The Online Payday Loan Premium *

Filipe Correia† Peter Han‡ Jialan Wang§

January 20, 2025

Abstract

Using data on payday loans and loan applications for online and storefront payday loans, we document a \$4 per \$100 borrowed (100 p.p. APR) online premium. This difference is not explained by ex-ante or realized credit risk. Loan-level risk-based pricing is not prevalent in payday loan markets. Using cross-section variation in statewide payday loan database implementation, we show that information asymmetry explains the equilibrium of higher prices and default rates online. State-level fee caps attenuate the premium. Our quantitative model suggests higher credit risk, higher cost structure, and more convenient services as the drivers of the online payday loan premium.

Keywords: Online Lending, Payday Loans, Fintech

JEL Codes: D18, G23, G52

*We are grateful to Heitor Almeida, Scott Baker, Brian Baugh, Laura Blattner, Tatyana Deryugina, Julia Fonseca, Diego Garcia, Jitka Hilliard, Anson Ho, Rustom Irani, Timothy Johnson, Charles Kahn, Mathias Kronlund, Tom Miller, Holger Mueller, Chao Liu, Nikhil Paradkar, George Pennacchi, Andrea Presbitero, Elizaveta Sizova, Alexei Tchistyi, Sergio Vicente, Malcolm Wardlaw, Constantine Yannelis, and participants at the Gies College of Business and Terry College of Business brownbag, the 28th Finance Forum, and the 7th International Young Scholars Conference, the Edinburgh Economics of FinTech Conference, the HEC Montreal Workshop on Household Finance, and the GA Tech - Atlanta Fed Household Finance Conference for valuable suggestions. Renhao Jiang, Peichen Li, Yunrong Zhou, Hejia Liu, Kevin Tzeng, Kashish Mehta, Raja Gajula, Matthew Boyd, Yiheng Yang, Kunal Bagali, and Avishi Biljani provided valuable research assistance.

†University of Georgia, Terry College of Business, B339 Amos Hall, 620 S Lumpkin St, Athens, GA 30602. filipe.correia@uga.edu

‡Purdue University and University of Illinois at Urbana-Champaign weitong2@illinois.edu

§University of Illinois at Urbana-Champaign & NBER. Gies College of Business, 1206 South 6th Street, Champaign, IL 61820. jialanw@gmail.com

1 Introduction

The payday lending market has become increasingly digitized in recent years, following trends in other types of lending. Digital infrastructures have the potential to reach new customers and improve screening. Loan origination becomes more efficient and faster, meeting the immediacy preferences of payday loan borrowers. However, the online sphere adds new risks and demands sophisticated physical and human capital.

Payday loans serve borrowers by providing instant liquidity in exchange for repayment and a fee due on the income receipt date. The fees charged by payday lenders, when converted to annual percentage rates, are much higher than those of other high-cost credit. Policy reports and regulator press releases have labeled payday lender practices as "predatory" (PEW, 2012) and "abusive" (CFPB, 2021; CFPB, 2024) , often tying these terms with the high prices charged by lenders.

In this paper, we leverage high-quality data on online and storefront loans to examine payday loan pricing. Online payday lending can potentially reduce the cost of lending due to lower overhead cost, but also introduce additional frictions such as higher information asymmetry and additional layers of financial intermediaries (e.g. costly lead generators, targeted advertising, affiliate programs, and lead-scoring agents). In addition, borrowing online can be convenient to the borrowers (Fuster, Plosser, Schnabl and Vickery, 2019). We pin down the role of each mechanism in determining payday loan prices.

We utilize a novel dataset from Clarity, a firm specializing in data collection from the subprime lending market and lead generation services, including the payday loan market. We observe loan applications and loan records. Our data contains loan amounts, repayments, maturity dates for each loan, and information on whether the loan originated at a store or online. We also have access to a variety of information about the borrower, such as their income, age, ZIP code, state of residence, housing status, and homeownership status. Our data set allows us to contrast online and storefront loans, as we observe the same data from each of the two business models.

We begin our analysis by documenting two stylized facts. First, we document a significant premium of $4 per $100 borrowed (100 p.p. APR) for the payday loans that are originated by online lenders. This premium is robust to controls for ex ante predictors of risk, time, and location fixed effects, and is consistent across different samples. Although realized default rates are higher online, they do not explain the online premium. The premium is larger when consumer fixed effects are included, and the same borrower displays a larger propensity to default online. Differences in realized default rates on pools of similar borrowers do not absorb the price difference between online and storefront lenders.

Second, we find that ex ante predictors of default are not priced at the loan level, but in aggregate, markets with riskier borrower pools experience higher loan prices. In particular, we show that loan-level predictors of default observed by the lender do not strongly correlate with loan pricing, and we do not detect any systematic pattern in prices or quantities along credit score or income. This result suggests that each lender sets similar prices for various consumers, regardless of observable characteristics, such as income. With online lenders using alternative sources of information and advanced algorithms (Jagtiani and Lemieux, 2018), risk-based pricing at the loan level would likely lead to an attenuation of the online payday loan premium.

To rationalize these results, we examine four mechanisms that can explain higher online prices, even in the absence of loan-level risk-based pricing: (1) Riskiness of borrower pool: our data indicate that the online lending sector attracts a riskier borrower population compared to traditional storefront lenders. (2) Convenience: Consumers may be willing to incur higher costs for the convenience offered by online lending. This convenience encompasses factors such as eliminating the need to visit a physical store, reducing the stigma associated with face-to-face interactions with loan officers, and avoiding the public visibility of obtaining a last-resort loan. (3) Regulation: Regulatory requirements may differentially impact online and storefront lenders. (4) Cost structure: The online business model typically entails higher operational costs, which are subsequently passed on to consumers. Specifically, the lead generation process involves significant expenditures related to the acquisition of lending priorities through mechanisms such as ping trees, lead scoring services, and the use of alternative data by lenders.

We start by recognizing information asymmetry as an inherent trait of the payday loan market. Payday lenders do not perform hard credit pulls and rely on self-reported information to make lending decisions. We exploit cross-sectional variation in information asymmetry between states that implemented statewide payday loan databases and states that did not. Statewide databases allow all lenders to share and access the same information about borrowers, thus reducing information asymmetry in the payday loan market. We find that in states with a database, the premium is about 2/3 of the premium in states without a database. This aligns with findings of DeFusco, Tang and Yannelis (2022) on credit price distortions caused by information asymmetry and establishes information asymmetry as a crucial friction to explain the pooling equilibrium.

We show that variation in regulation is unlikely to explain the higher price of online payday loans. In the United States, state laws can limit loan amounts, the number of loans, loan prices, and maturities for online and storefront payday loans. Stores are physically located in a jurisdiction where state law applies. Online lenders can locate themselves in territories where laws can be more advantageous. We investigate the role of geographical heterogeneity in state laws in contributing to the online premium. Consistent with Fekrazad (2020), in states with fee caps, these laws bind, and both online and storefront loan prices bunch at the legally allowed limit. This fact has two implications: (i) if anything, state laws hinder the prevalence of the online payday loan premium, as a significant fraction of both online and storefront loans are priced at the legal limit; and (ii) within a given market, online lenders show limited ability to benefit from regulatory arbitrage, as their prices are bound by the law. We observe the largest discrepancies between online and storefront prices in states without a fee cap.

We are left with three candidate mechanisms to explain the online payday loan premium: riskiness of the borrower pool, utility of convenience, and cost structure. We build a quantitative model to study the roles of credit risk, convenience, and cost structure in the price of payday loans. The model is a variation of the quantitative model in Buchak, Matvos, Piskorski and Seru (2018) adapted to our setting. To capture our empirical findings, we allow online and storefront business models to differ along the credit risk they face and the convenience provided to customers. We also allow their costs to be different, and calibration results show that online lenders appear to operate in a costlier setting. Loan prices are endogenously determined when the two types of lenders compete for borrower demand.

We calibrate the model using our main Clarity sample. Counterfactual estimates show that absent differences in cost structure or convenience, default rates fall short in driving price levels or the online premium. Only with differences in both convenience and business cost structures are we able to approximate both the loan price levels in the online and storefront markets and the price difference between the two markets. The idea that the premium arises even if storefront and online businesses are equally convenient shows the importance of lender cost structures in determining prices faced by consumers.

Our paper directly contributes to the broader literature that focuses on subprime credit markets (e.g., Adams, Einav and Levin (2009)), namely the payday loan market (e.g., Nunez, Shaberg, Hendra, Servon, Addo and Mapillero-Colomina (2016)). Montezemolo (2013) reviews the legal framework of payday loans in the United States and documents the abusive practices of payday lenders. Wang and Burke (2022) find a significant drop in payday lending volume after mandatory state disclosure. Within the payday lending literature, our paper speaks to the interplay between pricing and business model innovation. With some leeway for regulatory arbitrage and a more expensive business ecosystem, online payday lenders charge higher loan prices.

Our paper is related to the literature on costly search and price dispersion in the consumer credit market, beyond credit cards (Stango and Zinman, 2016), mortgages (Alexandrov and Koulayev, 2018), and auto loans (Argyle, Nadauld and Palmer, 2023).our paper is among the first to document price dispersion in the payday lending market and explain it, using differences in regulation and lender costs.

Existing works on the payday lending market focus on welfare implications[1]. We speak to this literature by documenting the existence of a premium on online payday loans, which have become very prevalent in the last decade. Only recently, the debate on payday loan welfare has started to pay attention to payday loan pricing. Saldain (2023) finds that borrowing limits and interest rate caps reduce household welfare. Similarly, Sridhar (2023) shows that existing rate caps are inefficiently regulated and that separating initial fees from rollover fees can improve welfare. Allcott, Kim, Taubinsky and Zinman (2022) estimate that while a pure payday loan ban likely generates welfare losses, limiting rollovers can increase welfare. Our paper is the first to examine the role of convenient and lender cost structures in determining loan prices.

We also contribute to the growing literature on how financial technology shapes consumer credit markets. So far, much attention has been paid to peer-to-peer lending (Morse, 2015; Li, Li, Yao and Wen, 2019), online mortgages (Fuster, Plosser, Schnabl and Vickery, 2019; Di Maggio and Yao, 2021; Chava, Ganduri, Paradkar and Zhang, 2021). Bartlett, Morse, Stanton and Wallace (2022) show that fintech does not mitigate consumer racial / ethnic discrimination in lending. Buchak, Matvos, Piskorski and Seru (2018) attribute the rise of the originate-to-distribute logic in credit to technological advancement and regulatory frictions. Li, Liao, Wang and Xiang (2018) study consumption responses to online cash loans and find consumption increases in the digital ecosystem. Payday loans and their online dimension have not yet been addressed in fintech research. We show how fundamental differences between the in-store and online business models lead to a price difference, where

[1]See Agarwal, Skiba and Tobacman (2009), Melzer (2011), Bertrand and Morse (2011), Morse (2011), Carrell and Zinman (2014), Bhutta (2014), Bhutta, Skiba and Tobacman (2015), Carter and Skimmyhorn (2017), Dobridge (2018), Skiba and Tobacman (2019), Gathergood, Guttman-Kenney and Hunt (2019), Li and Sun (2021).

online payday loans are more expensive.

The remainder of the paper is organized as follows. Section 2 provides an institutional background on payday lending and online payday lending; Section 3 describes the dataset, explains the data processing procedure, and places the data in context; Section 4 documents the absence of risk-based pricing at the loan level and provides evidence of the online payday loan premium; Section 5 documents asymmetric information and explains the pooling equilibrium; Section 7 quantifies the role of credit risk, business cost structure and convenience in payday loan prices; Section 8 concludes.

2 Background on the Payday Loan Market

Payday loans are a common source of short-term credit among low- to middle-income Americans. Between 2015 and 2019, about 2 percent of households reported using at least one payday loan per year, with higher shares among low income groups and higher shares that had ever used a payday loan (Kutzbach, Lloro, Weinstein and Chu, 2020). The payday lending industry has always been at the center of controversy and regulatory scrutiny due to high annualized costs and the high occurrence of repeat borrowing.

2.1 Payday Loan Pricing

They are typically between \$300 and \$500 in principal and are structured as a single balloon payment of the amount borrowed and fees, timed to coincide with the borrower's next payday. Fees generally average between \$10 and \$20 per hundred dollars borrowed and typically do not vary with the duration of the loan. A flat \$15 per \$100 fee annualizes to nearly 400% APR for a 14-day loan corresponding to biweekly pay dates (Consumer Financial Protection Bureau, 2013).

In payday loan stores, loan prices are announced in both cost per \$100 and APR terms.

The store quotes these amounts on a banner visible to the borrowers, where they see their fee and APR for each possible loan amount and the total expected repayment. Quoting the price in APR has been defended by regulators (e.g. Truth In Lending Act) as it allows the consumer to draw direct comparisons among different credit products. However, there are some arguments against the use of APR as an adequate communication of the price of a payday loan. Stoesz (2014) discusses that annualizing the payday loan fee is akin to annualizing the per-night hotel room rate. Others justify the use of dollar cost (cost per $100) as being easier for the consumer to compare with overdraft and NSF fees, or transportation dollar costs (Bolen, Elliehausen and Miller Jr, 2020).

