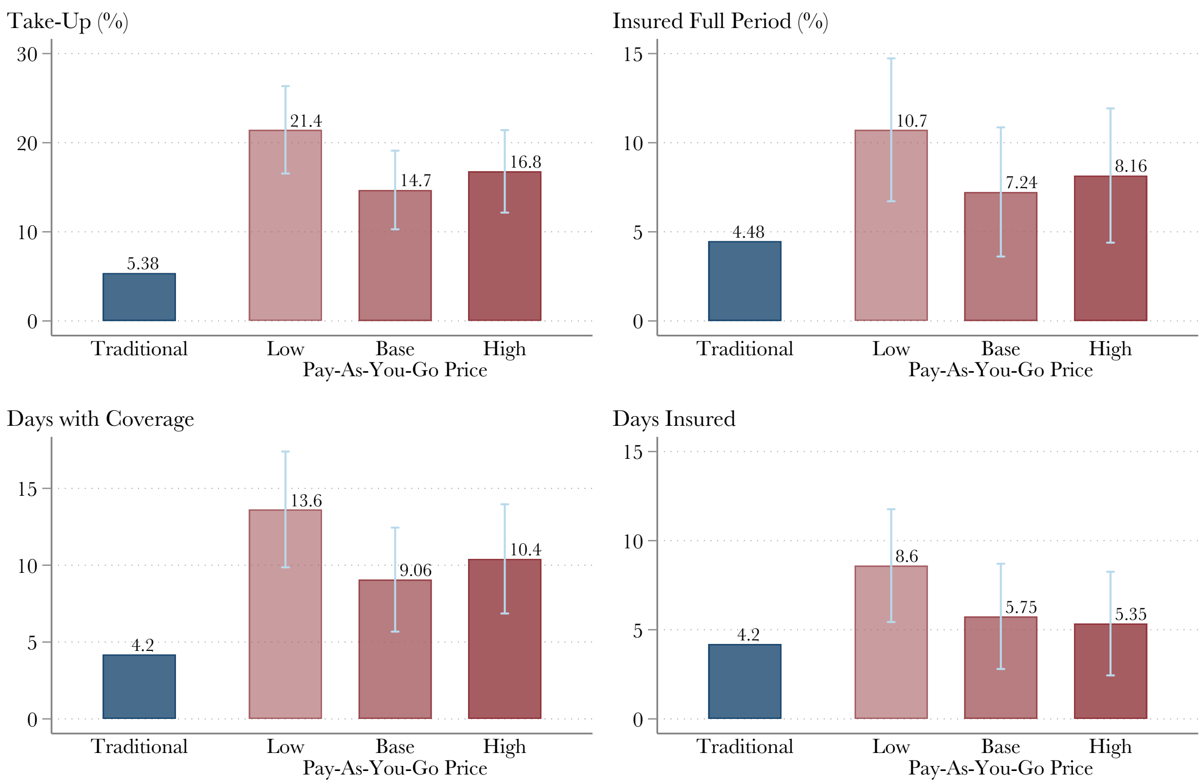
Notes: The figures plot the ITT effect of the pay-as-you-go contract offer by day separately for coverage through the experiment and through any insurer. The blue and red lines plot the share with insurance coverage for drivers offered the traditional contract and pay-as-you-go contract, respectively. The shaded region of the figures display the 95% confidence interval of the ITT as estimated by a fixed effects regression of insurance coverage on the interaction between the running day variable and whether the driver was offered the pay-as-you-go contract, absorbing the running day variable and clustering the standard error at the driver level.

Figure A4. Pay-As-You-Go User Activity by Day



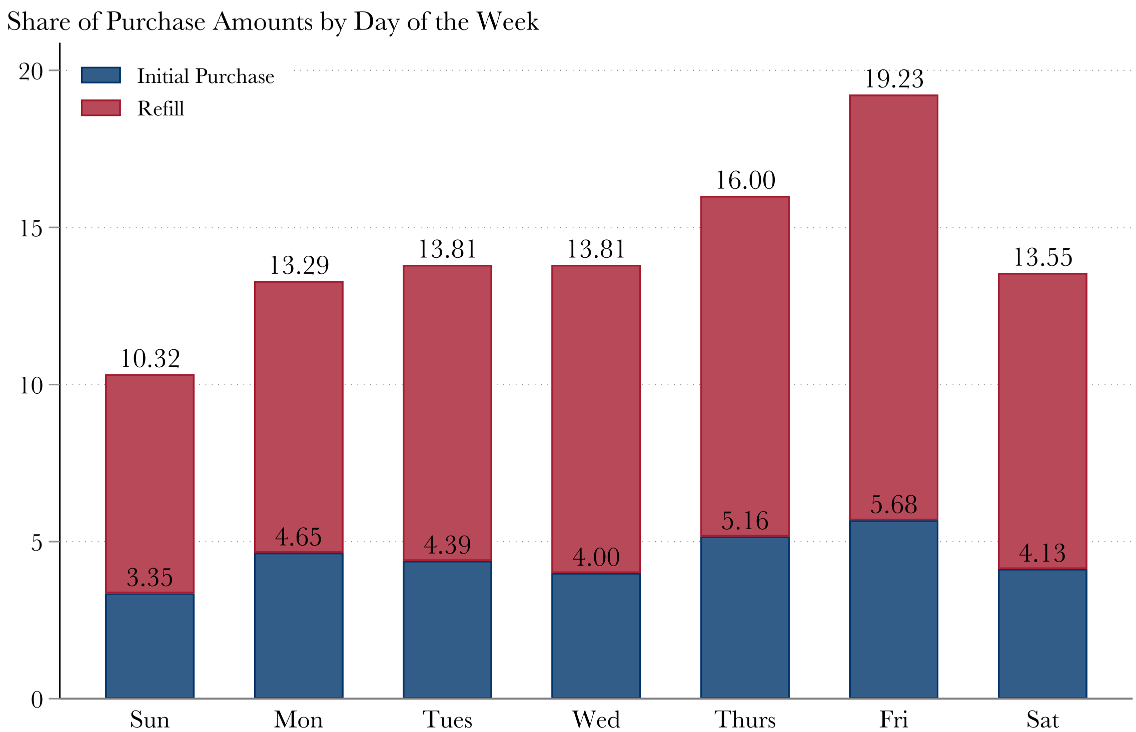
Notes: The figure presents insurance activity by day relative to enrollment for all of the drivers enrolled in a pay-as-you-go insurance plan by treatment group assignment.

Figure A5. Intent-to-Treat Effects of Pay-As-You-Go by Price Treatment Group



Notes: The figure presents the mean values of take-up and days with coverage through the experiment and from any carrier, separately for those offered the traditional and pay-as-you-go insurance contract, split by whether they were assigned to the Low, Base, or High price group. Error bars represent the 95 percent confidence interval of the treatment effect as estimated in equation 1, replacing the indicator for treatment with an indicator for treatment at each price level.

Figure A6. Share of Purchases by Day of the Week



Notes: The plot shows the share of purchase amounts for refills and initial purchases by day of the week for drivers who enrolled in a pay-as-you-go contract.