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

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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, despite a universal mandate, 17 percent of drivers are uninsured. The pay-as-you-go contract increases insurance take-up by 10.6 percentage points (87%) and days with insurance available by 4.5 days over the 3-month experiment (26%). Demand is price-sensitive and coverage increases are smaller at higher prices. The pay-as-you-go contract increases insurance coverage in part by relaxing liquidity requirements: purchase behavior for more than half of drivers is consistent with a cost of credit in excess of payday lending rates and 19 percent of enrolled drivers have a purchase rejected for insufficient funds. Insurance coverage converges between the traditional and pay-as-you-go contract over time. I discuss potential explanations and their implications for similar financial technologies (e.g., buy-now-pay-later, earned wage access) and the uninsured driver problem.

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1 Introduction

Pay-as-you-go contracts facilitate purchases of smaller quantities at flexible (typically higher) frequencies than traditional contracts with regular, longer-term billing cycles. Many markets, particularly those serving low-income consumers, offer smaller quantities at higher prices to increase market participation (Attanasio and Pastorino, 2020). Participation in many insurance markets is suboptimally low, and because premiums are typically paid upfront, liquidity requirements to enroll present a barrier to coverage (Cole et al., 2013; Casaburi and Willis, 2018; Rampini and Viswanathan, 2022). Pay-as-you-go contract structures, which have proliferated across other domains serving low-income consumers including cell phone and utility contracts, have the potential to alleviate this barrier to insurance coverage by allowing households to retime insurance purchases to periods of higher liquidity.[1] Pay-as-you-go contracts may also increase coverage by allowing households to buy smaller durations of coverage that they can more easily afford, but this may come at the risk of attrition from coverage by eliminating the consumption commitment aspect of the contract. While pay-as-you-go contracts address commonly cited barriers to insurance market participation, we know little about their effects on take-up of coverage, at what prices these contracts may be viable, or the demand for smaller quantities at relatively higher prices.

This paper provides experimental evidence on the introduction of a novel pay-as-you-go insurance contract to the California auto insurance market where, despite a universal insurance mandate, 16.6 percent of drivers operate their vehicles without the legally mandated 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). Auto insurance contracts may be inefficient for reasons dating back at least to Vickrey (1968), who observed that traditional "all-you-can-drive" auto insurance contracts induce moral hazard. Enrolling in auto insurance often requires large upfront payments, especially if drivers are purchasing coverage in the nonstandard auto insurance market.[2]

The pay-as-you-go contract I study allows drivers to choose the purchase timing and duration

[1] Rampini and Viswanathan (2022) note specifically that their theory predicts that InsurTech innovations like pay-as-you-go reduce the financing need of insurance and could reduce uninsured driving substantially.

[2] 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).

of insurance coverage by offering 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 the effects of the contract vary 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 10.6 percentage points (87 percent) and days with insurance available by 4.5 days (26 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 a 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. 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. The treatment effect of the pay-as-you-go contract offer erodes over time, with similar coverage rates for applicants offered the pay-as-you-go as the traditional contract three months after they entered the study. While the coverage effects of the contracts converge on average, there is suggestive evidence that the contract is particularly valuable for drivers who have historically struggled to maintain regular coverage.

The price of the pay-as-you-go contract mediates its effect on insurance take-up and coverage. 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), 120% of the base price, or 80% of the base price. Applicants in the lowest price group have much larger effects on take-up of the contract offer from the implementing partner (15.6 percentage points versus between 9.3 and 11.3 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 (9.1 days versus 4.9 days for the base price group and 6.1 days for the high price group).[3] Applicants have a high estimated elasticity of demand (days purchased with respect to price) of -0.59 for all applicants and an even higher elasticity of -0.72 for those who enrolled. These estimates are larger than comparable estimates of the elasticity of demand with respect to prescription drugs and gas (Einav et al., 2018; Coglianese et al., 2017). The pay-as-you-go contract has a significant positive effect on days with coverage available at all price levels but the increase in the number of days insured is only statistically significant for the low-price treatment group.

Half of drivers randomly assigned the pay-as-you-go contract are also offered a bundle discount which are designed such that forgoing the discount in favor of repeated purchases of smaller quantities implies a cost of borrowing similar to a payday loan. Without the discount, 28 percent of days purchased are in bundles of 14 or 30 days. The bundle discount induces an increase in the share of large-quantity purchases by just 12.0 percentage points. 51 percent of drivers forgo discounts for all of their purchases and 77 percent of drivers forgo them at least once. Drivers may prefer to purchase smaller quantities for other reasons, such as uncertainty in their forecasted demand for driving and other consumption needs, present-bias, or low demand for coverage (perhaps due to limited liability provided by the option to file for bankruptcy). While these explanations are likely to contribute to elevated demand for smaller quantities of coverage and I do not rule them out as alternative explanations, there is evidence to suggest that liquidity constraints are binding and play a significant role 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: 80.7 percent have zero dollars of available credit on their credit report, compared to 28.1 percent of a random sample of

[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.

Californians. 19 percent of drivers who enroll in pay-as-you-go coverage have at least one 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 contract to an uninsured population and to randomize insurance contract features including the type of the contract, price, and nonlinearity in price with respect to quantity; furthermore, uninsured drivers are 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 early wage access, brick-and-mortar payday lending) over short periods of time. In a July 2020 survey of 2,000 Americans, 38 percent of respondents had used a by-now-pay-later service; in March 2021, it was up to 56 percent[4]. In the context of auto insurance, the pay-as-you-go contract increases insurance take-up and coverage. However, the high degree of price sensitivity and erosion of these increases over the course of the experiment suggests that – in the absence of subsidies or policies addressing the financial precarity of uninsured drivers – contract structure alone may not present a persistent solution to the uninsured driving problem. 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 insufficient to alleviate these constraints over longer periods of time without addressing the persistent underlying financial situations.

This paper contributes to several areas of research. First, 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

[4] https://www.fool.com/the-ascent/research/buy-now-pay-later-statistics/

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.[5] While not focused on pay-as-you-go contract structures, 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.

Second, this paper contributes to our understanding of the role of liquidity constraints in mediating 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, 2018; 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 payments at a 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, but that alleviating them by allowing consumers to retime their behavior with smaller, periodic purchases has more limited – though measurable and significant – coverage benefits. 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 the connection between financing and insurance can increase participation in insurance markets for low-resource households in the short-run, but competing consumption priorities may limit longer-run benefits.

[5] 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.

Finally, 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 advantage of this contract feature on 32.5 percent of days they have coverage available. Drivers retain the option to drive without insurance or intertemporally substitute driving to days they are insured, so this is an upper bound on the reduction in driving that could be achieved by adjusting premiums based on miles driven. 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]

[6] An earlier version of this experiment attempted to incentivize enrolled drivers to install on-board diagnostic devices to monitor their driving but no drivers took us up on our offer.

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

2 Setting

Despite regulations which require all drivers to carry auto insurance,[8] 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).[9] This paper focuses on uninsured drivers in California shopping for minimum liability insurance coverage. Uninsured drivers are exposed to large 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 worth highlighting 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, filing for bankruptcy may provide a substitute for insurance by limiting their liability in the event of an accident 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.[10] While annual mileage is nominally one of three primary pricing factors (alongside driving record and experience), in practice the cost of verifying mileage

[8] 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).

[9] 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.

[10] 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 B for additional details on the auto insurance market and premium pricing.

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 true distribution of miles driven and shows that the vast majority of drivers are binned into common bins (often 10,000 or 12,000 miles) without regard for actual 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. 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," in this case drivers deemed high-risk. 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). 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.[11] 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 a substantial upfront payment.[12] Collectively, the risk pool of drivers insured by nonstandard carriers (high-risk drivers combined with 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 ($450 of fines and fees for a first offense, up to $2,500 for a second offense) and vehicle impoundment at the discretion of the police. 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-

[11] 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.

[12] 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."

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 limited scope to improve the situation given the limited resources of uninsured drivers. These limitations on the ability of policymakers to address the uninsured driving problem highlight the potential value of innovations that could help improve affordability and increase insurance coverage.

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 limited assets to collect; (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. Other features of the setting such as inadequate enforcement of mandated coverage and minimum coverage standards may also impact the decision to purchase insurance coverage, but this paper will focus on the role of the insurance contract duration and flexibility, price, and liquidity requirements to enroll on demand for insurance among uninsured drivers.

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`.[13] 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 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.[14] 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 insurer.[15] The duration of the experiment was three months from the time of insurance enrollment. Between March 8 and August 30, 2019, 1,547 participants applied and were offered quotes for insurance coverage through the experiment.

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

[13] 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.

[14] 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

[15] 456 applicants (22.7%) could not be underwritten. 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).