2.2 Payday Loan Regulation

The storefront payday industry expanded through the 1990s and early 2000s, driven in part by the loosening of state usury laws and partnership structures between payday lenders and banks to "import" regulations across state lines, a practice ended by the FDIC in the mid-2000s.[2] The online payday industry grew from a small share of loans to a significant market share over the 2010s, reaching a steady state of between 35% to 45% of the overall payday market between 2013 and 2019, with overall loan volumes including storefront and online declining from $46 billion to $25 billion annually during this period (Hecht, 2014, 2018; Graham and Golden, 2019).

In recent years, state regulators have imposed restrictions that include loan size caps, fee caps, rollover activity limits, cooling periods, and absolute bans, among other measures (Kaufman, 2013). The Consumer Financial Protection Bureau became the industry's first federal regulator in 2011. The CFPB issued rules governing the payday industry in 2017 which were largely rescinded in 2020, so regulation still largely falls on the states[3] (Kirsch, Mayer and Silber, 2014).

[2]See Mann and Hawkins (2007) for more information on the "rent-a-bank" model.
[3]See https://www.consumerfinance.gov/payday-rule/

In 2015, 15 states had banned traditional storefront lending. State payday laws are complex, and jurisdiction over online lending remains contested in the court system, despite many state and federal regulators enforcing laws that restrict online loans in states that also regulate storefront lending (King and Standaert, 2013; Consumer Federation of America, 2010). In addition to regulatory considerations, other features that differ between the online and storefront payday loan markets include payment and collection mechanisms that involve Automated Clearing House (ACH) transactions and bank account access instead of dated checks and in-person payment, and online advertising market (PEW, 2014).

2.3 Cost Structure of Online Payday Loans

Although the payday lending industry is believed to be highly profitable, early studies do not support this idea (Flannery and Samolyk, 2005; Huckstep, 2007). Thus, the cost structure of payday lending is a fundamental component of the price passed on to consumers (Ernst & Young, 2009). Online payday loans have structural differences from the storefront business model in that the former requires two additional layers of financial intermediaries, which add to the lending costs.

In the first step, online payday lending starts with online lead generation. A lead is an opportunity to do business, proxied by an expression of interest by a potential customer. Leads can be tracked and traded. A merchant who sells leads to potential lenders is a lead generator. As is common in digital marketing, lead generation is heavily targeted and follows consumers in every action they perform online. According to a Wall Street Journal article[4], 75% of online payday loan volume is sourced from lead generators, at the same time that lead generators have a large space to conduct fraudulent and abusive behavior, such as selling personal financial information without consent.

In the second step, lead aggregators do auctions to sell their lead portfolios. These

[4]See "Middlemen for Payday Lenders Under Fire", The Wall Street Journal, April 7, 2014. Link: https://www.wsj.com/articles/SB10001424052702304819004579487983000120324

auctions can be conducted via ping trees. Ping trees can be used when leads can be sold more than once to different buyers and when leads are exclusive and only sold once. They are electronic queues lenders pay to define their priority in receiving a lead. As a lead aggregator explains it on their website, placement in the ping tree can range from $2 to upward of $120. Online lenders set their price points, and as leads come in, they are shown to lenders willing to pay the highest price per lead. The lead information helps lenders decide whether to purchase the lead. Lower bids from the lender result in a lower tree position and a higher chance of lower lead quality. Higher returns from lending are promised in exchange for a higher bid for a privileged ping tree position.

3 Data

Our storefront and online payday loan data are sourced from Clarity, an alternative credit bureau and a subsidiary of Experian, one of the three major credit reporting agencies. Previous research using Clarity data includes Di Maggio, Ma and Williams (2020), Miller and Soo (2020), Miller and Soo (2021), and Fonseca (2023). Blattner and Nelson (2021) use similar data from FactorTrust, another alternative credit bureau. Clarity compiles application, origination, and repayment information for subprime loans to help lenders make underwriting decisions. Its database includes about 63 million borrowers and over 70% of non-prime consumers in the United States. Like other credit reporting agencies, Clarity relies on voluntary reporting of inquiries, originations, and performance by its network of lenders and data providers, which may not reflect the full universe of subprime loans or the universe of information from all participating lenders. Nonetheless, it is among the best sources of nationwide subprime credit activity.

The Clarity database contains information on various subprime credit products, including payday, rent-to-own, installment, auto, and auto title loans. Our focus is on online and storefront payday loans in this study, which represent about 32% of inquiries and 47% of tradelines in the full database. For each inquiry, Clarity reports information about the type of loan applied for and some self-reported demographics, including ZIP code and state of residence, monthly income, age, housing status, months at the same address, and paycheck frequency. Although some lenders may employ income and identity verification and fraud detection mechanisms, the information reported in inquiries is self-reported by the borrowers and might not be verified before submission to Clarity. For originated tradelines, we observe loan type, highest credit, scheduled and actual payment amounts, payment dates, and delinquency status.

We use two samples provided by Clarity in our analysis. The first one, known hereafter as the "standalone" or "random Clarity" sample, consists of 1 million consumers randomly drawn from Clarity's database from 2013 to 2017. According to the data provider, Clarity's full database consisted of approximately 63 million consumers as of 2020, so our sample contains about 1.5% of the database. The sample of borrowers includes those who apply for payday loans and other products, and only a subset of applications result in originated loans, which we use in our main analysis. In 1 million unique borrowers who submitted an inquiry for any subprime credit tradeline, 366,327 applied for a payday loan online or in store. Of these, 65,733 originated a payday loan, comprising our final sample.

The second sample, known hereafter as the 'credit visible' sample, consists of payday borrowers matched to a random 1% sample of all consumers in the traditional Experian credit report database as of 2018. All payday loans originated by 35,550 unique borrowers between 2013 and 2019 are included in this sample. The random Clarity and credit visible samples are drawn independently.

Because payday loan fees typically do not vary with duration, they are generally marketed to customers in terms of the cost per $100 borrowed. However, lenders are also required by the Truth in Lending Act to disclose prices in APR terms. While usury laws on are usually written in interest rate terms, laws on payday loan fee caps are expressed in cost per $100 terms. Therefore, we examine both measures of loan prices. We do not observe prices directly in the Clarity data, and infer them based on loan amounts and repayment amounts:[5]

$$Cost\ per\ 100 = 100 \times \frac{Repayment - LoanAmount}{LoanAmount} \tag{1}$$

$$APR = \frac{365}{LoanMaturity} \times \frac{Repayment - LoanAmount}{LoanAmount}$$

Payday loans have fairly simple and standardized structures. Therefore, these basic formulas accurately capture the realized prices of most loans. However, one caveat is that scheduled payment amounts are missing in much of the data, so we need to use realized payments instead. This means that prices will not be accurately captured for loans not repaid in full (e.g. prices would be inferred to be -100% for loans that are fully defaulted on). Although defaults represent a small fraction of loans, if defaulted loans are systematically priced differently from repaid loans, our method would lead to measurement error that could be correlated with our variables of interest.

Risk-based pricing at the loan level is very limited in the online and storefront payday markets. Therefore, we do not think this potential source of measurement error drives our results. To impute prices for defaulted loans, we employ a waterfall methodology to match defaulted loans to the median price of similar non-defaulted loans within cells by origination month, loan type, state, ZIP code, and terciles of loan and borrower characteristics. We try to match defaulted loans to non-defaulted ones in cells of decreasing granularity until all loans are matched (e.g. ZIP code is matched first, and if no available priced loans are matched by ZIP code, then state-level matches are used). In the analysis below, we show the results for both the full sample and the 'non-imputed' sample of loans where we measure prices from Equation (1) instead of via matching. We winsorize APR and cost per $100 at the 99th percentile in all analyses to reduce the effect of outliers.

[5] See DeYoung and Phillips (2006a,b)

3.1 Summary Statistics and External Validity

In this section, we report summary statistics for our sample. Table 1 presents summary statistics for the random Clarity sample in Panel A and the credit visible sample of loans matched to Experian consumer credit records in Panel B. Despite differences in the sample periods and the existence of traditional credit reports between the two samples, the descriptive statistics are extremely similar across our two samples. Figure 1 shows the geographical distribution of loans by state in both of our samples, comparing the online and storefront markets. Online loans are available in all 50 states. Storefront loans are absent in some sparsely populated states and those where state laws are likely to effectively prohibit traditional payday lending during our sample period (e.g., Montana, New Mexico, and much of New England).

The random Clarity sample in Panel A of Table 1 consists of 336,690 loans from more than 65,733 borrowers, 65% of which are online. The credit visible sample in Panel B includes 188,913 loans and 35,550 borrowers with a 70% online share. By scaling our random Clarity sample by the size of the entire Clarity universe and comparing to industry payday market size estimates, we calculate that Clarity represents 8% of the storefront market and 23% of the online payday market as of 2017, with coverage of the total payday market growing from 4% to 15% of loan volume originated between 2015 and 2017 (Hecht, 2014, 2018; Graham and Golden, 2019). The larger market share of online versus storefront loans likely reflects the historical evolution of Clarity's client base and online lenders' greater use of reporting and verification systems to mitigate fraud risk.

The characteristics of loans and consumers in our samples are consistent with those from previous literature and policy reports, with average loan amounts of \$365 to \$370 across our two samples and average maturities of 19 to 20 days corresponding to a combination of consumers with weekly, biweekly, and monthly pay dates (Skiba and Tobacman, 2008, Consumer Financial Protection Bureau, 2013, PEW, 2014, Wang and Burke, 2022). While loan and customer characteristics are fairly comparable to previous studies using storefront payday data (e.g. Skiba and Tobacman 2008, Wang and Burke 2022), the average borrower income of $2822 to $2849 is significantly lower in the Clarity online payday data compared with $4334 among online payday borrowers in an account aggregator sample studied by Baugh (2016), which could reflect differences in income measurement or the likely higher income of consumers included in account aggregator data.

We consider a lower bound for the default rate loans reported to Clarity as not paid in full by lenders. The average default rate of 7% in the full Clarity samples and 4% in the storefront samples is comparable to that of previous studies using administrative data from storefront payday lenders. Skiba and Tobacman (2008) report a 4% charge-off rate and Wang and Burke (2022) report a 3% default rate. Both of these previous papers report substantially higher delinquency rates than default rates, suggesting that the default rate we measure in Clarity likely corresponds to ultimate charge-offs and not to temporary delinquency. We do not attempt to distinguish between delinquency and default, track the ultimate recovery rate of defaulted loans, or account for reporting errors or reporting lags (e.g. lenders failing to report defaults to Clarity).

The average default rates for online loans range from 8% to 9% in our samples, about double that of storefront loans. This contrasts with the general demographics associated with a lower risk of credit for online loans and borrowers. In our sample, we observe a slightly lower propensity for late payments on online loans (31%) versus storefront (35%). This discrepancy is consistent with technological advances in the online world. ACH processing via routing and account numbers can be done to avoid delays, and cashing checks can generate payments posterior to due dates.

Online loans are significantly smaller, and online borrowers report significantly higher income and home ownership and slightly longer months at address compared to storefront borrowers in panels A and B. The main exception to this pattern is that online borrowers in the credit visible sample are more than twice as likely to be unscoreable compared with storefront borrowers (21% vs. 10%), and have lower Vantage scores conditional on being scoreable (500 vs. 535). Although we classify all borrowers with a traditional Experian credit report as part of our 'credit visible' sample, some nonetheless lack valid Vantage scores, which likely reflects borrowers with thin or potentially incomplete or incorrect credit files (Blattner and Nelson, 2021). The higher income, lower age, and higher risk of default associated with online payday loans are consistent with previous survey evidence (PEW, 2014).

Based on the pricing formulas and the imputation algorithm described in Equation (1), we find average loan prices of $16.6 in the random Clarity sample (Panel A) and $16.9 in the credit visible sample (Panel B).Despite the assumptions needed to calculate prices in the Clarity data, these estimates are consistent with those from previous studies that use prices directly observed in administrative data from storefront payday lenders. Skiba and Tobacman (2008) report a cost per $100 of $17.9 using a sample from Texas, one of the most expensive lending markets. Wang and Burke (2022) report an average cost per $100 of $12 in a multi-state sample and $20 in Texas, corresponding to APRs of 281% and 508%. For comparison, the average prices for storefront loans range from $12.4 to $13.3 per $100 and 295% to 300% APR in our Clarity samples.

Price statistics for online payday loans are rarer, and we are unaware of previous academic studies on this topic. In a survey of lender websites, Consumer Federation of America (2011) reports an average cost per $100 of $25 and an APR of 652%, which are substantially higher than the average cost per $100 of $18.5 - $18.9 and APRs of 416% - 417% in the Clarity samples. Despite Clarity's substantial market share of online payday loans, less-compliant or more predatory lenders who may charge higher prices and engage in other unfriendly practices toward consumers may be less likely to report to Clarity, causing a disparity relative to the sample of lender websites. However, the significant price disparity between storefront and online loans has been widely described in industry and policy reports, so we believe that the difference between these two loan types reflects true underlying heterogeneity, even if its magnitude in the full universe of payday loans is unknown. To our knowledge, this paper is the first attempt to quantify the price difference between online and storefront payday loans.

Although we use the pricing formulas in Equation (1) to measure prices for most loans, these formulas rely on realized payments, which would not accurately measure prices for defaulted loans. The fourth column of Table 1 shows statistics for the non-imputed loan sample. By construction, the default rate in this sample is zero and the proportion of loans with late payments is lower. The average loan amount is also slightly lower and the repayment amount is significantly higher, but other characteristics, including prices, are similar between the imputed and non-imputed samples.

Using imputed prices allows us to investigate the important role of default rates in loan pricing, which is impossible in the non-imputed sample. To support the validity of this analysis, we show that other results are remarkably similar across the imputed and non-imputed loan samples due to the lack of risk-based pricing at the individual loan level. Few loans realize default even in higher-default groups, allowing us to use non-defaulted loans to impute prices for defaulted loans. In general, the summary statistics in Table 1 establish a basic level of external validity for our analysis and show that the pricing differences between online and payday loans are not driven by sample selection or measurement error.

Our payday loan sample statistics are well-aligned with Liu, Lu and Xiong (2022), who describe online loans as smaller, higher interest, earlier repayment, and more repeated borrowing. Despite not studying payday loans, they suggest that online lenders specialize in serving short-term liquidity needs, rather than providing long-term financing solutions.

4 Stylized Facts

Online payday loans are contracted at a higher price than storefront payday loans. We begin our analysis by documenting descriptive facts about payday loan pricing. Then, we establish and accurately measure the online payday loan premium.

The price of payday loans is heterogeneous in locations and business models. However, because they are expressed mainly in the cost per $100 borrowed, they tend to be anchored at round numbers, to facilitate the calculation of the repayment amounts. Usually, stores present a list of plausible loan amounts with the fee associated with them and the total expected repayment amount in a factsheet. This factsheet does not vary between borrowers.

Internet Appendix Figure A1 plots the kernel densities for cost per $100 in graphs (a) and (c) and APR in graphs (b) and (d) for the two Clarity samples. As with other descriptive statistics, the distributions are almost identical between the random Clarity and credit visible samples, suggesting that payday loan pricing is not substantially different for borrowers with and without existing credit reports. This is consistent with the segmentation between the traditional and alternative credit markets.

Consistent with pricing schedules based on integer values of cost per $100, the distributions in graphs (b) and (d) exhibit several local modes for both online and storefront loans. Even though both distributions have common support, higher price points are more common for online loans. The pricing function is more continuous for online loans, where the cost per $100 is an exact integer in 17% of observations compared to 32% for the storefront. The most common integer values of cost per $100 are $15, $17, $20, and $25 for online and $8, $10, $15, and $20 for storefront loans. The interaction of discrete price points for cost per $100 and common pay frequencies leads to a multi-modal distribution of APRs, especially for storefront loans.

4.1 Risk-Based Pricing

An immediate candidate for higher prices online is increased credit risk. We observe a higher default incidence in Table 1. All the lender observes are ex-ante predictors of default: housing status, income, credit score, past credit activity, etc. We now describe how credit risk predictors map into prices at the loan level across the two business models. To shed initial light on these relationships, Figures 2 through 3 present unconditional binscatter plots of how prices and default rates change depending on customer income and Vantage score.

Figure 2 shows the relationships between prices and default risk by self-reported income. As with loan duration, Panel B shows that cost per $100 is flat for both online and storefront loans, across levels of borrower income. As shown in Panel A, APR is also flat across borrower income for online loans but is significantly positively related to income for storefront loans, which is driven by a strong negative correlation between income and loan duration. The lack of price differentiation by income contrasts with a significant negative relationship between income and default risk, shown in Panel C, which is stronger for online loans.

The greater use of credit reporting agencies such as Clarity, greater price dispersion,more continuous pricing functions, and the high overall levels of credit risk could make underwriting technology particularly valuable in this market. However, we do not observe this sophistication resulting in risk-based pricing at the loan level or driven by default predictors. Another potential demographic driving credit risk is housing stability, as measured by the number of months a consumer has lived at their current address, shown in the Internet Appendix Figure A2, but we find limited evidence of a relationship with default or prices, possibly due to noise in this self-reported measure.

While monthly income predicts default, credit scores encompass other dimensions of consumer credit risk. Beer, Ionescu and Li (2018) show evidence of a limited correlation between self-reported income and Vantage scores. Figure 3 presents binscatter plots of prices and default risk by Vantage score, one of the most widely used consumer credit scores. Vantage advertises a particular ability to predict default risk for subprime and near-prime consumers who are not scoreable by other widely used models such as FICO. In all three subfigures, consumers that are in the credit visible sample but without a valid Vantage score in the year the loan was originated are pooled and shown in the leftmost data point on the x-axis (marked as a Vantage score of 300) for comparison with scoreable consumers. The figure shows that the Vantage score predicts the risk of default for online and storefront payday loans, even conditional on taking out subprime credit. However, as with income, online payday loans have significantly greater risk of credit at every Vantage score level. Despite its strong correlation with credit risk, loan prices are only weakly correlated with Vantage score in the online and storefront markets, consistent with a general lack of risk-based pricing at the individual loan level.

Internet Appendix Figure A3 shows a similar exercise along loan maturities. With the cost per $100 for all maturities, APR is greater in absolute terms for a shorter loan duration. Default risk is slightly negatively correlated with loan duration only for online loans, but there is generally a limited relationship between these two dimensions, outside of a precisely controlled setting as in Hertzberg, Liberman and Paravisini (2018). Lastly, putting together loan prices and loan amounts, and correlate them with credit score, in Figure 4. We do not find any systematic pattern in pricing along the credit score and loan amount spectra. As in Dobbie and Skiba (2013), loan amounts can be seen either as a proxy for income-based eligibility or adverse selection. The highest prices occur for large loan amounts, but we cannot assert a monotonic trend between quantities and prices.

All in all, we find systematically higher default rates online than those at the storefront for borrowers with similar observable credit risk predictors. We also find higher online prices. However, we do not find evidence of risk-based pricing at the loan level.

4.2 Loan Pricing and Default in the Online Market

A regression framework allows us to measure the online payday loan premium, controlling for variables observable to the lender and to the econometrician, as well as absorbing fixed effects. We test for the existence of conditional pricing differences between the online and the storefront business models using the following specification:

$$Y_{ist} = \alpha_{is} + \alpha_t + \beta Online + X_{ist} + \epsilon_{ist} \tag{2}$$

where Y_{ist} is a price or default outcome for a given loan from customer i living in state or ZIP code s originated at time t. All regressions include borrower-location fixed effects α_{is} at borrower-ZIP code or borrower-state level, depending on the specification. α_t are time fixed effects for day of week, day of month, month of year, and calendar year. X_{ist} is a vector of controls that includes deciles of loan duration, loan size, age, and income, categorical variables for housing status and pay frequency, and number of inquiries per week as a measure of time-varying credit demand. For variables that include missing values, we include a separate category for missing values to maximize sample size. The regressions include a dummy variable for online loans with the coefficient of interest β. It estimates differences in means of the outcome, conditional on all the controls and fixed effects employed. Standard errors are clustered at the state level, as loans originated in the same state are subject to similar legal and market circumstances.

Table 2 presents our results. The table includes three columns for each outcome: cost per \$100, APR, and a dummy variable indicating whether the loan defaults. The three different specifications per outcome variable include either state fixed effects, ZIP code fixed effects, or customer fixed effects. Panel A shows results for the random Clarity sample, which covers loans originated between 2013 and 2017. Panel B shows results for the credit visible sample, which covers 2013 through 2019, and Panel C includes deciles of Vantage score as an additional control in the credit visible sample.

The online payday loan premium is very similar across the two samples, and robust to the inclusion of Vantage score as a control. As shown in column (1), when state fixed effects are included, the premium is between \$3.4 and \$4.4 per \$100 borrowed (92 to 98 p.p. APR). The magnitude increases when ZIP code or customer fixed effects are included instead of state fixed effects. The online dummy coefficient ranges from \$3.7 to \$4.7 (103-110 p.p. APR) when including ZIP code fixed effects, and from \$4.9 to \$6.5 (127 to 141 p.p. APR) when including customer fixed effects. For comparison, the descriptive statistics in Table 1 showed an unconditional price difference of\$5.2 to \$6.5 per \$100 borrowed (117-121 p.p.

APR) which are within the range of the regression estimates. Overall, these results show that the online payday loan premium is not explained by differences in observable loan or customer characteristics predictive of default.

As shown in columns (7) through (9), the default risk is between 2.6 p.p. and 8.4 p.p. higher for online loans, although the online coefficient is imprecisely estimated in some models and samples using the linear probability specification. These estimates are within the range of the unconditional difference of 4 to 5 p.p. in the default probability of Table 1. The large increase in both prices and default risk when including customer fixed effects reflects the fact that only 2-3% of consumers have both online and storefront loans, and these customers on average face both higher prices and higher default risk. Nonetheless, the results show that even customers with both types of loans are more likely to default on an online payday than on a storefront loan. Thus, differences in default risk are not explained by time-invariant customer characteristics.

Consistent with the lack of risk-based pricing, the inclusion of controls for Vantage score does not produce detectable differences in the estimated price premia, as shown in panel C. Interestingly, although the Vantage score is closely correlated with default risk, its inclusion does not explain the gap in default risk between online and storefront loans. Thus, the findings in Panel C further confirm that consumer characteristics explain neither the price premium nor the default gap for online payday loans.

To maximize precision and sample size, we use all available loans in both Clarity samples in the regression analysis. However, there were very few storefront payday loans in the Clarity data in 2013, so we replicate the analysis dropping 2013 in Internet Appendix Table A1, which shows similar results to our main sample. We also replicate the analysis on the subsample of non-defaulted loans, where we calculate prices directly using Equation (1) instead of imputing them from matching non-defaulted loans. These results are shown in Internet Appendix Table A2. While this sample by definition has a default rate of zero, the estimated price premia are similar to those using the full sample that includes imputed and non-imputed prices.

Using loan-level observations, we cannot control for realized default, as they are bad controls. Additionally, our approach does not factor in the possibility that the customer bases of the storefront and online business models can be different. To establish a comparable set of loan prices, we bin our loans with two different schemes. In the first scheme, we bin loans according to age $\times$ income quintiles, totaling 25 bins for online and 25 bins for storefront market. This is done in both the standalone and credit visible samples. In the second scheme, we bin loans according to credit score quintiles, only possible in the credit visible sample. This procedure ensures that we always compare similar loans between markets and within the same risk class. Then, for each loan, we control for the realized default of the loan's bin in the week prior to loan origination. Therefore the coefficient on the online dummy is identified by average differences between the storefront and online prices within the same borrower bin.

Table 3 reports the results. We obtain very precise estimates of around \$4.1-\$4.7 per \$100 (88-120 p.p. APR) for the online payday loan premium, among observably similar borrowers, controlling for ex-post credit risk. All in all, our binning scheme does not eliminate the online payday loan premium.

Together with the graphical analysis in subsection 4.1, our results suggest an online payday loan premium of about \$4 per \$100 borrowed, or 100 p.p. APR, not explained by ex-ante predictors of default, nor by aggregate realized default among similar borrowers.

5 Role of Information Asymmetry on Payday Loan Pricing

Our analysis reveals two key findings: (i) online payday loans are more expensive than their storefront counterparts, even after controlling for observable loan-level risk factors; and (ii) predictors of default identified ex-ante are not reflected in loan prices.

The payday loan market is likely information asymmetric, as there are no hard credit pulls involved, and a lot of the application process is based on self-reported information. In online markets, the absence of face-to-face interactions and the heightened risk of fraud and identity theft could increase prices and credit risk. Moreover, the complexities underlying higher default rates are further compounded by variations in collection mechanisms. It is widely believed that collection methods tend to be more assertive for online loans, given that lenders have direct access to consumers' bank accounts through the ACH network (CFPB, 2016).

Under asymmetric information, even though it is not possible to distinguish each customer's credit risk, the lender knows their customer mass and chooses the optimal price that compensates them for the credit risk of the borrower pool (Stiglitz and Weiss, 1981). With two alternative types of lenders, choosing different prices, riskier borrowers will face higher prices, either because they adversely select, or because conditional on defaulting, borrowers will default first on more expensive debt. (Arnold and Riley, 2009; Cassar and Wydick, 2012). Previous literature has empirically examined how information asymmetry in payday loan markets affects the relationship between credit quantities (loan amounts) and default (Dobbie and Skiba, 2013).