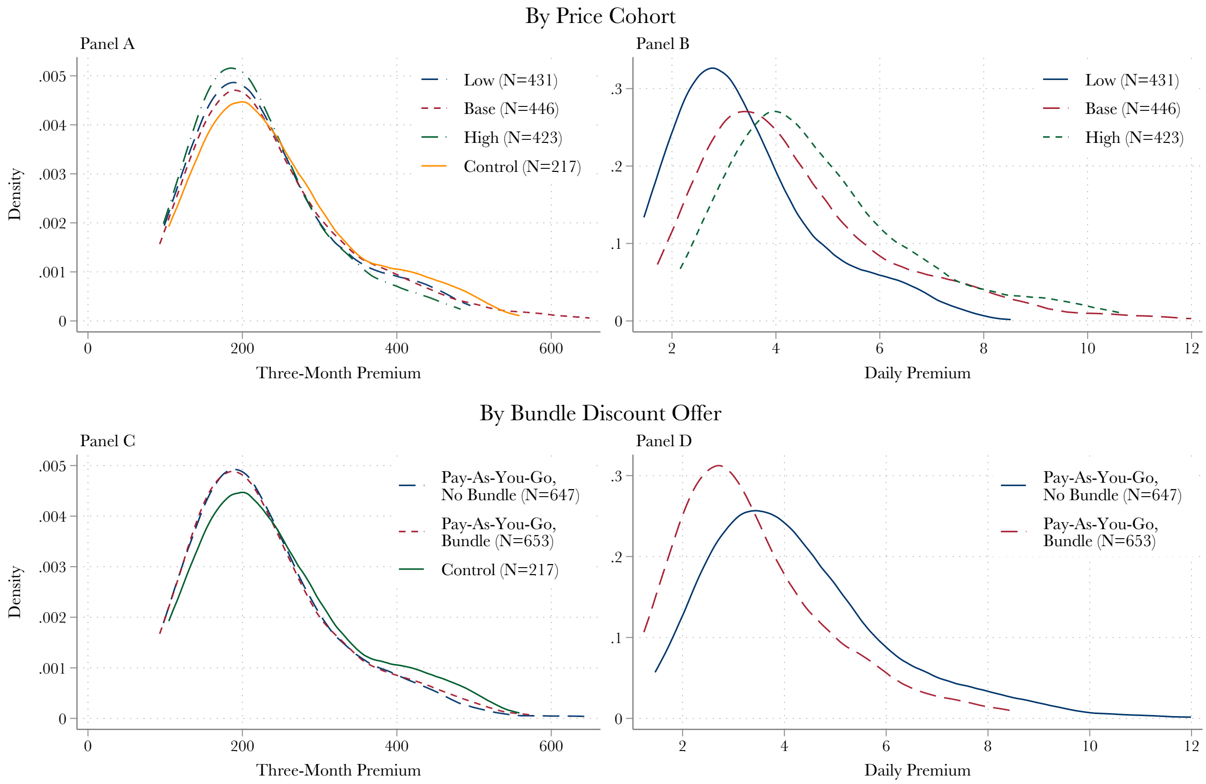
minimum-liability-insurance contract with three months of premiums due at enrollment, or the pay-as-you-go contract. The traditional contract is the contract that would be offered to the applicant by the backing insurance company outside the experiment. The first dimension of the randomization is the 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.

In order to estimate willingness-to-pay for the pay-as-you-go contract, the second dimension of randomization is the price of a day of insurance. We translate an applicant's traditional premium to a daily premium (see Appendix B for details) 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.[16] 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 insurance at relatively higher prices by offering discounts for 14 or 30 day purchases. By randomly varying the relative prices for smaller (three or seven 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

[16] A Kolmogorov-Smirnov test of distributional equality between the premium distributions of applicants offered the traditional vs. pay-as-you-go contract is weakly significant (p-value of 0.088). 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. To address any concerns about differences on observable attributes across the treatment groups, I show robustness to multiple methods of selecting controls including the three-month premium and other observables in Appendix Table A4.

Figure 1. Premium Distributions and Experimental Variation



Notes: Panels A and C plot the distributions of market-rate, three month premiums split by assigned contract and price group (Panel A) or bundle discount group (Panel C). Panels B and D plot the distributions of daily premiums split by assigned contract and price group (Panel B) or bundle discount group (Panel D) to demonstrate 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). The distributions are calculated via kernel density plots with bandwidths of 40 and .6 for the three-month and daily premiums, respectively.

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 are in the range of a 391 to 600 annual percentage rate (APR).[17] 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

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

the average utilization rate of 67.5 percent (share of days insurance is active among users with a positive balance of days).[18] The APR implied by forgoing the bundle ranges from 261% for drivers who opt for 3 days relative to the 30-day bundle to 1,409% for drivers who opt for 7 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 group 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.[19] 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 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, ZIP Code), a ledger of purchase (number of days purchased, amount, and current balance) and coverage actions (coverage activations and deactivations) for each applicant. 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 directly access the third-party data sources, Hugo provides relevant derived information including the three-month premium (which embeds information from

[18] 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%.

[19] The initial intent was to block every 49 *applicants* as specified in the pre-registration for the experiment; however, this was not feasible, 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.

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.

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.[20] I merge in additional statistics on the racial composition and median income of the ZIP Code from the 2018 5-year American Community Survey (ACS) (U.S. Census Bureau, 2019).

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. Experian also provides an "Income Insight Score", an estimate of user income derived from a combination of proprietary and verified income data.[21] 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.

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 for which to estimate the ITT effects.

[20] 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.

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

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 is defined as any enrollment in a plan offered through the experiment. Take-up by any insurer is defined as take-up within seven days of their account creation date.

Table 1 presents summary statistics on the sample of applicants. Applicants are around 38 years old on average. Their vehicles are old (mean and median age 15 years) with low resale value (mean resale value of $1,921, median resale value of just $564). Appendix Table A3 compares summary statistics for the sample of applicants with a random sample of one million 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 ZIP Code median income and the mean national Income Insight Score. Drivers applying for coverage appear to have limited access to credit, with a mean credit score that is firmly subprime and revolving credit limits below $1,000 on average. 80.7 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 35.6 percent of the sample have an outstanding auto loan (with an average outstanding balance of $1,800), which is lower than the California mean of 51.6 and the national mean of 55.3.[22]

[22]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.

Table 1. Applicant Summary Statistics

	Mean	SD	Median
Panel A: Hugo			
3-Month Premium	232	95.7	208
Daily Premium	4.26	1.84	3.83
Vehicle Resale Value	1,921	3,311	564
Age	37.8	10.4	36.7
ZIP Share Black	7.31	8.39	4.42
ZIP Share Hispanic	42.3	22.1	39.1
ZIP Share White	36.4	23.2	33.5
ZIP Median Income	54,986	19,720	50,720
N	1,547		
Panel B: Experian			
Income Insight Score	37,487	15,675	34,000
Vantage Credit Score	515	128	532
Total Inquiries	5.49	6.8	3
Total Revolving Credit Limit	687	3,457	0
Credit Card Limit	515	3,013	0
Credit Card Balance	403	1,583	0
Is Credit Constrained	80.7	39.4	100
Has Auto Loan	35.6	47.9	0
Auto Loan Amount	1,783	5,852	0
Medical Collections	1,005	5,319	0
Non-Medical Collections	1,429	2,939	280
N	1,318		
Panel C: Clarity			
Clarity Total Inquiries	5.14	18.9	0
Clarity Credit Limit	84.2	715	0
Clarity Credit Balance	44.2	433	0
N	373		

Notes: The table presents mean (Mean), standard deviation (SD), and median (Median) summary statistics for the experiment sample of 1,547 drivers, separated by data source; Panel A presents statistics directly from Hugo, and Panels B and C present credit statistics from Experian and Clarity credit reporting firms, respectively. The number of observations in each panel corresponds to the number of drivers for whom credit data is available, and measures of credit such as inquiries, limits, and balances are assumed to be zero if missing.

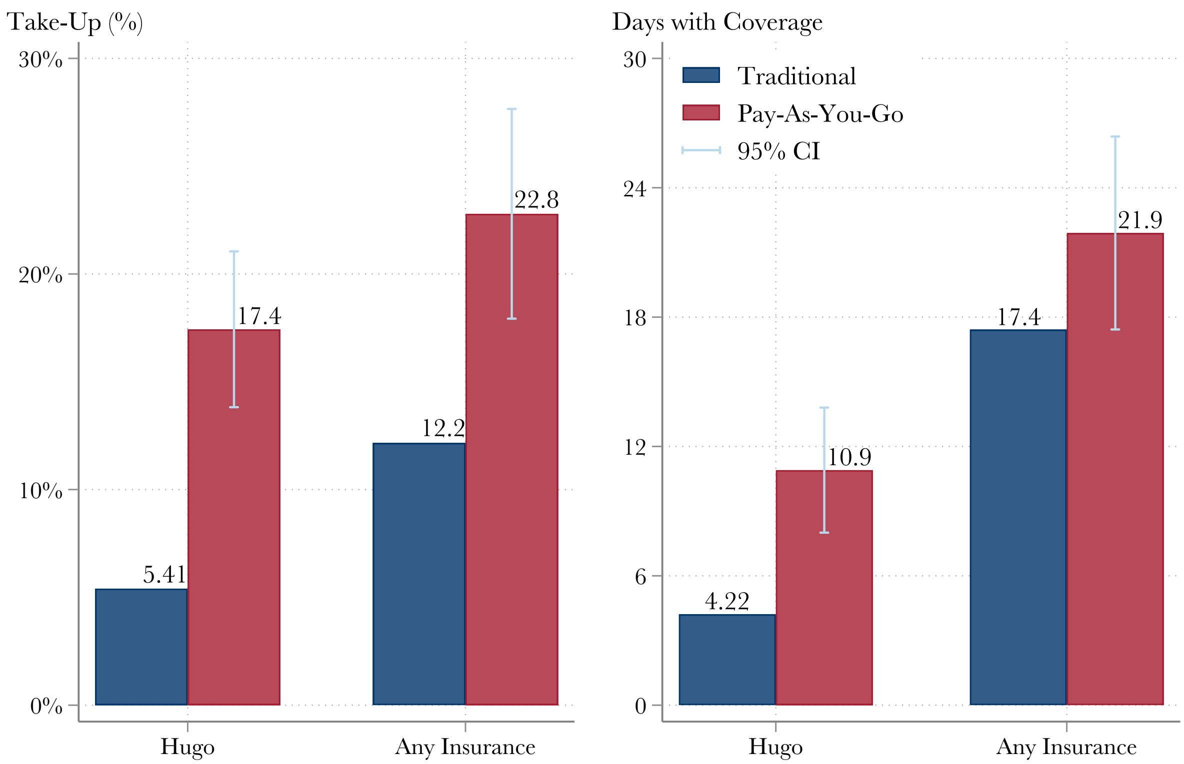
4 Results

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. 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 from Hugo and from any insurance, separately for those offered the Traditional (three months of insurance paid up front at the market rate) and Pay-As-You-Go (allowing drivers to purchase insurance in 3-, 7-, 14-, or 30-day bundles and pause insurance on days they don't drive) insurance contract. Error bars represent the 95 percent confidence interval of the treatment effect as estimated in equation 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 percentage points (222 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: 22.8 percent of applicants offered the pay-as-you-go plan took up insurance within seven days of their account creation, an 87 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 4.5 more days with coverage available (26 percent) in the three months after the account creation date.