In this section, we discuss information asymmetry to rationalize prices in the payday loan market, how they relate to default, and to explain the online payday loan premium. We hypothesize that there is information asymmetry in payday loan markets, while explicitly remaining agnostic as to whether it manifests through adverse selection, moral hazard, or both. As is common in cases where asymmetric information is present, we test for correlations between the outcome of interest (loan prices) and default. A positive correlation indicates information asymmetry, either because riskier borrowers adversely select loans with higher rates, or because a rate that is too high might make it optimal to default on a loan. Our goal is to test whether asymmetric information occurs to a greater extent in the online market than in the storefront market. To our knowledge, this paper is the first to conduct such an analysis in the payday lending market.

Using our binning scheme, we test for asymmetric information and to what extent it is more prevalent online. A direct test of asymmetric information correlates loan pricing with default for observably similar individuals. We test this hypothesis as suggested by Chiappori and Salanie (2000) and implemented by Dobbie and Skiba (2013). If similar borrowers obtain different prices on their loans, and higher prices are associated with higher default rates, there is evidence of asymmetric information in this market. We take the evidence in Internet Appendix Table A3 as support for asymmetric information in the payday loan market. Our point estimates suggest that such an asymmetry is higher online, where lenders observe only self-reported information until far later in the process, making these results reasonably expected. We also use an alternative test, as proposed by Chiappori and Salanie (2000), where we use a bivariate probit estimation to recover the correlation between prices and default. We report our results in Internet Appendix Table A4. Across all samples and all outcomes, there is a positive correlation between credit prices and default. That correlation is higher in the online payday loan market.

Graphically, we explore this relation separately for online and storefront loans using binscatter plots of each loans' APR relative to their bins' average APR and default. What we aim to compare is the slope of the relation. The steeper it is, the more robust the evidence of asymmetric information in credit markets. We report our findings in the credit visible sample in Figure 5. In the two left panels, we show the binscatter plot for storefront loans. On the two right panels we report the same graph for online loans. Panels (a)-(b) report correlations between APR (relative to the bin average) and default. Panels (c)-(d) report correlations between the cost per $100 borrowed (relative to the bin average) and the default. The results are consistent with Internet Appendix Table A3. There is an upward-sloping relationship between APR and credit risk within the same bin, and it is stronger in the online market, suggesting a higher degree of asymmetric information online. These results are robust to sampling, as shown in Internet Appendix Figure A4, where we plot the same analysis using the random Clarity sample.

The crucial question that arises is whether attenuating information asymmetry would impact the magnitude of the online payday loan premium. Most importantly, if both online and brick-and-mortar lenders had access to identical information, would such a significant disparity in their prices still exist?

To test this, we use cross-sectional variation across state laws that establish a statewide payday loan database, where lenders are mandated to report the loans they provide, and which can be accessed through the payment of a small fee. There are 13 states with these databases in place: Alabama, Delaware, Florida, Illinois, Indiana, Kentucky, Michigan, North Dakota, Oklahoma, South Carolina, Virginia, Washington, and Wisconsin, where 19% of the loans in our sample are originated. Fee caps in states with a payday loan database requirement range from no fee caps (as in Delaware) to 10% of the repayment check (as in Florida). These databases reduce information asymmetry because they provide the lender with information that the borrower may not report.

A limitation arising from our samples ranging from 2013-2017 and 2013-2019 is that we cannot directly exploit the effects of introducing a database in a given state, as the 13 states implemented databases during 2002-2012. Notwithstanding, the cross-sectional variation is worthy to test the asymmetric information hypothesis.

We estimate the following specification:

$$Y_{ist} = \alpha_t + \alpha_s + \beta_O Online_{ist} + \beta_{DID} Online_{ist} \times Database_s + X_{ist} + \epsilon_{ist} \tag{3}$$

where Y_{ist} is the price of a loan i, both measured as cost per \$100 borrowed (in dollars) and APR, for a customer living in state s originating at time t. We run the specification with and without time fixed effects α_t, and loan and customer level controls X_{ist}. We include state fixed effects, which absorb the variation in variable $Database_s$. The three most important coefficients are β_O, which measures the online premium in states without a database, where the asymmetric information is higher; and β_{DID} the difference in online premia between states with and without databases. The size of β_{DID}, relative to β_O allows us to speak to the economic significance of information asymmetry in explaining the two-price, two-default regimes equilibrium.

Table 4 reports the results for the estimation of Equation (3) on both the random Clarity sample (Panel A) and the credit visible sample (Panel B). The online payday loan premium ranges between \$4.1-\$5.8 per \$100 dollars borrowed (102-122 p.p. APR) in states without a database. Even though accessing the database incurs a cost for the lender, legislation provisions such as Wis.Stat. § 138.14(10)(b)1. state "A licensee may not assess a customer any fee or charge for database access or usage."

In states with a database, our point estimates indicate that the online premium has about half of the magnitude of the premium in states without a database. The β_{DID} coefficient is statistically significant at the 10% level in all specifications for cost per \$100 borrowed, but is not, when using APR as the dependent variable.

In our best attempt to use all the time series variation we can, we study pricing dynamics following the implementation of a database, and whether the records added to it through time have any impact on (i) loan prices on the market as a whole, and (ii) in the online payday loan premium. To do so, we decompose the database indicator into multiple indicators, according to years since the database inception in that state. Figure A5 reports the results for our two price outcomes, estimated in our two different samples. The *Baseline* estimates are estimates of online (green) and storefront (orange) prices, and the premium (black) in states without a database. We then plot estimated prices for each market and the premium (obtained from the estimates in Internet Appendix Table A5) for each time bin relative to database implementation in the state.

The equilibrium interest rates in states without payday loan database are higher than those in the states without the database. This pattern is consistent with the estimates in

Table 4. (ii) As time passes, after the introduction of the payday loan database, the average equilibrium interest rates in both the online and the storefront markets decrease. This pattern is consistent with the increase in market efficiency in payday loan markets via the reduction in information asymmetry when all the lenders share the same information set; and (iii) the gap between online prices and storefront prices remains statistically indistinguishable from zero as time goes by. The standard deviation of the interest rate gap is large in the first few years and drops to a much lower value as time passes. This pattern is consistent with the stabilization of the payday lending market after the changes from the introduction of a shared database. All three patterns are robust across samples and different definitions of price.

Lastly, if our interpretation of the pooling market equilibrium is correct, we can make two testable claims. First, a smaller online market share leads to an online borrower pool that is more risky compared to the larger, much safer storefront borrower pool. Second, as a result, the online premium should be higher when the online market share is lower. In Figure 6, we report binscatter plots of default rates of each pool (online vs storefront) in each market (state-year), in panels (a) and (c), and the online premium in each market, in panels (b) and (d), sorted by online market share. We observe exactly what our predictions indicate: a larger online market share, which captures safer borrowers into the online pool, and makes the riskiness of the two pools similar, reducing the online payday loan premium.

All in all, we show that the payday loan market is information asymmetric. We also show that in markets where information asymmetry is attenuated, the magnitude of the premium shrinks. Thus, information asymmetry rationalizes the equilibrium in which markets with a higher incidence of defaults can also have higher prices, even if the risk of default is not priced at the loan level. However, information asymmetry alone does not fully explain the levels of online and storefront payday loan prices or the extent of the price gap between them.

6 Regulation: the Role of Fee Caps

Payday loans are regulated at the state level. Each state determines what is necessary for a lender to apply for and obtain a license, and imposes limits on loan terms, such as amount, number of simultaneous loans a borrower can have, number of rollovers, and prices. Fee caps, if they are binding, are likely a strong determinant of payday loan prices. The literature is vast on the effects of capping consumer credit prices,[6] but there is no work documenting how payday loan fee caps relate with the storefront-online dichotomy. The absence of explicit consensus as to whether the payday state fee cap applies over the borrower's state of residence, or the lender's state of incorporation, makes this topic complex. Additionally, as pointed by Stoesz (2014), "[t]he internet has altered [alternative financial services] fundamentally by allowing vendors to evade state regulators. Because they enjoy sovereignty, Tribal Lending Entities (...) compete on a global market".

To understand how the legal framework permeates into pricing, we start by documenting the heterogeneity in state payday loan laws regarding fee caps. Then, we take a data-driven approach and let our data speak to whether these laws are binding, or if it is easier to circumvent state laws in the online market. Table 5 summarizes the state laws regarding fee caps as of 2019 in every state for which we observe more than 50 loans in both online and storefront markets. The regulation of fee caps is highly heterogeneous, going from a one-size-fits-all dollar amount per \$100 borrowed, to fee caps, which depend on the loan amount, to no limit at all.

The difference between online and storefront prices is substantially greater in states with no fee cap or with fee caps that do not bind, such as Idaho, Missouri, Nevada, Ohio, Texas, and Utah. We plot the price distributions for these states in panel (a) of Figure 7. In panel (b), we perform the same exercise for loans to borrowers in states where the payday loan fee cap binds. In states where lenders do not have constraints on the setting of their

[6] See, for example, Peterson (1983); Benmelech and Moskowitz (2010); Zinman (2010); Rigbi (2013); Lukongo and Miller Jr (2022); Bolen, Elliehausen and Miller Jr (2023)

fee, online loans are much more expensive than in states with restrictions. If anything, the prevalence of fee caps is attenuating the premium, rather than contributing to its existence. However, even in states with a binding fee cap, online loans are statistically more expensive than storefront loans (t-statistic of 12.96).

We further define, based on the applicable state law in the borrower's state of residence, the maximum applicable fee for each loan. Then we compute the distance between the loan cost per $100 and the legal limit. We plot the distributions in Figure 8. The figure shows two interesting results: (i) state fee caps are binding in payday loan markets; and (ii) online lenders do not seem to evade this fee cap, conditional on operating in the borrower's state. Regulatory arbitrage is not a driver of the online payday loan premium.

In summary, our analysis also shows the role of state-level payday loan fee caps in containing both online and storefront prices, thereby reducing the premium. Thus, it is unlikely that geographical variation in regulation drives the stylized facts we documented in Section 4.

7 Quantitative Model

Our empirical analysis in Sections 5 and 6 shows that the data patterns observed in Section 4 are likely driven by a high level of information asymmetry in the online market. Moreover, we show that the price discrepancy between online and storefront payday loans is, if anything, attenuated by binding fee caps across states.

In addition to information asymmetry, there are two alternative potential explanations for why online lenders set their prices higher than their storefront counterparts. One alternative explanation is convenience, whereby similar to the mortgage market (Buchak, Matvos, Piskorski and Seru, 2018; Fuster, Plosser, Schnabl and Vickery, 2019), consumers are willing to pay more for a more convenient borrowing experience. Unlike storefront lenders, online payday lenders provide near-instant loan approvals and fund transfers, often accessible

24/7 from any location, allowing borrowers to bypass the time and effort required for an in-person application. This immediacy is particularly attractive to borrowers facing urgent financial needs, who may value quick access to funds over the potential savings associated with lower-cost loans. Consequently, online lenders can potentially capitalize on this demand for convenience by charging higher fees given the same level of credit risk.

Another alternative explanation is that of the differences in the cost structure of each business model. Customer acquisition, fraud detection, and infrastructure are fundamentally different between the online and storefront business models. In addition, the market for lead generation, lead scoring, ping trees, and alternative data adds a new layer of costs to the online business model.

We propose a quantitative model where we feature some of the previously documented facts to evaluate the roles of credit risk, convenience, and cost structure in explaining payday loan prices and the online payday loan premium. In the model, in corporate the three remaining dimensions where the differences between the lenders in the two markets could potentially explain the stylized facts in Section 4: (1) difference in credit risk, which is a manifestation of different levels of information asymmetry; (2) difference in convenience; and (3) difference in cost structure.

7.1 A Model of Payday Loan Pricing

We adapt the framework of Buchak, Matvos, Piskorski and Seru (2018) to our setting. Online lenders and payday loan stores compete for borrowers. They differ in the credit risk they face, in the convenience of their service, and their cost structure. A mass of borrowers faces the payday loan market and chooses optimally. Prices are defined in equilibrium.

Demand. Borrower b's utility from choosing a payday loan from lender l is:

$$u_{lb} = -(\alpha - \kappa_l)c_l + \epsilon_{lb} \tag{4}$$

The borrower's utility decreases as the loan price c_l increases, and $\alpha > 0$ measures the sensitivity to loan prices. κ_l is a convenience term that decreases consumer sensitivity to loan prices. c_l is the cost per \$100 borrowed from the lender l. ϵ_{lb} are borrower-lender pair-specific preference shocks, identically and independently distributed, following a type 1 extreme-value Gumbel distribution. Some borrowers will prefer to save themselves from the stigma of being seen at the neighborhood stores, some others have high disutility from providing sensitive information online, for example.

Aggregating borrowers' optimal choices over the utility function leads to logistic market shares desired by borrowers as a function of loan prices by each lender:

$$s_l(c_l, c_{-l}) = \frac{\exp(-(\alpha - \kappa_l)c_l)}{\exp(-(\alpha - \kappa_l)c_l) + \exp(-(\alpha - \kappa_{-l})c_{-l})} \tag{5}$$

Supply. There are online (O) and storefront (S) lenders. Lenders differ in operating costs $\phi_l, l \in \{O, S\}$, to allow the different cost structures between a brick-and-mortar business and a digital business to differ. They differ in the convenience of the borrowing experience they provide, κ_l. Lenders also differ in the exogenous credit risk they face λ_l, representing default rates.

Lenders induce backwards to decide (i) whether to enter the market and (ii) if so, at what price. Conditional on entry, they set the price of loans to maximize expected gross profit per \$100 lent:

$$c_l^* = \underset{c_l}{\text{argmax}} \;\; c_l s_l(c_l, c_{-l})(1 - \lambda_l) \tag{6}$$

where $s_l(c_l, c_{-l})$ represents the probability that the loan offer is accepted. With F denoting the total face value of loans in the market, in hundreds of dollars, the net profit of the lender, in equilibrium, can be written as:

$$\pi_l = c_l^* s_l(c_l^*, c_{-l}^*)F(1 - \lambda_l) - \phi_l \tag{7}$$

Equilibrium. The equilibrium will be a market structure s_O, s_S, c_O, c_S, such that:

1) Borrowers maximize utility taking prices and market structure as given.

2) Lenders set loan prices to maximize gross profit, taking other lenders' decisions, credit risk, and market structure as given.

3) There is free entry and exit within lender type, leading to zero profits.

We normalize the convenience of storefront loans to zero $\kappa_S = 0$ and let κ_O measure the difference in convenience between the online and storefront markets. The market shares become:

$$s_O = \frac{\exp(-(\alpha - \kappa_O)c_O)}{\exp(-(\alpha - \kappa_O)c_O) + \exp(-\alpha c_S)} \quad s_S = \frac{\exp(-\alpha c_S)}{\exp(-(\alpha - \kappa_O)c_O) + exp(-\alpha c_S)} \tag{8}$$

The lender's maximization problem leads to the optimal cost per \$100 borrowed as a function of consumer sensitivity to loan prices and market shares:

$$c_l^* = \frac{1}{\alpha - \kappa_l}\frac{1}{1 - s_l} \tag{9}$$

The market entry condition defines entry and exit. It assumes that the entry of lenders of a given type will happen until there are profit opportunities, given the cost structure of operating in that ecosystem:

$$c_l^* s_l(c_l^*, c_{-l}^*)F(1 - \lambda_l) - \phi_l = 0 \tag{10}$$

Our solution will rely on the zero-profit entry and exit condition, and so will the calibration of cost parameters. While the payday loan industry is believed to be highly profitable, the few academic studies in finance (Flannery and Samolyk, 2005) and law (Huckstep, 2007) show otherwise: payday lending profit margins are thin (around 3-4%), and business costs are four times larger than default losses. We validate this reasoning, by plotting a binscatter of repayment amounts against loan amount and relying on the slope of the best-fit line, as an indication for the gross profit margin. Figure 9 reports the results. Most of the loans in our dataset (more than 75%) are smaller than \$550. For loans up to \$550, the slopes of the lines of best fit are informative about the gross profit margin of each business model. The slope for storefront loans is 1.07 and for online loans it is 1.11, which corresponds to 7% and 11% average gross profit margins, respectively.

Jointly, conditions (9) and (10) allow us to write the optimal price for each of the lender types as a function of the problem's parameters:

$$c_l^* = \frac{\phi_l}{F}\frac{1}{(1-\lambda_l)} + \frac{1}{\alpha - \kappa_l} \tag{11}$$

Comparative statics are intuitively valid: loan prices would increase with cost structures, credit risk, convenience, and decrease with consumers' sensitivity to loan prices.

7.2 Calibration

We observe the market share for each type of lender s_O and s_S, the loan price for each lender type c_O and c_S, the incidence of default λ_O and λ_S, and the total volume of each market F. We collapse our data set into averages and total loan volume for each state in each year. We obtain primitive α, as well as operating costs ϕ_O and ϕ_S, and online convenience κ_O.

To obtain α, we invert the optimal price setting condition for storefront lenders

$$\alpha = \frac{1}{c_S^*}\frac{1}{1 - s_S^*} \tag{12}$$

We obtain the online convenience parameter by using the optimal price setting condition for online lenders, taking α as given from above:

$$\kappa_O = \alpha - \frac{1}{c_O^*} \frac{1}{1 - s_O^*} \tag{13}$$

Lastly, to obtain operating costs, we use the market clearing condition for each state in each year and each lender type. We scale it by the size of each market in hundreds of dollars, so that the metric is comparable across states and years, and we get operating cost per hundred dollars originated:

$$\frac{\phi_l}{F} = c_l s_l (1 - \lambda_l) \tag{14}$$

Table 6 shows our estimates. α is estimated to be positive, indicating that consumers are sensitive to loan prices. We find a positive difference in convenience between online and storefront loans, where online loans appear to be more convenient. For empirical validation, we take two approaches to measure online convenience, conditional on the variables we observe. First, we state that borrowing online should be more convenient for younger borrowers. Thus, given a similar price structure across the age spectrum, we should observe a higher online market share for younger borrowers. Second, we argue that online credit is not affected by physical capacity constraints, such as a long wait time at the store when demand peaks. Figure 10 confirms exactly this intuition. Despite a relatively similar price structure, young borrowers lean toward borrowing online and older borrowers borrow at the storefront. In panel C, we observe that on Fridays, stores originate twice as many loans as on other weekdays, while online originations are relatively stable throughout the week.

Online costs are estimated to be larger than those in the storefront, consistent with the online business model bringing a new layer of costs that are not part of the storefront model: targeted online advertising, lead generation, fraud prevention, and others. Also, consistent with the nature of costs, the estimated confidence interval for online costs is much narrower, as a percentage of the point estimate, than the estimate for storefront costs. Intuitively, the cost setting up an IT infrastructure will vary less across states and years than the actual rent and labor costs of running storefront businesses. Consistently, Fekrazad (2020) constructs a cost index to compare payday lenders in states, consisting of rental prices for real estate, wages and loan losses. We empirically validate this logic by computing payday loan prices for both business models, splitting loans originated in rural, suburban, and urban areas. Figure 11 reports the results. Online prices are fairly constant across the three categories. However, storefront payday loan prices are more expensive, despite increased competition in urban areas. We relate this finding with urban areas that have higher rental prices and higher labor costs.

Credit risk, convenience, and cost structures are relevant to explain payday loan prices, and they differ between online and storefront businesses. To understand the contribution of each of these aspects to the online payday loan premium, we use equation 11 to estimate three counterfactual scenarios. In the first, we force the cost parameters to be very low (25% of the estimated cost of the storefront model) and equal for both the storefront and online ($\phi_O = \phi_O$) and eliminate the differences in convenience ($\kappa_0 = 1$), leaving only differences by default. In the second one, we allow for both differences in default and convenience, but keep costs low and equal. In the last one, we allowed both costs and default rates to take their actual values and shut down the differences in convenience.

Figure 12 reports the results. The first two bars confirm our results that differences in default alone do not explain the online premium or the levels of loan prices, in general. The second set of bars allows for a different convenience provided by the storefront and online lenders. That would raise the online price level, but not the storefront price level. The third set of bars shows that our estimated operating costs would make the price levels rise closer to the observed ones, as well as generate a premium in the right direction. Taken together, these counterfactual exercises suggest that the observed premium is a product of the three mechanisms together, where operating costs are the strongest driving force.

8 Conclusion

This paper presents novel evidence of an online payday loan premium. Using data from a national subprime credit bureau, we show that despite the potential of online technology to lower fixed costs and increase lending efficiency, online payday loans are$4 per $100 (100 p.p. APR) more expensive, even conditioning on loan and customer characteristics. Interestingly, neither brick-and-mortar nor online payday loans appear to utilize loan-level risk-based pricing, and available metrics of default risk fail to elucidate the price premium.

We show that default rates for online payday loans are approximately twice as high as those for storefront loans. Additionally, customers who utilize both types of loans are significantly more likely to default on their online loans. Importantly, the predictors of default and the realized default rates do not fully account for the observed premium associated with online lending.

We investigate several potential explanations for these patterns in the data. First, we demonstrate that the observed patterns can be reconciled within an information asymmetry framework. However, differences in the regulatory burdens faced by online and storefront lenders do not explain these patterns.

Using a quantitative model, we argue that disparities in cost structures between the two business models and the consumers' willingness to pay for the convenience offered by online lending contributes to higher prices in the online market can explain the high risk-adjusted price discrepancy between the online and storefront markets.

This is the first paper to assert the existence of a premium in online payday loans, measuring it, and decomposing it. The study of online lending business models is pivotal for understanding their pricing mechanisms and the impact of FinTech players on consumer credit, particularly in markets catering to the most vulnerable borrowers.

References

Adams, William, Liran Einav, and Jonathan Levin, "Liquidity constraints and imperfect information in subprime lending," *American Economic Review*, 2009, *99* (1), 49–84.

Agarwal, Sumit, Paige Marta Skiba, and Jeremy Tobacman, "Payday loans and credit cards: New liquidity and credit scoring puzzles?," *American Economic Review*, 2009, *99* (2), 412–17.

Alexandrov, Alexei and Sergei Koulayev, "No shopping in the us mortgage market: Direct and strategic effects of providing information," *Consumer Financial Protection Bureau Office of Research Working Paper*, 2018, (2017-01).

Allcott, Hunt, Joshua Kim, Dmitry Taubinsky, and Jonathan Zinman, "Are high-interest loans predatory? theory and evidence from payday lending," *The Review of Economic Studies*, 2022, *89* (3), 1041–1084.

Argyle, Bronson, Taylor Nadauld, and Christopher Palmer, "Real effects of search frictions in consumer credit markets," *The Review of Financial Studies*, 2023, *36* (7), 2685–2720.

Arnold, Lutz G and John G Riley, "On the possibility of credit rationing in the stiglitz-weiss model," *American Economic Review*, 2009, *99* (5), 2012–21.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace, "Consumer-lending discrimination in the FinTech era," *Journal of Financial Economics*, 2022, *143* (1), 30–56.

Baugh, Brian, "Payday borrowing and household outcomes: Evidence from a natural experiment," 2016.

Beer, Rachael, Felicia Ionescu, and Geng Li, "Are income and credit scores highly correlated?," *FEDS Notes*, 2018.

Benmelech, Efraim and Tobias J Moskowitz, "The political economy of financial regulation: Evidence from US state usury laws in the 19th century," *The Journal of Finance*, 2010, *65* (3), 1029–1073.

Bertrand, Marianne and Adair Morse, "Information disclosure, cognitive biases, and payday borrowing," *The Journal of Finance*, 2011, *66* (6), 1865–1893.

Bhutta, Neil, "Payday loans and consumer financial health," *Journal of Banking & Finance*, 2014, *47*, 230–242.

_ , Paige Marta Skiba, and Jeremy Tobacman, "Payday loan choices and consequences," *Journal of Money, Credit and Banking*, 2015, *47* (2-3), 223–260.

Blattner, Laura and Scott Nelson, "How costly is noise? Data and disparities in consumer credit," *Unpublished Working Paper, arXiv preprint arXiv:2105.07554*, 2021.

Bolen, J Brandon, Gregory Elliehausen, and Thomas W Miller Jr, "Do consumers need more protection from small-dollar lenders? Historical evidence and a roadmap for future research," *Economic Inquiry*, 2020, *58* (4), 1577–1613.

_ , _ , **and** _ , "Credit for me but not for thee: the effects of the Illinois rate cap," *Public Choice*, 2023, *197* (3), 397–420.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 2018, *130* (3), 453–483.

Bureau, Consumer Financial Protection, "Online Payday Loan Payments," Technical Report, Consumer Financial Protection Bureau 2016.

Carrell, Scott and Jonathan Zinman, "In harm's way? Payday loan access and military personnel performance," *The Review of Financial Studies*, 2014, *27* (9), 2805–2840.

Carter, Susan Payne and William Skimmyhorn, "Much ado about nothing? New evidence on the effects of payday lending on military members," *Review of Economics and Statistics*, 2017, *99* (4), 606–621.

Cassar, Alessandra and Bruce Wydick, "Credit rationing with behavioral foundations: Revisiting Stiglitz and Weiss," *Unpublished Working Paper*, 2012.

CFPB, "Statement by CFPB Acting Director Uejio on CFPB Victory in Legal Challenge to Payday Lending Rule Protections," 2021. Accessed: 2024-12-17.

_ , "New protections for payday and installment loans slated to take effect next year," 2024. Accessed: 2024-12-17.

Chava, Sudheer, Rohan Ganduri, Nikhil Paradkar, and Yafei Zhang, "Impact of marketplace lending on consumers' future borrowing capacities and borrowing outcomes," *Journal of Financial Economics*, 2021, *142* (3), 1186–1208.