Table 2. ITT of Pay-As-You-Go Contract

	Take-Up	Days with Coverage	Days Insured	Insured End of Study
	Panel A: Hugo Outcomes			
Pay-As-You-Go	12.03	6.68	2.28	4.10
	(1.84)	(1.48)	(1.37)	(1.59)
	[0.000]	[0.000]	[0.097]	[0.010]
Constant	5.41	4.22	4.22	4.50
	(1.52)	(1.28)	(1.28)	(1.39)
	[0.000]	[0.001]	[0.001]	[0.001]
N	1,547	1,547	1,547	1,547
Mean	15.7	9.94	6.17	8.02
	Panel B: Any Insurance Outcomes			
Pay-As-You-Go	10.63	4.48	0.47	2.29
	(2.48)	(2.28)	(2.23)	(2.91)
	[0.000]	[0.050]	[0.834]	[0.431]
Constant	12.16	17.42	17.42	19.82
	(2.20)	(2.09)	(2.09)	(2.68)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,547	1,547	1,547	1,547
Mean	21.3	21.3	17.8	21.8

Notes: The table presents the main results of the effect of being offered a Pay-As-You-Go insurance contract on take-up (defined as any time after receiving their Hugo quote for Hugo insurance and within 7 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 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, and the mean of the dependent variable are also presented.

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 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 have less than half an additional day insured and it is not statistically significant. The coverage benefits of the pay-as-you-go contract appear to erode 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.

An internal company survey of 36 drivers whose insurance was cancelled prior to the end of the three months 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, 3 percent moved to a different state, and the remaining 6 percent cancelled for unknown reasons.[23] These results suggest that, at least according to drivers, some of the attrition from the pay-as-you-go contract may be specific to the contract features offered in this context (specifically, the deactivation feature and minimum liability-only coverage), in contrast to the pay-as-you-go contract structure.

Estimates in Table 2 suggest the pay-as-you-go contract structure increases insurance take-up and days with coverage. The evidence is somewhat less promising that the increase in take-up and coverage is sustainable over longer contract durations. 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.

[23] This survey covered some drivers who were insured by the same product but who predated the experiment.

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.

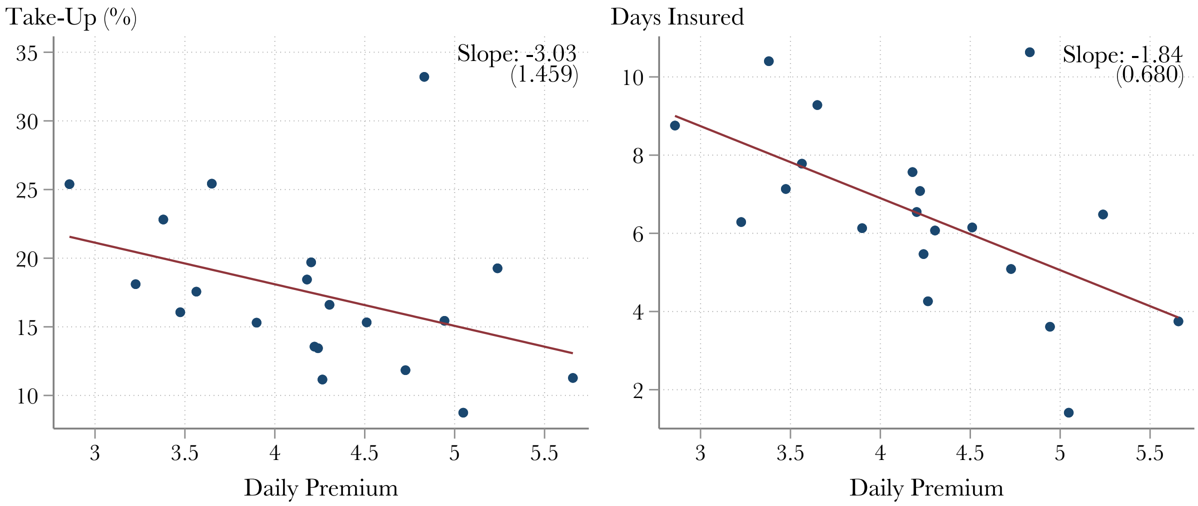
In general, estimating demand for insurance is challenging: higher risk applicants face higher prices. Further, variation uncorrelated with applicant risk is rare and often relies on local discontinuities where it does exist (e.g., Finkelstein et al. (2019)). This experiment offers a rare opportunity 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 B, 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. Residualizing the base premium allows me to isolate the randomly induced variation in the price of the pay-as-you-go contract. 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. To begin, I residualize the base premium and estimate the impact of price on take-up of the pay-as-you-go contract and days insured:

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

Applicants are price-sensitive. 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 3.03 percentage points (17.4 percent off the pay-as-you-go mean take-up rate of 17.4) and days insured by 1.84 (28.3 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

Figure 3. ITT Daily Premium Binscatters



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.

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 for those who do not take up insurance.[24] 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 1.2 percentage points. The significant price sensitivity of demand for the uninsured drivers in my sample is even more pronounced when looking at how the number of days of insured respond to an increase in price: the elasticity of demand is -0.59 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 A4 and Appendix Table A5, show strong effects on coverage for the low-price group with smaller effects on

[24] Appendix Table A6 presents $log(y_i)$ and $log(y_i + 1)$ as alternative transformations with similar results.

Table 3. Demand for Enrollment

	Take-Up	Take-Up, > 3	ihs(Days Insured)	
	(1)	(2)	(3)	(4)
log(Daily Premium)	-11.62	-12.95	-0.59	-0.72
	(6.52)	(5.25)	(0.27)	(0.34)
	[0.075]	[0.014]	[0.028]	[0.032]
log(Base Daily Premium)	4.61	2.95	0.23	0.17
	(7.09)	(5.63)	(0.29)	(0.35)
	[0.516]	[0.601]	[0.435]	[0.637]
Bundle Discount Offered	-1.18	-0.83	-0.05	-0.03
	(2.08)	(1.67)	(0.09)	(0.11)
	[0.572]	[0.619]	[0.571]	[0.814]
Constant	27.47	24.43	1.22	4.75
	(4.08)	(3.35)	(0.17)	(0.18)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,325	1,325	1,325	231
Sample	All	All	All	Enrolled

Notes: The table reports estimates from linear regressions estimating demand elasticity of outcomes over daily premium with controls for base daily premium and whether the driver was offered the bundle discount. Each of the dependent variables is the outcome for Hugo insurance. The dependent variable in Column (1) is whether the driver took up the Hugo contract, while Column (2) is whether the driver took up the Hugo contract 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 all drivers offered the Pay-As-You-Go contract, while the sample for Column (4) is those 231 users who enrolled in the Pay-As-You-Go contract. The coefficients are reported along with standard errors in parentheses and p-values in square brackets.

take-up and days with coverage for the base and high-price treatment groups. Elasticity estimates are higher than other settings like demand for prescription drug and gas.[25] The availability of the pay-as-you-go contract appears to increase take-up and days with coverage, but does not drive statistically significantly higher days insured at higher price levels.

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 over time relative to typical payment cycles by purchasing smaller quantities. 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

[25] For example, Einav et al. (2018) estimate an average elasticity of demand for prescription drugs of -0.24 and Coglianese et al. (2017) estimate an elasticity of demand for gas of -0.37.

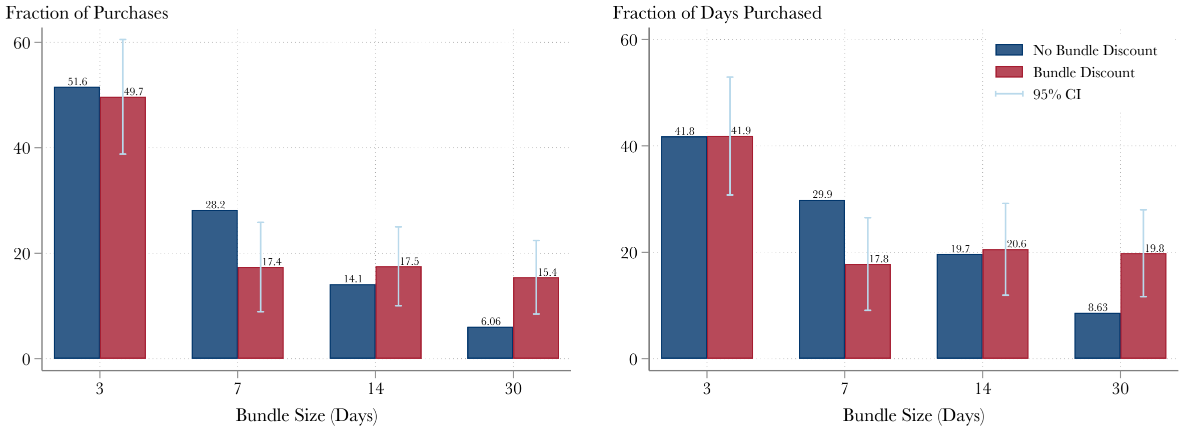
same price for small and large quantities. Next, I test whether preferences for smaller quantities persist even when applicants are offered a "bundle discount" for purchasing more days of insurance at a time. Drivers who forgo the bundle discounts reveal that they prefer to buy smaller quantities of insurance even when prices are higher.

The size of the bundle discounts are designed such that forgoing the discounts implies a cost of borrowing similar to a payday loan, which feature APRs between from 391 to 600. The bundle discount provides 14 days for the price of 12 (14 percent discount) or 30 days for the price of 24 (20 percent discount) and does not change the price of three or seven day purchases. When a user offered the bundle discount forgoes the savings from the bundle, which I calculate by dividing the foregone savings ("interest") by the difference in price ("loan size") and scaling by the average utilization rate of 67.5 percent to calculate the number of days on average it takes to "spend" the difference ("loan duration"). The costs of credit implied by forgoing the bundle are shown in Appendix Table A2.

There is high demand for smaller quantities of days when offered at similar prices: 79.8 percent of drivers who are not offered the bundle choose to purchase three or seven days at a time. Demand remains high even as the relative prices of smaller quantities are higher. Figure 4 plots a bar chart of the distribution in purchases by the quantity of days by whether the driver was offered the bundle discount. Appendix Table A7 presents the share of purchases by quantity and accompanying ITT regression estimates are presented in Appendix Table A9. Bundles comprise 20.2 percent of purchases and 28.3 percent of days purchased for those offered the pay-as-you-go contract without the bundle, the bundle discount increases the share of bundle purchases by 12.8 percentage points and the share of days purchased via the bundle by 12.0 percentage points. Nearly all of those induced to purchase the bundle by the discount would have counterfactually purchased seven (rather than three) days of coverage at a time: the share of days purchased in three-day quantities is 51.6 vs. 49.7 percent between the no-discount and discount groups while the share of seven-day quantities purchased falls from 28.2 to 17.4 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 unsurprising given those selecting three days are more likely to have stronger demand for smaller

Figure 4. ITT Bundle Size Fraction



Notes: The figures above show the distribution of purchased bundle sizes among the 231 drivers who purchased the Pay-As-You-Go contract in which drivers could purchase insurance in bundles of 3, 7, 14, or 30 days. The figure on the left presents the average within-driver fraction of purchases of each bundle size, while the figure on the right presents the average within-driver fraction of total days purchased via ecah bundle size. Error bars represent the 95% confidence interval of the treatment effect of being offered the bundle discount on bundle size fraction.

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.

The demand behavior in response to the bundle discount treatment can inform the degree to which participation in auto insurance markets is limited by liquidity constraints. 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. 78.9 percent of purchases are for smaller, undiscounted quantities of coverage (three or seven days) even when discounts are available, and 56 percent of drivers forgo discounts for all of their purchases. These can provide reasonable upper bounds on the share of uninsured drivers applying for coverage in my sample who are liquidity constrained, though this could overstate the degree of liquidity constraints if drivers have a high degree of demand uncertainty. One might expect demand uncertainty to be highest for first purchases, however drivers may shop for insurance during periods of relatively high liquidity. 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. Pay-as-you-go contracts may be less effective in the absence of liquidity constraints if discount rates are high. In the presence of hyperbolic discounting, the consumption commitment aspect of traditional contracts may increase coverage despite barriers they present to market participation.[26]

In addition to inferences from demand behavior, there is complementary evidence that speaks to the financial condition of these applicants. 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. 80.7 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 A5 presents the share of insurance purchases made by day of the week. While the absence of data on other consumption patterns by day of the week renders this somewhat suggestive, drivers are 40 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

[26] A natural exercise to quantify the value of this commitment would be to run an instrumental variables regression, instrumenting for larger quantities of days purchased using the randomized discount on bundle purchases. However, given the limited number of compliers taking up the bundle discount, the regression suffers from a weak first stage.

funds bounces from prepaid cards may be less of a "smoking gun" for liquidity constraints than failed debit transactions, but these drivers may also be more likely to be unbanked.

In either case, it is informative to track behavior after the failed transaction. 39 percent of insufficient funds failures are followed by another insufficient funds failure, 46 percent are followed by a successful payment, and 15 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 13% of those daily users who attrit. Successful payments following an insufficient funds failure occur on average 3.5 days after the failed transaction, suggesting that these are true constraints that take time to alleviate (in contrast to, for example, trying another card immediately afterwards). Five 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, that demand for these contracts is price sensitive, and that many of the drivers enrolling in pay-as-you-go coverage are liquidity constrained. Next, I ask whether the pay-as-you-go contract has differential treatment effects for applicants with lower incomes, who are credit constrained, or who have historically struggled to stay insured.

To explore heterogeneity in the impacts of the pay-as-you-go contract on insurance coverage along these three dimensions, I interact the ITT regression with indicators for whether the applicant has below median income (as proxied by the Experian income insight score), is credit constrained (defined as zero dollars of available credit on their credit report or a missing credit report), and whether the applicant has no regular policy history (a variable defined by Hugo as the absence of any record of plans of normal length):

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

Table 4 presents results for take-up through Hugo or any insurer and days insured by Hugo or any insurer. The interaction terms are not statistically significant for either having a below-

Table 4. ITT of Pay-As-You-Go Contract Interactions

	Take-Up	Take-Up Any Insurance	Days Insured	Days with Any Coverage
		Panel A: Income Insight Score		
Pay-As-You-Go=1	15.90	11.72	4.40	1.70
	(2.39)	(3.76)	(1.77)	(3.62)
	[0.000]	[0.002]	[0.013]	[0.639]
Below Median Income Insight Score=1	4.31	1.44	3.07	-4.80
	(3.20)	(4.84)	(2.80)	(4.56)
	[0.179]	[0.766]	[0.272]	[0.293]
Pay-As-You-Go=1 × Below Median Income Insight Score=1	-6.80	-3.25	-4.19	4.85
	(3.95)	(5.48)	(3.00)	(5.01)
	[0.085]	[0.553]	[0.164]	[0.333]
Constant	3.06	12.24	2.79	20.96
	(1.74)	(3.32)	(1.59)	(3.32)
	[0.079]	[0.000]	[0.079]	[0.000]
N	1,283			
Median Income Insight Score	34,000			
		Panel B: Credit Constrained		
Pay-As-You-Go=1	14.28	13.94	0.59	4.80
	(4.52)	(5.80)	(3.65)	(5.37)
	[0.002]	[0.016]	[0.871]	[0.372]
Credit Constrained=1	-1.58	-1.47	-2.51	-0.85
	(4.07)	(5.63)	(3.72)	(5.43)
	[0.698]	[0.794]	[0.500]	[0.875]
Pay-As-You-Go=1 × Credit Constrained=1	-2.76	-4.07	2.12	-0.38
	(4.95)	(6.41)	(3.92)	(5.93)
	[0.577]	[0.526]	[0.590]	[0.948]
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	1,547			
Share Credit Constrained	80.7			
		Panel C: No Regular Policy History		
Pay-As-You-Go=1	6.35	3.02	-2.21	-2.71
	(4.19)	(5.42)	(3.33)	(4.70)
	[0.130]	[0.577]	[0.508]	[0.565]
No Regular Policy History=1	-7.22	-12.51	-6.06	-11.10
	(4.00)	(5.45)	(3.42)	(4.93)
	[0.071]	[0.022]	[0.076]	[0.025]
Pay-As-You-Go=1 × No Regular Policy History=1	8.13	10.91	6.42	10.30
	(4.60)	(6.02)	(3.58)	(5.33)
	[0.077]	[0.070]	[0.073]	[0.054]
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	1,547			
Share with No Regular Policy History	70.3			

Notes: The table presents the intent-to-treat effect of being offered a Pay-As-You-Go insurance contract interacted with three different sources of heterogeneity per equation 4. Panels A, B, and C interact $\mathbb{1}\{PAYG_i\}$ with the drivers' income insight score (annual income as estimated by Experian), whether the driver is credit constrained (defined as having credit balances at or above credit limits or having no credit limit), and 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), respectively. The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets.

median Income Insight Score or being credit constrained. This is somewhat surprising considering the potential mechanisms by which the pay-as-you-go contract drives increases in insurance market participation, but may be limited by the available variation in credit constraints (80.7 percent are credit constrained) and income.

There is suggestive evidence (p-value generally between 0.05 and 0.08) that those who have historically struggled to stay insured differentially increase their coverage under the pay-as-you-go contract. Those without regular policy history have much lower take-up rates of traditional contracts (8.4 percent through any carrier, compared with 20.9) and days with coverage (14.1 compared to 25.2) than those with prior regular policy history, but the interacted treatment effect of the pay-as-you-go contract closes that coverage gap. This is true for both take-up and insured days measures. This suggests the pay-as-you-go contract may hold some promise for helping to increase insurance coverage among those who have historically struggled the most to stay insured.

5 Discussion

In this section, I contextualize the key results of the paper and briefly discuss their implications for pay-as-you-go and similar financial products (e.g., buy-now-pay-later, earned wage access) and the uninsured driver problem. The pay-as-you-go contract increases insurance take-up and number of days insured, though the benefits of the contract on coverage erode over time. Drivers appear to face binding financial constraints which the pay-as-you-go contract helps alleviate by offering smaller minimum purchase quantities. To avoid attrition from coverage, drivers nevertheless 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,[27] the pay-as-you-go contract may not increase coverage though drivers may nevertheless be better off if it allows them to shift consumption to meet more pressing needs.