Chiappori, Pierre-André and Bernard Salanie, "Testing for asymmetric information in insurance markets," *Journal of Political Economy*, 2000, *108* (1), 56–78.

Consumer Federation of America, "States Have Jurisdiction over Online Payday Lenders," Technical Report 2010.

_ , "CFA Survey of Online Payday Loan Websites," Technical Report 2011.

Consumer Financial Protection Bureau, "Payday Loans and Deposit Advance Products: A White Paper of Initial Data Findings," Technical Report 2013.

DeFusco, Anthony A, Huan Tang, and Constantine Yannelis, "Measuring the welfare cost of asymmetric information in consumer credit markets," *Journal of Financial Economics*, 2022, *146* (3), 821–840.

DeYoung, Robert and Ronnie J Phillips, "Payday loan pricing," *Networks Financial Institute*, 2006, pp. 09–07.

_ **and Ronnie Phillips**, "Strategic pricing of payday loans: Evidence from Colorado, 2000-2005," *Networks Financial Institute Working Paper*, 2006.

Di Maggio, Marco and Vincent Yao, "Fintech borrowers: lax screening or cream-skimming?," *The Review of Financial Studies*, 2021, *34* (10), 4565–4618.

Dobbie, Will and Paige Marta Skiba, "Information asymmetries in consumer credit markets: Evidence from payday lending," *American Economic Journal: Applied Economics*, 2013, *5* (4), 256–82.

Dobridge, Christine L, "High-cost credit and consumption smoothing," *Journal of Money, Credit and Banking*, 2018, *50* (2-3), 407–433.

Ernst & Young, "The Cost of Providing Payday Loans in a US Multiline Operator Environment," Technical Report 2009.

Fekrazad, Amir, "Impacts of interest rate caps on the payday loan market: Evidence from Rhode Island," *Journal of Banking & Finance*, 2020, *113*, 105750.

Flannery, Mark J and Katherine Samolyk, "Payday lending: Do the costs justify the price?," *FDIC Center for Financial Research Working Paper*, 2005, (2005/09).

Fonseca, Julia, "Less mainstream credit, more payday borrowing? Evidence from debt collection restrictions," *The Journal of Finance*, 2023, *78* (1), 63–103.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, "The role of technology in mortgage lending," *The Review of Financial Studies*, 2019, *32* (5), 1854–1899.

Gathergood, John, Benedict Guttman-Kenney, and Stefan Hunt, "How do payday loans affect borrowers? Evidence from the UK market," *The Review of Financial Studies*, 2019, *32* (2), 496–523.

Graham, Karen and Elaine Golden, "Financially Underserved Market Size Study 2019," Technical Report 2019.

Hecht, John, "Alternative Financial Services: Innovating to Meet Customer Needs in an Evolving Regulatory Framework," Technical Report 2014.

_ , "Short Term Lending Update: Moving Forward with Positive Momentum," Technical Report 2018.

Hertzberg, Andrew, Andres Liberman, and Daniel Paravisini, "Screening on loan terms: evidence from maturity choice in consumer credit," *The Review of Financial Studies*, 2018, *31* (9), 3532–3567.

Huckstep, Aaron, "Payday lending: Do outrageous prices necessarily mean outrageous profits," *Fordham J. Corp. & Fin. L.*, 2007, *12*, 203.

Jagtiani, Julapa and Cathy Lemieux, "The Roles of Alternative Data and ML in Fintech Lending: Evidence from LendingClub Consumer Platform," *Unpublished Working Paper*, 2018.

Kaufman, Alex, "Payday Lending Regulation," *Finance and Economics Discussion Series*, 01 2013, *2013*, 1–38.

King, Uriah and Diane Standaert, "Effective State and Federal Payday Lending Enforcement: Paving the Way for Broader, Stronger Protections," Technical Report, Center for Responsible Lending 2013.

Kirsch, Larry, Robert N Mayer, and Norman I Silber, "The CFPB and payday lending: New agency/old problem," *Journal of Consumer Affairs*, 2014, *48* (1), 1–16.

Kutzbach, M, A Lloro, J Weinstein, and K Chu, "How America Banks: Household Use of Banking and Financial Services, 2019 FDIC Survey," 2020.

Li, Emma, Li Liao, Zhengwei Wang, and Hongyu Xiang, "Individual Consumption Response to Expanding Credit Access: Evidence from online cash loan platform," *PBCSF-NIFR Research Paper*, 2018.

Li, Tsung-Hsien and Jan Sun, "The Payday Loan Puzzle: A Credit Scoring Explanation," *Available at SSRN 3954233*, 2021.

Li, Zhiyong, Ke Li, Xiao Yao, and Qing Wen, "Predicting prepayment and default risks of unsecured consumer loans in online lending," *Emerging Markets Finance and Trade*, 2019, *55* (1), 118–132.

Liu, Lei, Guangli Lu, and Wei Xiong, "The big tech lending model," *National Bureau of Economic Research*, 2022.

Lukongo, Onyumbe Enumbe Ben and Thomas W Miller Jr, "The cost of rate caps: Evidence from Arkansas," *Journal of Financial Research*, 2022, *45* (4), 881–909.

Maggio, Marco Di, Angela T Ma, and Emily Williams, "In the Red: Overdrafts, Payday Lending and the Underbanked," 2020.

Mann, Ronald J and Jim Hawkins, "Just Until Payday," *UCLA Law Review*, 2007, *54*, 855.

Melzer, Brian T, "The real costs of credit access: Evidence from the payday lending market," *The Quarterly Journal of Economics*, 2011, *126* (1), 517–555.

Miller, Sarah and Cindy K Soo, "Does increasing access to formal credit reduce payday borrowing?," 2020.

— **and** — , "Do neighborhoods affect the credit market decisions of low-income borrowers? evidence from the moving to opportunity experiment," *The Review of Financial Studies*, 2021, *34* (2), 827–863.

Montezemolo, Susanna, "Payday lending abuses and predatory practices," *The State of Lending in America & Its Impact on US Households, Center for Responsible Lending*, 2013.

Morse, Adair, "Payday lenders: Heroes or villains?," *Journal of Financial Economics*, 2011, *102* (1), 28–44.

— , "Peer-to-peer crowdfunding: Information and the potential for disruption in consumer lending," *Annual Review of Financial Economics*, 2015, *7*, 463–482.

Nunez, Stephen, K Shaberg, Richard Hendra, Lisa Servon, Mina Addo, and A Mapillero-Colomina, "Online payday and installment loans: Who uses them and why? A demand side analysis from linked administrative, survey, and qualitative interview data," *Subprime Lending Data Exploration Project*, 2016.

Peterson, Richard L, "Usury laws and consumer credit: A note," *The Journal of Finance*, 1983, *38* (4), 1299–1304.

PEW Charitable Trusts, "Payday Lending in America: Who Borrows, Where They Borrow, and Why," *Washington, DC*, 2012.

— , "Fraud and abuse online: Harmful practices in internet payday lending," *Washington, DC*, 2014.

Rigbi, Oren, "The effects of usury laws: Evidence from the online loan market," *The Review of Economics and Statistics*, 2013, *95* (4), 1238–1248.

Saldain, Joaquin, "High-Cost Consumer Credit: Desperation, Temptation and Default," *Unpublished Working Paper*, 2023.

Skiba, Paige and Jeremy Tobacman, "Payday Loans, Uncertainty and Discounting: Explaining Patterns of Borrowing, Repayment, and Default," Vanderbilt Law and Economics Research Paper No. 08-33 08 2008.

Skiba, Paige Marta and Jeremy Tobacman, "Do payday loans cause bankruptcy?," *The Journal of Law and Economics*, 2019, *62* (3), 485–519.

Sridhar, Sharada, "Liquidity Based Contracting: A Path to Greater Efficiency in Payday Lending," *Unpublished Working Paper*, 2023.

Stango, Victor and Jonathan Zinman, "Borrowing high versus borrowing higher: price dispersion and shopping behavior in the US credit card market," *The Review of Financial Studies*, 2016, *29* (4), 979–1006.

Stiglitz, Joseph E and Andrew Weiss, "Credit rationing in markets with imperfect information," *American Economic Review*, 1981, *71* (3), 393–410.

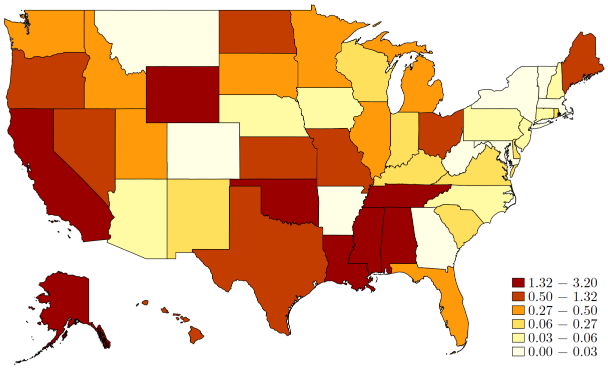
Stoesz, David, "Are Payday Loans Really Evil-Controversy, Regulation, and Innovation in the Secondary Financial Services Market," *Journal of Sociology & Social Welfare*, 2014, *41*, 3.

Wang, Jialan and Kathleen Burke, "The effects of disclosure and enforcement on payday lending in Texas," *Journal of Financial Economics*, 2022, *145* (2), 489–507.

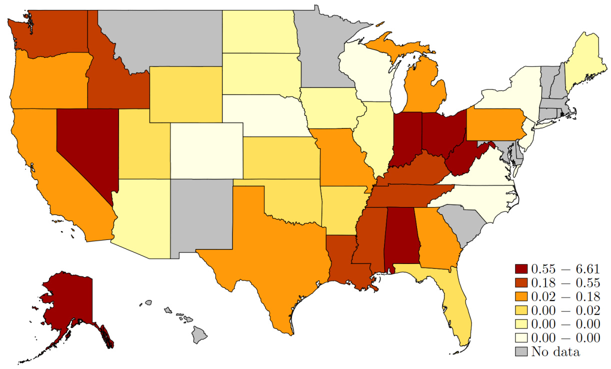
Zinman, Jonathan, "Restricting consumer credit access: Household survey evidence on effects around the Oregon rate cap," *Journal of Banking & Finance*, 2010, *34* (3), 546–556.

Figure 1: Geographic Distribution of Loans per Capita

Panel A: Random Clarity sample

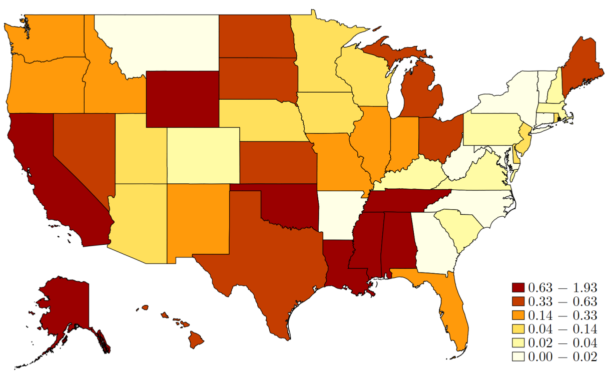


(a) Online

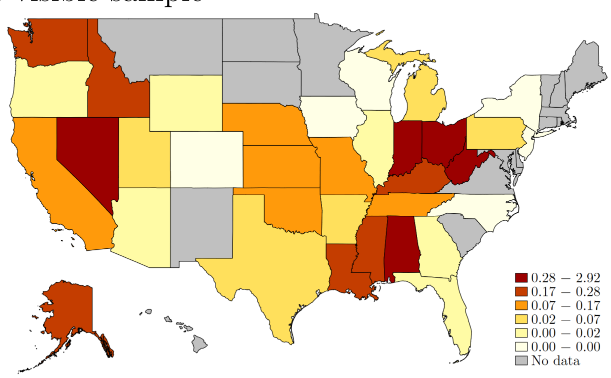


(b) Storefront

Panel B: Credit visible sample



(c) Online

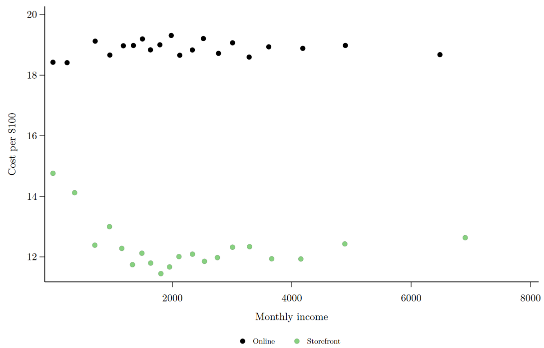


(d) Storefront

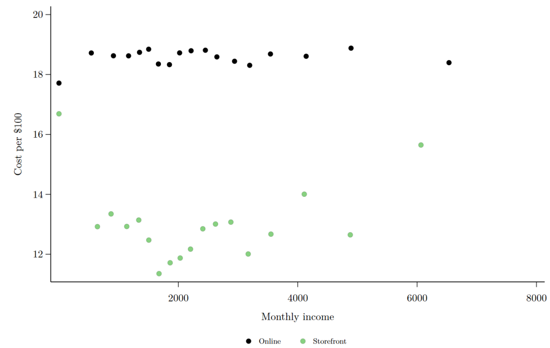
Note: In this figure we map the geographical distribution of payday loans by state. Graphs show total numbers of online and storefront loans per 1000 people in the state population based on the 2010 Census. The random Clarity sample presented in Panel A consists of a random sample of 1 million unique borrowers that submitted loan inquiries in Clarity's full database between 2013 and 17. Only originated payday loans from this sample of consumers are included in the analysis sample. The credit visible sample shown in Panel B consists of payday borrowers that are matched to a random 1% sample of all consumers in the Experian credit bureau database in 2018. All loans originated by matched borrowers between 2013 and 2019 are included in this sample.