Demand for the pay-as-you-go contract may also be limited by the willingness-to-pay for auto insurance among low-asset households. In the presence of limited liability constraints and given the minimum liability insurance coverage offered does not protect the driver's assets, drivers may be

[27] 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.

unable or unwilling to pay the high price of coverage. Jack and Smith (2015) and Jack and Smith (2020) offer a complementary setting, pay-as-you-go contracts for utilities in South Africa, where liquidity constrained households preferred to make frequent, small payments and electricity use fell. The drivers I study here are already consuming the legally mandated minimum amount of insurance coverage (conditional on driving) so attrition may reflect that auto insurance is lower in the hierarchy of consumption than electricity. This is consistent with the Rampini and Viswanathan (2022) conceptualization of insurance as state-contingent savings and supported by the high elasticity of demand observed, despite the universal coverage mandate.

Features of the auto insurance market make the market failure presented by uninsured drivers (premium externalities alone total $29 billion per year in the United States according to Sun and Yannelis (2016)) exceedingly difficult to solve by the private sector. While recent progress has been made mitigating traditional asymmetric information and moral hazard problems in auto insurance,[28] less progress has been made addressing rates of uninsured driving. Two features in particular make this problem difficult. First, the cost of acquiring a new insurance customer is remarkably high. Second, the rates of attrition among drivers shopping for minimum coverage are high. Nonstandard insurance carriers offer contracts that include high fees and upfront liquidity requirements, which may optimally maximize their profits given these features of the market but serve to make insurance less affordable for the kinds of drivers studied here. 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. This seems particularly salient given the recent evidence on the limited effects of mandates on coverage relative to subsidies (Frean et al., 2017). 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).

By reducing the upfront liquidity required to enroll and providing flexibility in the coverage duration and timing of insurance purchases, the pay-as-you-go contract addresses several barriers to insurance coverage. Additional innovation in this contract space could reduce uninsured driving,

[28] See, for example, Jin and Vasserman (2021), Jin and Yu (2021).

particularly as pay-as-you-go contracts offer low coverage at lower premiums (for instance, by eliminating the feature of the contract that allows drivers to deactivate their insurance coverage) and expand to provide comprehensive 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 10.6 percentage points (87 percent) and days insured in the three months following application by 4.5 days (26 percent) relative to a traditional contract. The coverage benefits erode over the course of the experiment and demand for the pay-as-you-go contract is price-sensitive. 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 some consumers benefit from the smaller minimum payments enabled by pay-as-you-go contracts.

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A Pay-As-You-Go Premiums

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.

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.

B 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 A11 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 5.3 more days with coverage through Hugo (187 percent) and 4.2 more days with coverage overall (40 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.

C Appendix Tables

Table A1. Share Uninsured 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	1408.8	0.0	0.0
APR Implied by Forgoing 30-Day Bundle (%)	260.9	378.3	513.6	0.0

Notes: The table presents the lower bound on the cost of borrowing implied by forgoing the bundle discount when purchasing the number of days indicated by each column. 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. Credit Summary Statistics

	Hugo		CA Sample		US Sample	
	Mean/SD	N	Mean/SD	N	Mean/SD	N
Panel A: Experian						
Income Insight Score	37,487	1,283	93,980	120,717	84,442	986,011
	(15,675)		(85,896)		(67,602)	
Vantage Credit Score	515	1,318	679	122,886	674	1,000,000
	(128)		(143)		(138)	
Total Inquiries	6.45	1,318	2.39	122,886	2.09	1,000,000
	(6.94)		(3.34)		(3.05)	
Total Revolving Credit Limit	806	1,318	22,490	122,886	19,582	1,000,000
	(3,733)		(56,745)		(42,616)	
Credit Card Limit	604	1,318	15,288	122,886	13,475	1,000,000
	(3,256)		(26,663)		(23,879)	
Credit Card Balance	473	1,318	3,683	122,886	3,511	1,000,000
	(1,705)		(8,313)		(7,950)	
Is Credit Constrained	77.4	1,318	28.1	122,886	31	1,000,000
	(41.9)		(44.9)		(46.3)	
Has Auto Loan	41.8	1,318	51.6	122,886	55.3	1,000,000
	(49.3)		(50)		(49.7)	
Auto Loan Amount	2,093	1,318	5,706	122,886	6,184	1,000,000
	(6,289)		(12,415)		(12,896)	
Medical Collections	1,179	1,318	294	122,886	388	1,000,000
	(5,746)		(3,116)		(2,967)	
Non-Medical Collections	1,678	1,318	348	122,886	374	1,000,000
	(3,119)		(2,223)		(1,819)	
Reports		1,318		122,886		1,000,000
Panel B: Clarity						
Clarity Total Inquiries	5.66	1,318	.77	122,886	.84	1,000,000
	(19.6)		(5.68)		(6.16)	
Clarity Credit Limit	96.5	1,318	72.9	122,886	88.3	1,000,000
	(772)		(886)		(1,051)	
Clarity Credit Balance	49.5	1,318	34.8	122,886	48.8	1,000,000
	(465)		(574)		(708)	
Reports		349		12,816		112,092

Notes: The table presents mean (Mean), standard deviation (SD), and median (Median) summary statistics for the subsample of 1,318 Hugo drivers who viewed their Hugo quote and have an Experian credit report, 122,886 in the Experian sample from California, and 1,000,000 in the full Experian sample throughout the US; Panel A contains the Experian credit variables of those samples, and Panel B contains the Clarity credit variables for the same main samples. Measures of credit such as inquiries, limits, and balances are assumed to be zero if missing for the Clarity variables; the subsets of individuals with Clarity reports are 349, 12,816, and 112,092 for the Hugo, California, and US samples, respectively.

Table A4. ITT with Controls

	(1)	(2)	(3)	(4)	(5)
Panel A: Take-Up Hugo					
Pay-As-You-Go	12.03	10.75	12.11	12.91	12.12
	(1.84)	(2.00)	(2.18)	(2.09)	(2.14)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	1,547	1,430	1,190	1,190	1,190
Controls	None	Selected	All	LASSO	LASSO
LASSO Method				Plugin	Adaptive
Selected Controls				0	12
Panel B: Take-Up Any Insurance					
Pay-As-You-Go	10.63	8.56	8.77	9.87	9.02
	(2.48)	(2.67)	(2.97)	(2.90)	(2.96)
	[0.000]	[0.001]	[0.003]	[0.001]	[0.002]
N	1,547	1,430	1,190	1,190	1,190
Controls	None	Selected	All	LASSO	LASSO
LASSO Method				Plugin	Adaptive
Selected Controls				0	12
Panel C: Days with Hugo Coverage					
Pay-As-You-Go	6.68	5.80	6.58	7.28	6.54
	(1.48)	(1.61)	(1.78)	(1.73)	(1.76)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	1,547	1,430	1,190	1,190	1,190
Controls	None	Selected	All	LASSO	LASSO
LASSO Method				Plugin	Adaptive
Selected Controls				0	13
Panel D: Days with Any Coverage					
Pay-As-You-Go	4.48	2.71	3.19	3.70	3.59
	(2.28)	(2.45)	(2.73)	(2.66)	(2.71)
	[0.050]	[0.269]	[0.243]	[0.164]	[0.186]
N	1,547	1,430	1,190	1,190	1,190
Controls	None	Selected	All	LASSO	LASSO
LASSO Method				Plugin	Adaptive
Selected Controls				1	6

Notes: The table presents the intent-to-treat estimate with outcomes by Panel and different sets of controls by column; the constant is not presented. We present the coefficient of interest for five different regressions: Column (1) presents the estimate with no controls, Column (2) presents the estimate for a set of six selected controls, Column (3) expands this list of controls to 20, and Columns (5) and (6) present the output of a double-selection LASSO using 'Plug-in' and 'Adaptive' selection of the penalization coefficient, λ, respectively. The LASSO selection process selects variables independently in each regression, and the number of control variables selected is included under the LASSO Method. The six selected controls are 3-month premium, vehicle value, median ZIP income, ZIP share hispanic, ZIP share white, and age; the full set of controls add the credit variables in Appendix Table A3. The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets. We also present the mean of the dependent variable under the number of observations, N.

Table A5. ITT of Pay-As-You-Go Contract by Price

	Take-Up	Days with Coverage	Days Insured	Insured End of Study
Panel A: Hugo Outcomes				
PAYG, Low Price	15.55	9.10	4.18	5.97
	(2.47)	(1.90)	(1.60)	(2.02)
	[0.000]	[0.000]	[0.009]	[0.003]
PAYG, Base Price	9.32	4.86	1.55	2.75
	(2.25)	(1.73)	(1.51)	(1.85)
	[0.000]	[0.005]	[0.306]	[0.138]
PAYG, High Price	11.30	6.15	1.11	3.62
	(2.36)	(1.81)	(1.48)	(1.92)
	[0.000]	[0.001]	[0.456]	[0.060]
Constant	5.41	4.22	4.22	4.50
	(1.52)	(1.28)	(1.28)	(1.39)
	[0.000]	[0.001]	[0.001]	[0.001]
N	1,547	1,547	1,547	1,547
Panel B: Any Insurance Outcomes				
PAYG, Low Price	13.58	6.62	2.18	4.10
	(3.03)	(2.67)	(2.53)	(3.37)
	[0.000]	[0.013]	[0.390]	[0.224]
PAYG, Base Price	6.74	1.93	-1.17	0.84
	(2.86)	(2.56)	(2.46)	(3.28)
	[0.019]	[0.452]	[0.635]	[0.798]
PAYG, High Price	11.74	4.99	0.46	1.99
	(3.01)	(2.66)	(2.52)	(3.34)
	[0.000]	[0.061]	[0.857]	[0.551]
Constant	12.16	17.42	17.42	19.82
	(2.20)	(2.09)	(2.09)	(2.68)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,547	1,547	1,547	1,547

Notes: The table reports the main results of the effect of being offered a Pay-As-You-Go insurance contract on take-up (defined as any time after receiving their Hugo quote for Hugo insurance and within 7 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 for both Hugo (Panel A) and Any Insurance (Panel B) outcomes. Here, the indicator for treatment from equation 1 is replaced with an indicator for treatment at each price level, Low, Base, or High; tk how much. The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets. The number of observations, N, and the mean of the dependent variable are also presented.