Figure 2: Prices and Default Rates by Borrower Income

Panel A: Cost per $100

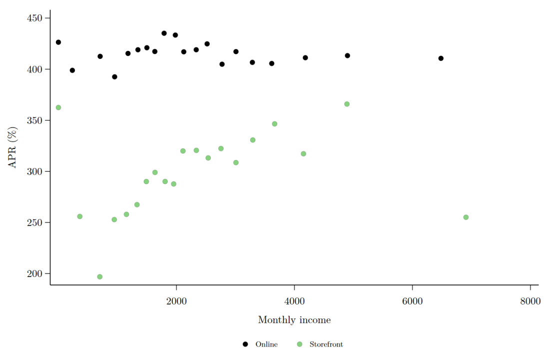


(a) Random Clarity sample

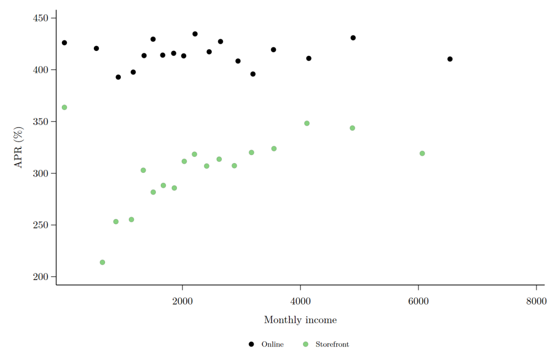


(b) Credit visible sample

Panel B: APR

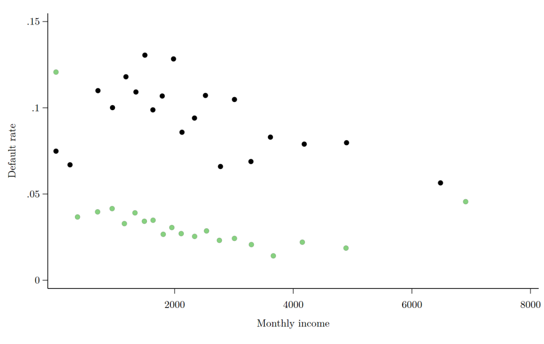


(c) Random Clarity sample

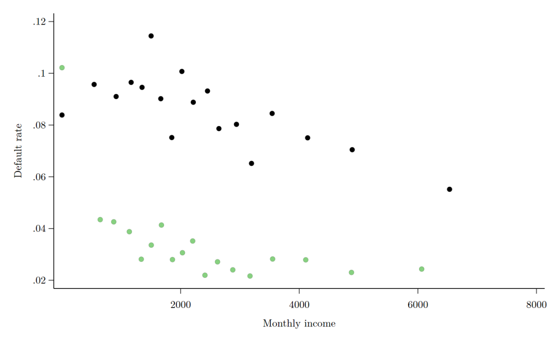


(d) Credit visible sample

Panel C: Default



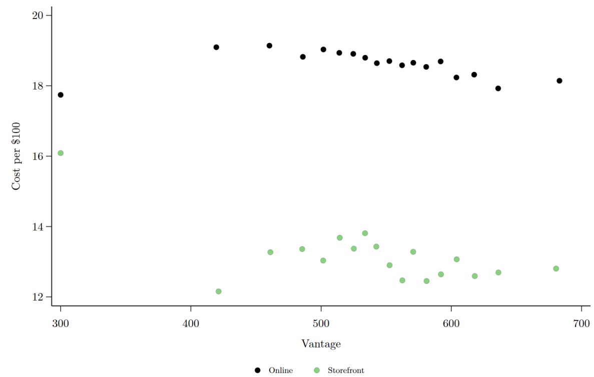
(e) Random Clarity sample



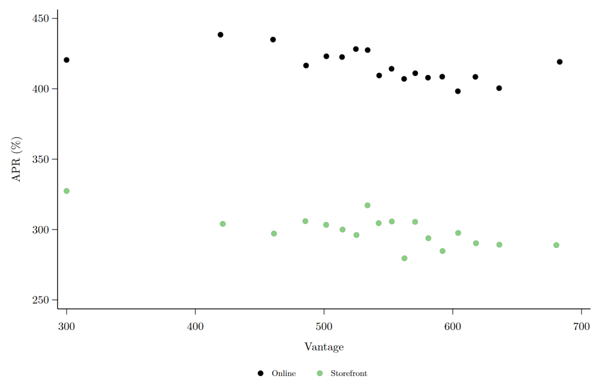
(f) Credit visible sample

Note: The figure presents binscatter plots of cost per $100 borrowed, APR, and default rates in the credit visible sample in graphs (b), (d), and (f), and in the standalone sample in graphs (a), (c), and (e). The x-axis represents the borrower's monthly income.

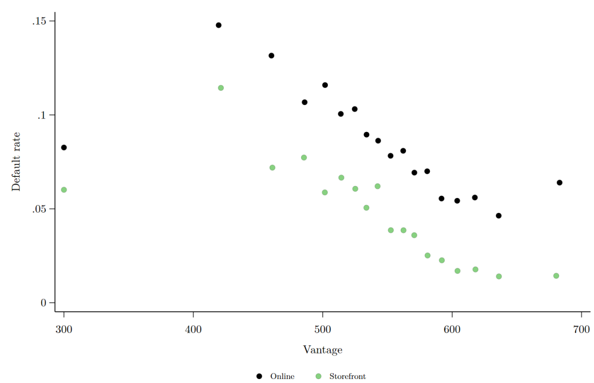
Figure 3: Prices and Default Rates by Vantage score



(a) Cost per $100



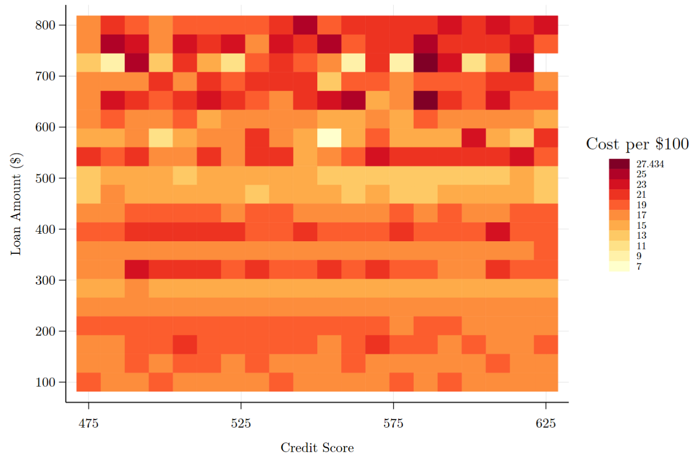
(b) APR



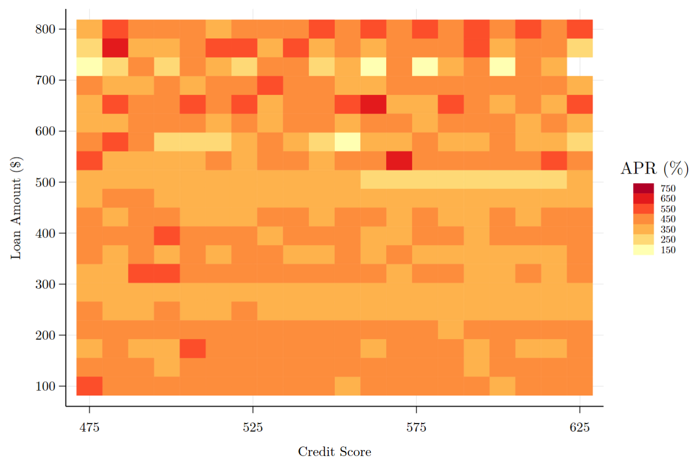
(c) Default rate

Note: The figure presents binscatters of cost per $100 borrowed, APR, and default rates in the credit visible sample. Missing Vantage scores are set to 300 and outcomes for these borrowers are shown as the leftmost data point in each graph.

Figure 4: Absence of Risk-Based Pricing



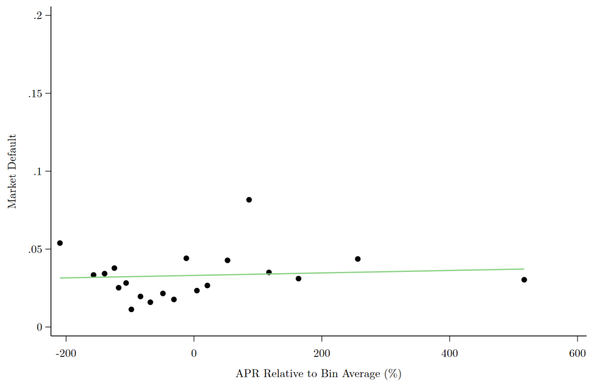
(a) Cost per $100



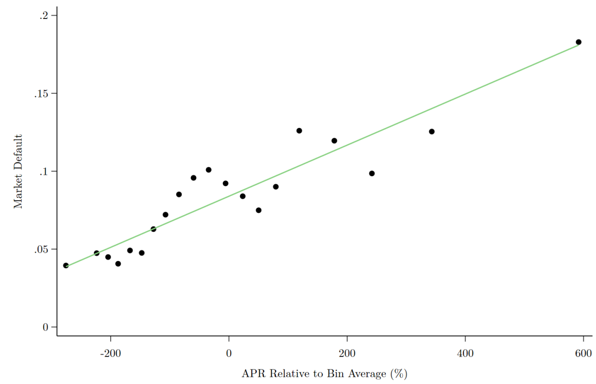
(b) APR (p.p.)

Note: We plot loan prices (in color scale) versus loan amounts and credit scores. In panel (a), loan price is measured as APR, and in panel (b) loan price is measured as cost per $100.

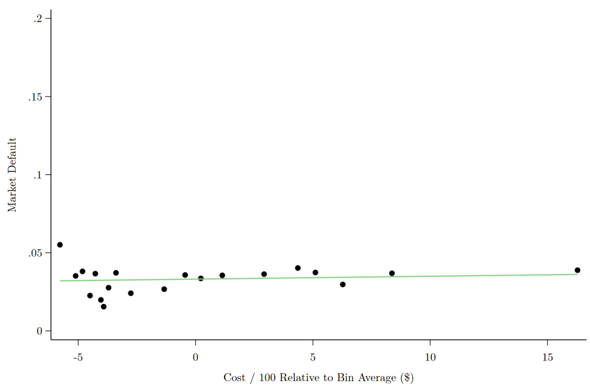
Figure 5: Prices and Default



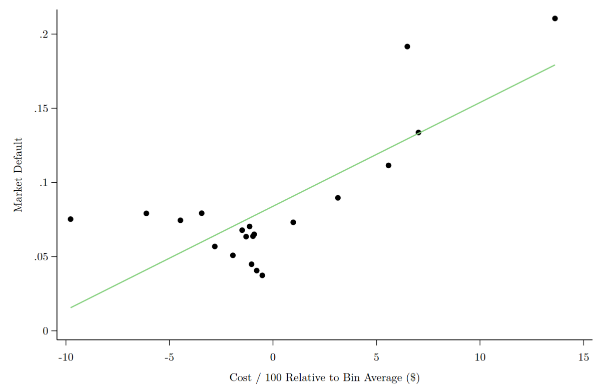
(a) APR vs Default, Storefront



(b) APR vs Default, Online



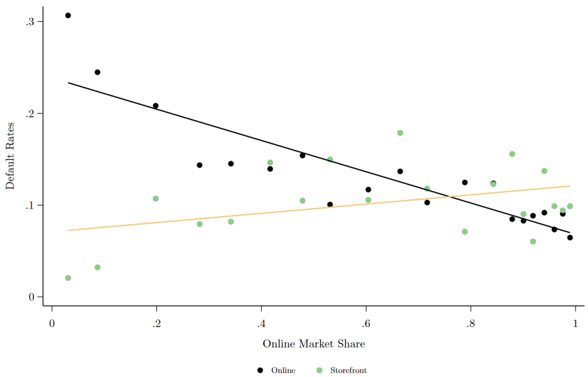
(c) Cost per $100 vs Default, Storefront



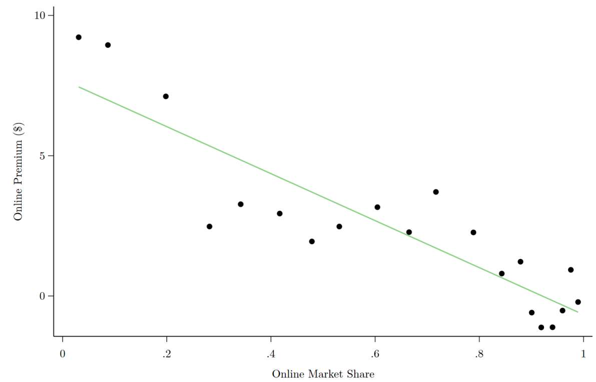
(d) Cost per $100 vs Default, Online

Note: The figure presents binscatter plots of default by bins of price relative to the bin average price in the credit visible sample. Prices are expressed as APR in panels (a) and (b) and cost per $100 borrower in panels (c) and (d). Bins are age-income bins.