Table A6. Elasticity Transforms

	log(Days Insured)			ihs(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]						
ihs(Daily Premium)		-0.69		-0.77	-0.61		
		(0.39)		(0.35)	(0.28)		
		[0.079]		[0.031]	[0.027]		
ihs(Base Daily Premium)		0.14		0.19	0.24		
		(0.39)		(0.37)	(0.30)		
		[0.721]		[0.616]	[0.431]		
log(Daily Premium + 1)			-0.87			-0.93	-0.66
			(0.48)			(0.40)	(0.28)
			[0.071]			[0.022]	[0.020]
log(Base Daily Premium + 1)			0.19			0.24	0.26
			(0.47)			(0.42)	(0.30)
			[0.686]			[0.568]	[0.394]
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]	[0.572]	[0.866]	[0.587]
Constant	4.02	4.45	4.38	5.19	1.51	4.44	1.24
	(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	1,325	231	1,325
F	6	6	6	8	6	8	6

Notes: The table reports estimates from linear regressions estimating demand elasticity of outcomes over daily premium with controls for base daily premium and whether the driver was offered the bundle discount. Each of the dependent variables is the outcome for Hugo insurance. 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) take advantage of the ability of their transforms to keep the zero values, estimating elasticities for all 1,325 drivers offered the Pay-As-You-Go contract. Columns (4) and (6) estimate elasticities for the sample of 231 drivers who signed up for the Pay-As-You-Go contract to compare to the estimates from Columns (1)-(3). The coefficients are reported along with standard errors in parentheses and p-values in square brackets. The bottom of the table reports number of observations, N, and the F-statistic for the regression.

Table A7. Bundle Size Shares

	Bundle Discount Offered	
	0	1
Fraction of Purchases 3-Day	51.6	49.7
	(40.7)	(43)
Fraction of Purchases 7-Day	28.2	17.4
	(36.2)	(29)
Fraction of Purchases 14-Day	14.1	17.5
	(25.3)	(31.8)
Fraction of Purchases 30-Day	6.06	15.4
	(19.7)	(32.2)
Fraction of Purchases 3- or 7-Day	79.8	67.1
	(31.3)	(41.2)
Fraction of Days Purchased from 3-Day	41.8	41.8
	(41.5)	(43.8)
Fraction of Days Purchased from 7-Day	29.9	17.8
	(37)	(30)
Fraction of Days Purchased from 14-Day	19.7	20.6
	(32)	(34.4)
Fraction of Days Purchased from 30-Day	8.63	19.8
	(25.6)	(36.2)
Fraction of Days Purchased from 3- or 7-Day	71.7	59.6
	(38.4)	(44)
N	231	

Notes: The table reports the average shares of bundle sizes as a fraction of number of payments and of total days purchased for each user separately by whether they were eligible for a bundle discount. The averages are accompanied by their standard deviations in parentheses.

Table A8. ITT of Bundle on Bundle Size Fraction of Purchases

	Fraction 3-Day	Fraction 7-Day	Fraction 14-Day	Fraction 30-Day	Fraction Bundle
Panel A: All Purchases					
Bundle Discount	-1.91	-10.87	3.41	9.37	12.78
	(5.52)	(4.30)	(3.80)	(3.54)	(4.84)
	[0.729]	[0.012]	[0.371]	[0.009]	[0.009]
Constant	51.59	28.24	14.11	6.06	20.17
	(3.73)	(3.32)	(2.32)	(1.81)	(2.87)
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
Users	231	231	231	231	231
Mean	50.66	22.97	15.76	10.61	26.37
User-Purchases	825	825	825	825	825
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	37.86	26.34	17.70	13.17	30.86
User-Purchases	231	231	231	231	231
Panel C: Follow-On Purchases					
Bundle Discount	-5.38	-7.89	6.78	6.48	13.27
	(6.77)	(4.72)	(5.27)	(3.65)	(5.96)
	[0.428]	[0.096]	[0.200]	[0.078]	[0.028]
Constant	60.47	21.90	13.86	3.76	17.62
	(4.44)	(3.56)	(3.22)	(1.65)	(3.55)
	[0.000]	[0.000]	[0.000]	[0.024]	[0.000]
Users	151	151	151	151	151
Mean	58.02	18.30	16.96	6.72	23.69
User-Purchases	594	594	594	594	594

Notes: The table reports the ITT effect of offering the bundle discount on the fraction of purchases by 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 all purchases after first 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 number of user-purchases.

Table A9. ITT of Bundle on Days Purchased in Bundles

	Fraction 3-Day	Fraction 7-Day	Fraction 14-Day	Fraction 30-Day	Fraction Bundle
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	41.82	24.01	20.12	14.05	34.17
User-Days	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	39.83	27.71	18.61	13.85	32.47
User-Days	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	49.71	19.82	20.72	9.76	30.48
User-Days	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 all purchases after first 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 number of user-purchases.

Table A10. ITT All Interaction with All Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Income Insight Score								
Pay-As-You-Go=1	15.90	9.46	4.40	6.94	11.72	1.70	-2.86	-2.25
	(2.39)	(1.99)	(1.77)	(2.14)	(3.76)	(3.62)	(3.54)	(4.68)
	[0.000]	[0.000]	[0.013]	[0.001]	[0.002]	[0.639]	[0.418]	[0.631]
Below Median Income Insight Score=1	4.31	3.07	3.07	3.25	1.44	-4.80	-4.80	-5.54
	(3.20)	(2.80)	(2.80)	(3.05)	(4.84)	(4.56)	(4.56)	(5.93)
	[0.179]	[0.272]	[0.272]	[0.286]	[0.766]	[0.293]	[0.293]	[0.350]
Pay-As-You-Go=1 × Below Median Income Insight Score=1	-6.80	-4.75	-4.19	-4.43	-3.25	4.85	5.26	7.03
	(3.95)	(3.26)	(3.00)	(3.52)	(5.48)	(5.01)	(4.90)	(6.46)
	[0.085]	[0.146]	[0.164]	[0.209]	[0.553]	[0.333]	[0.283]	[0.277]
Constant	3.06	2.79	2.79	3.06	12.24	20.96	20.96	24.49
	(1.74)	(1.59)	(1.59)	(1.74)	(3.32)	(3.32)	(3.32)	(4.35)
	[0.079]	[0.079]	[0.079]	[0.079]	[0.000]	[0.000]	[0.000]	[0.000]
N	1,283							
Median Income Insight Score	34,000							
Panel B: Credit Constrained								
Pay-As-You-Go=1	14.28	6.54	0.59	4.40	13.94	4.80	-0.41	0.70
	(4.52)	(3.92)	(3.65)	(4.21)	(5.80)	(5.37)	(5.25)	(6.75)
	[0.002]	[0.095]	[0.871]	[0.297]	[0.016]	[0.372]	[0.938]	[0.917]
Credit Constrained=1	-1.58	-2.51	-2.51	-2.71	-1.47	-0.85	-0.85	-3.01
	(4.07)	(3.72)	(3.72)	(4.00)	(5.63)	(5.43)	(5.43)	(6.88)
	[0.698]	[0.500]	[0.500]	[0.498]	[0.794]	[0.875]	[0.875]	[0.661]
Pay-As-You-Go=1 × Credit Constrained=1	-2.76	0.21	2.12	-0.33	-4.07	-0.38	1.09	2.01
	(4.95)	(4.22)	(3.92)	(4.54)	(6.41)	(5.93)	(5.80)	(7.48)
	[0.577]	[0.960]	[0.590]	[0.942]	[0.526]	[0.948]	[0.850]	[0.788]
Constant	6.67	6.22	6.22	6.67	13.33	18.10	18.10	22.22
	(3.72)	(3.47)	(3.47)	(3.72)	(5.07)	(4.91)	(4.91)	(6.21)
	[0.074]	[0.074]	[0.074]	[0.074]	[0.009]	[0.000]	[0.000]	[0.000]
N	1,547							
Share Credit Constrained	80.7							
Panel C: No Regular Policy History								
Pay-As-You-Go=1	6.35	2.15	-2.21	-0.05	3.02	-2.71	-6.90	-0.98
	(4.19)	(3.49)	(3.33)	(3.78)	(5.42)	(4.70)	(4.62)	(5.63)
	[0.130]	[0.537]	[0.508]	[0.990]	[0.577]	[0.565]	[0.136]	[0.862]
No Regular Policy History=1	-7.22	-6.06	-6.06	-6.37	-12.51	-11.10	-11.10	-5.82
	(4.00)	(3.42)	(3.42)	(3.72)	(5.45)	(4.93)	(4.93)	(6.06)
	[0.071]	[0.076]	[0.076]	[0.087]	[0.022]	[0.025]	[0.025]	[0.338]
Pay-As-You-Go=1 × No Regular Policy History=1	8.13	6.49	6.42	5.95	10.91	10.30	10.56	4.70
	(4.60)	(3.78)	(3.58)	(4.09)	(6.02)	(5.33)	(5.23)	(6.57)
	[0.077]	[0.087]	[0.073]	[0.146]	[0.070]	[0.054]	[0.044]	[0.475]
Constant	10.45	8.45	8.45	8.96	20.90	25.17	25.17	23.88
	(3.74)	(3.21)	(3.21)	(3.49)	(4.97)	(4.39)	(4.39)	(5.22)
	[0.005]	[0.009]	[0.009]	[0.010]	[0.000]	[0.000]	[0.000]	[0.000]
N	1,547							
Share with No Regular Policy History	70.3							

Notes: The table reports the main intent-to-treat results of the effect of being offered a Pay-As-You-Go insurance contract on both Hugo (Columns(1)-(4)) and Any Insurance (Columns(5)-(8)) outcomes of take-up (Columns (1) and (5)), days with coverage (Columns (2) and (6)), days insured (Columns (3) and (7)), and being insured at the end of the three-month study (Columns (4) and (8)), interacted with three different sources of heterogeneity per equation 4; Panel A estimates the intent to treat effect interacted with the drivers' income insight score (annual income as estimated by Experian), Panel B estimates the intent to treat effect interacted with whether the driver is credit constrained (defined as having credit balances at or above credit limits or having no credit limit), and Panel C estimates the intent to treat effect 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). The coefficients are listed with robust standard errors below in parentheses and p-values in square brackets. The number of observations, N, and the mean of the dependent variable are also presented.

Table A11. ITT of Two-Month Outcomes

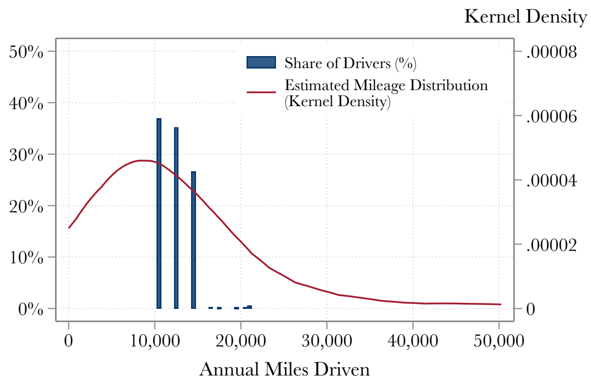
	Take-Up	Days with Hugo Coverage	Days Insured	Insured End of Study
		Panel A: Hugo Outcomes		
Pay-As-You-Go	12.03	5.28	2.40	5.23
	(1.84)	(1.00)	(0.93)	(1.61)
	[0.000]	[0.000]	[0.010]	[0.001]
Constant	5.41	2.83	2.83	4.50
	(1.52)	(0.85)	(0.85)	(1.39)
	[0.000]	[0.001]	[0.001]	[0.001]
N	1,547	1,547	1,547	1,547
		Panel B: Any Insurance Outcomes		
Pay-As-You-Go	10.63	4.20	1.64	3.36
	(2.48)	(1.53)	(1.50)	(3.01)
	[0.000]	[0.006]	[0.275]	[0.265]
Constant	12.16	10.66	10.66	21.62
	(2.20)	(1.39)	(1.39)	(2.76)
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,547	1,547	1,547	1,547

Notes: The table presents the main results 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 Hugo outcomes and two months from when the driver received their quote for Any Insurance outcomes. The outcomes are take-up (defined as any time after receiving their Hugo quote for Hugo insurance and within 7 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.

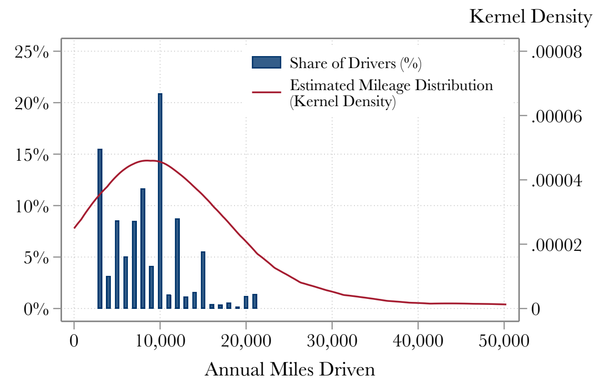
D Appendix Figures

Figure A1. Insurance Policies by Mileage Against Mileage Distribution

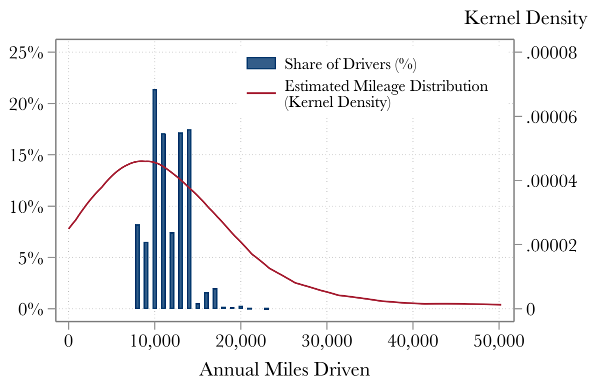
(a) Aspire



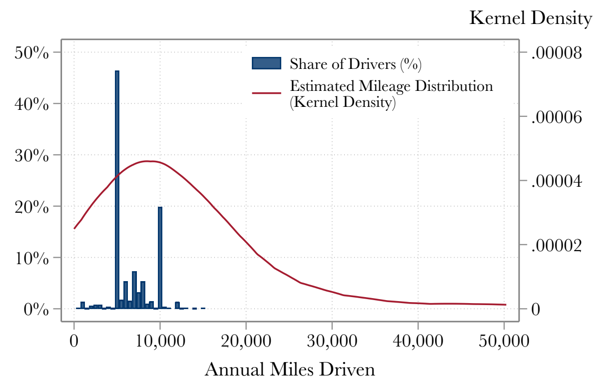
(b) Mercury



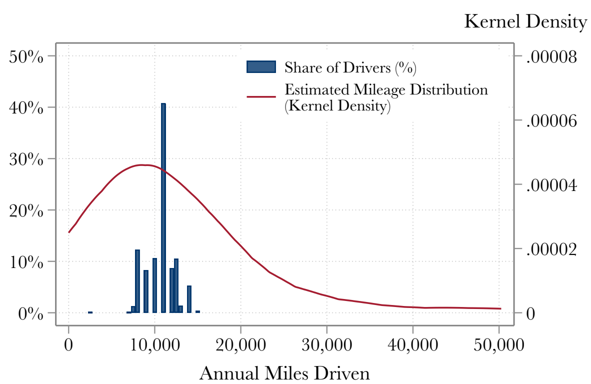
(c) Sterling



(d) Viking

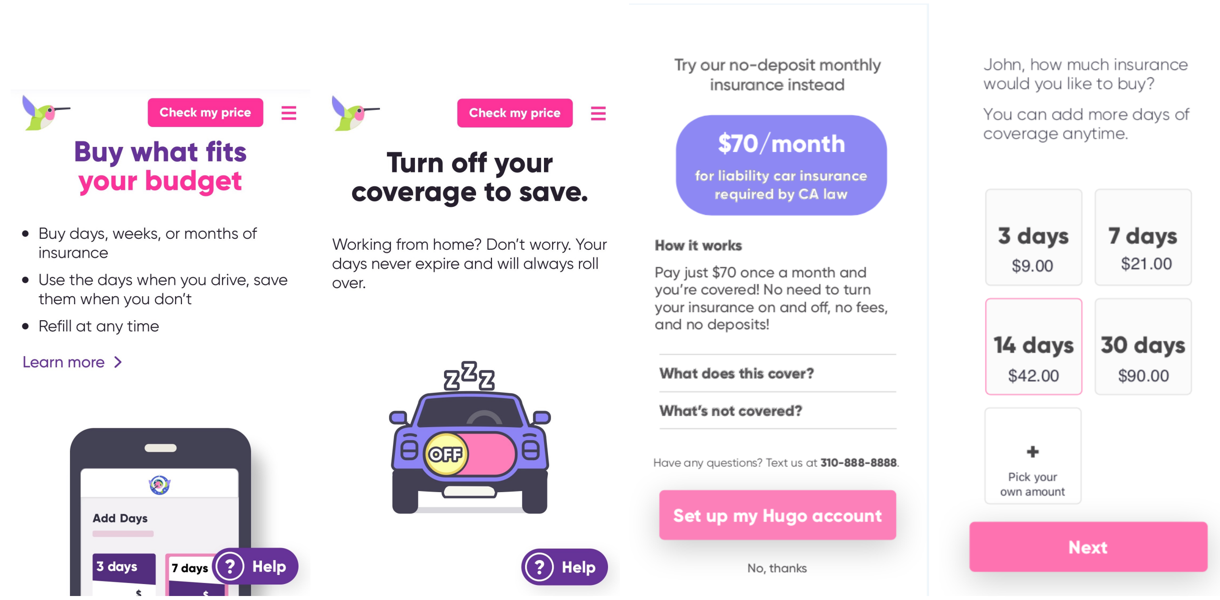


(e) Western



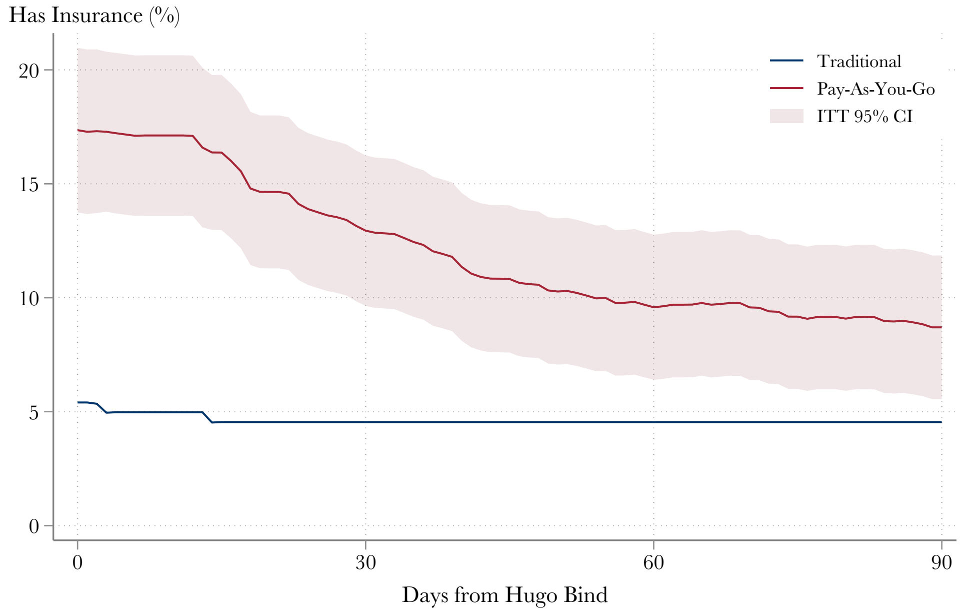
Notes: The figures above compare the share of drivers placed in each mileage bin for five different insurance companies: Aspire (Panel A), Mercury (Panel B), Sterling (Panel C), Viking (Panel D), and Western (Panel E); the discrete bins are represented as bar charts and compared to the kernel density estimation of the true distribution of drivers according to NHTS data.

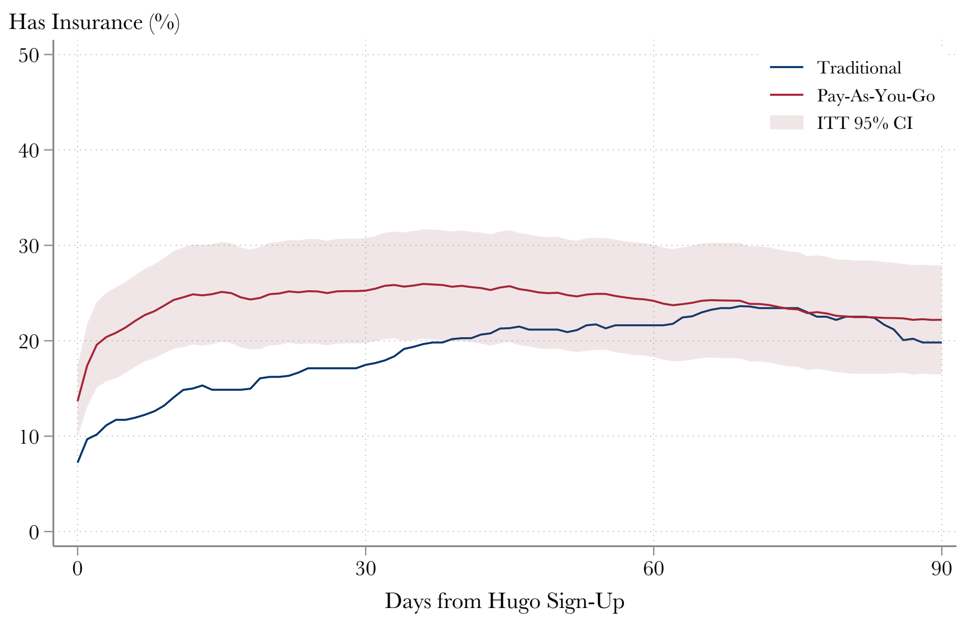
Figure A2. Hugo Screenshots



Notes: Screenshots from Hugo quote application.

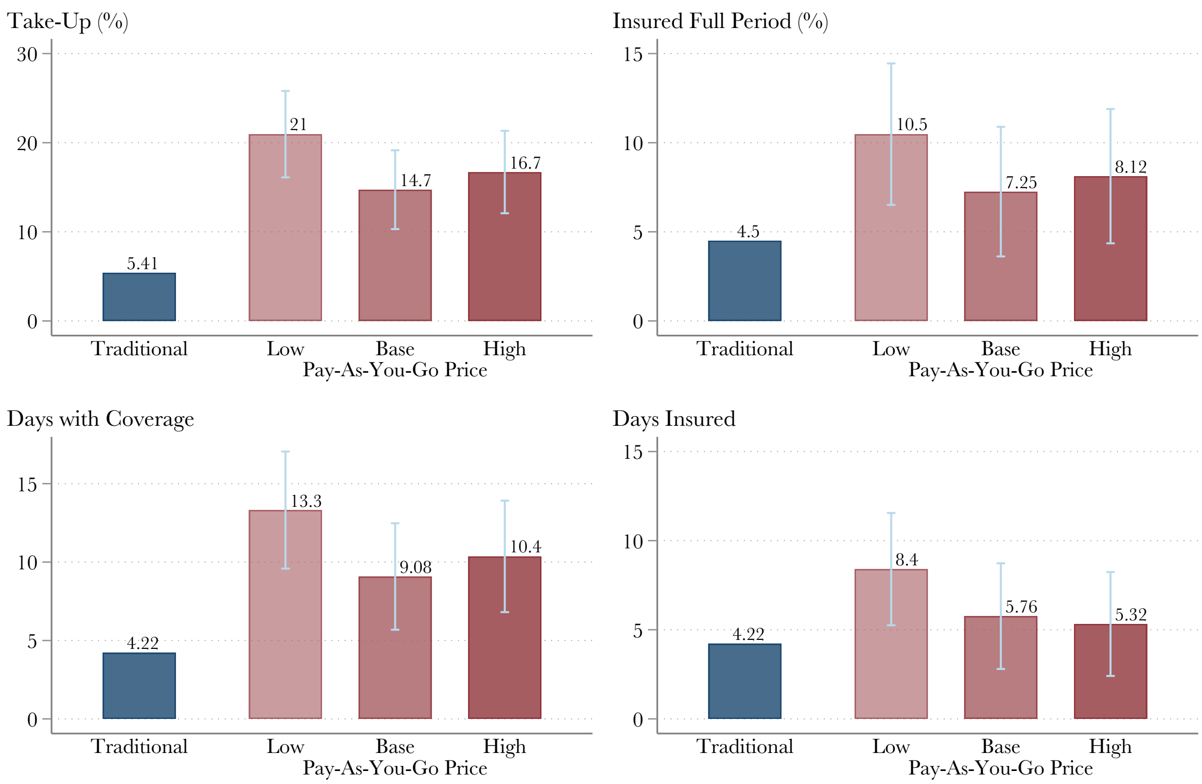
Figure A3. ITT PAYG Over Time





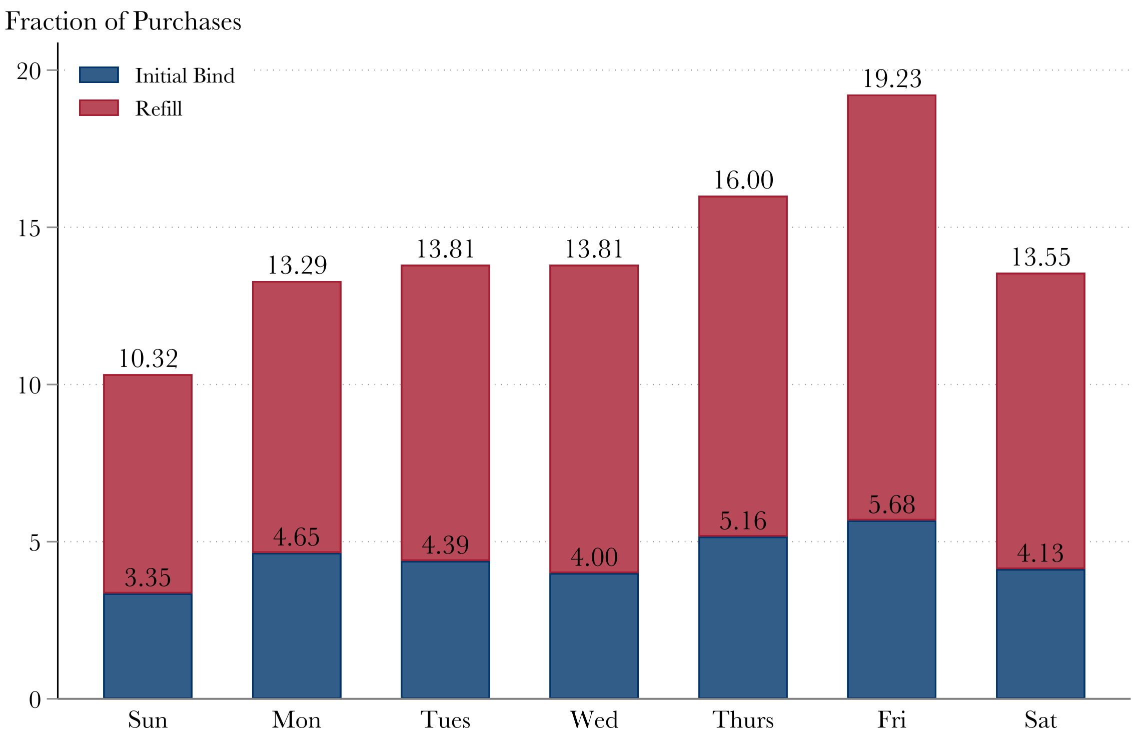
Notes: The above figures show the ITT effect of the Pay-As-You-Go contract over time for whether a driver was covered by Hugo (having a nonzero reserve balance of insurance, above) and whether a driver is covered by any insurance (below) separately for those 1,325 drivers offered the Pay-As-You-Go and 222 drivers offered the Traditional contract. The 95% confidence interval of the ITT effect is shown in the shaded portion of the graphs, calculated from a fixed effects regression of the given outcome over the interaction between the running day variable and whether the user was offered the Pay-As-You-Go contract, absorbing the running day variable and clustering the standard error at the user level.

Figure A4. ITT Barchart by Price



Notes: The figure presents the mean values of take-up and days with coverage from Hugo and from any insurance, separately for those offered the Traditional and Pay-As-You-Go insurance contract; drivers offered the Pay-As-You-Go contract are further separated by their assigned price group, Low, Base, or High. 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 A5. Payment Day of Week Fractional Shares



Notes: The plot shows the fraction of Refill ("Manual SMS" and "Manual Web") and Initial Bind (payments upon signing up for the contract) payments for each day of the week among the 231 drivers who signed up for the Pay-As-You-Go contract.