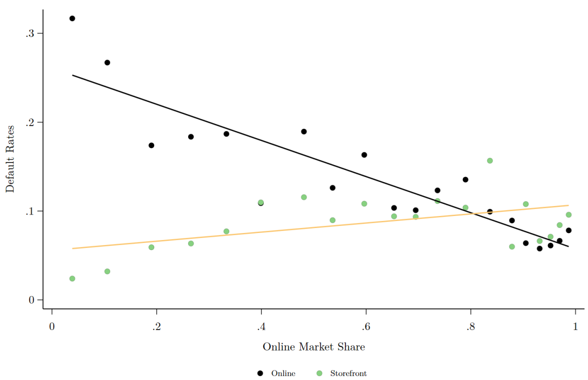
Figure 6: Online Market Shares, Pool Risk, and the Online Premium



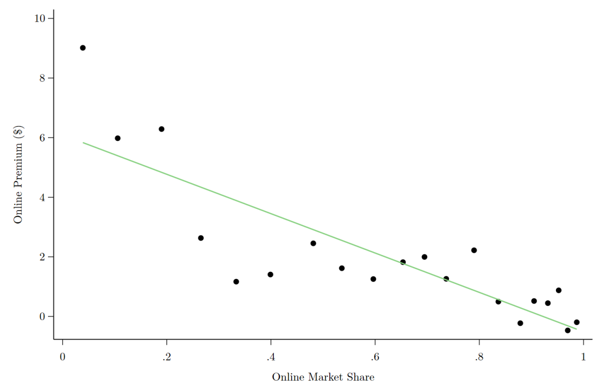
(a) Pool risk, Random Clarity Sample



(b) Online Premium, Random Clarity Sample



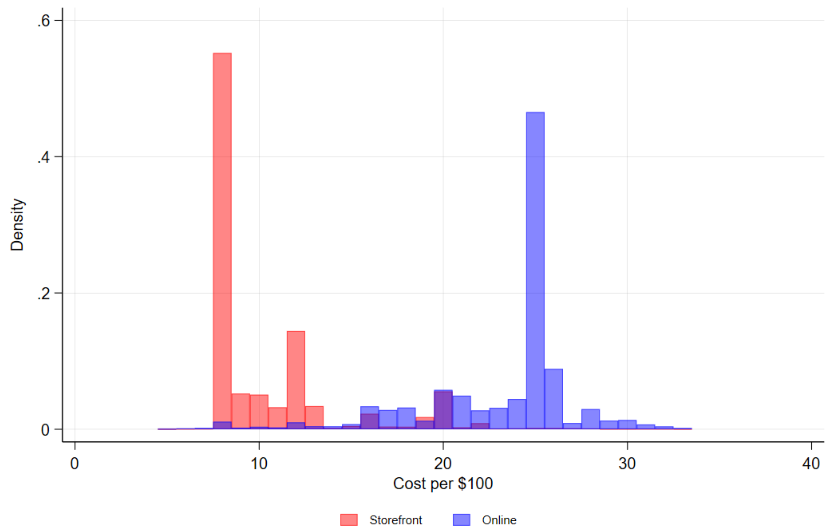
(c) Pool risk, Credit Visible Sample



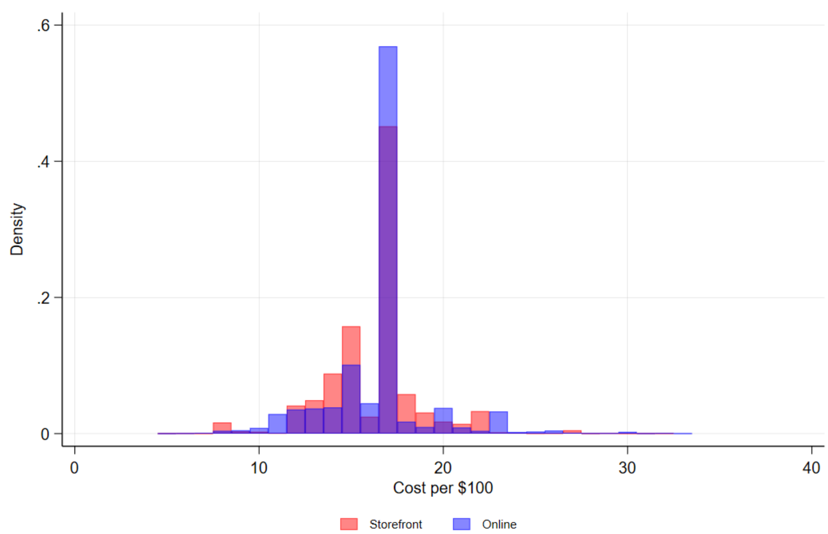
(d) Online Premium, Credit Visible Sample

Note: The figure presents binscatter plots of default rates online and storefront, in panels (a) and (c), and the online premium, in panels (b) and (d), along markets with different online market shares. Panels (a) and (b) are built from the random Clarity sample, and panels (c) and (d) are built from the credit visible sample.

Figure 7: Payday Loan Prices and State Laws



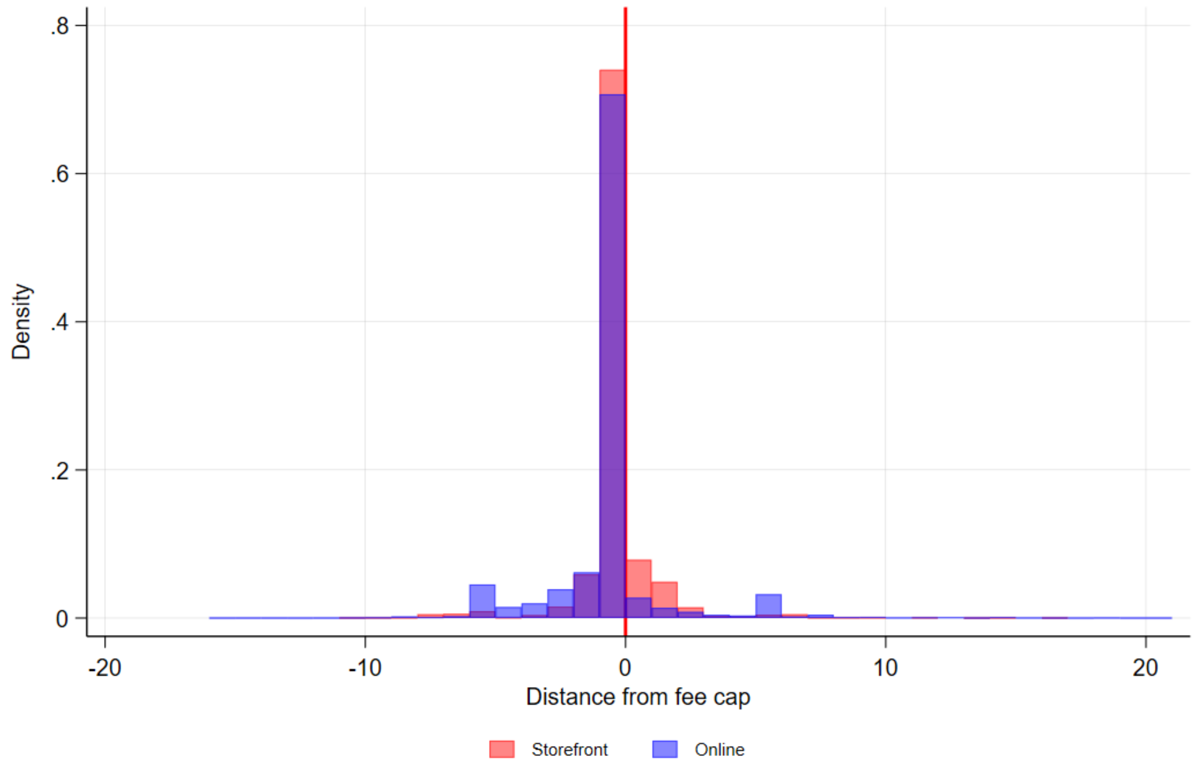
(a) No Binding Fee Cap



(b) Binding Fee Cap

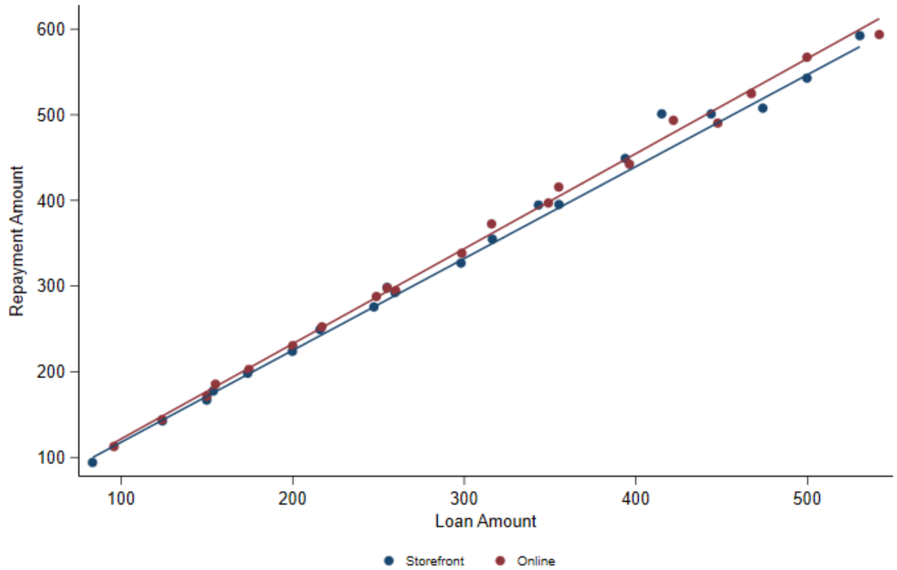
Note: This figure shows histograms for online (in blue) and storefront (in red) payday loan prices, expressed in cost per $100 borrowed, in states without a binding fee cap in panel (a) and in states with a binding fee cap in panel (b).

Figure 8: Binding State Payday Loan Fee Caps

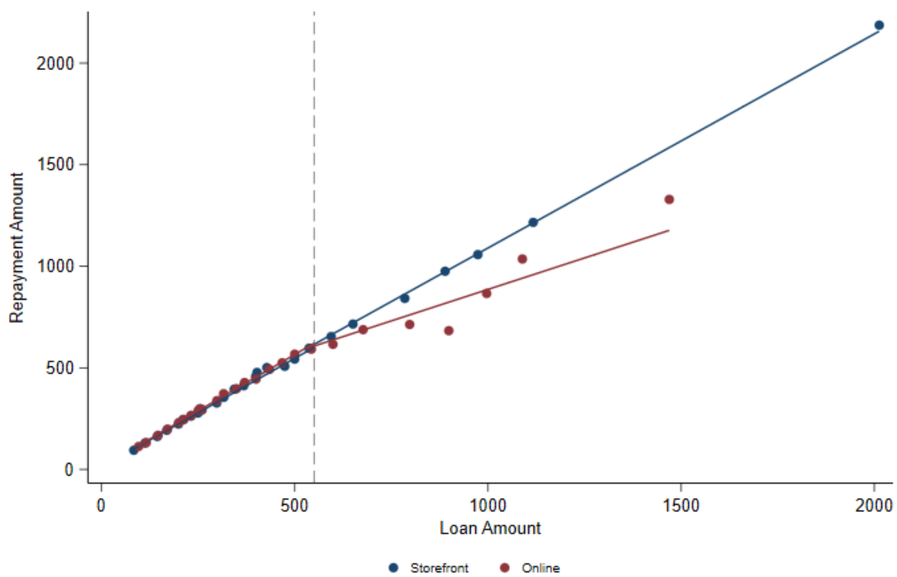


Note: This figure contains the histograms for the deviation between each loan's maximum fee cap, as allowed by the borrower's location state law and the actual loan price, for online loans (in blue) and storefront loans (in red).

Figure 9: Payday Lending Profitability



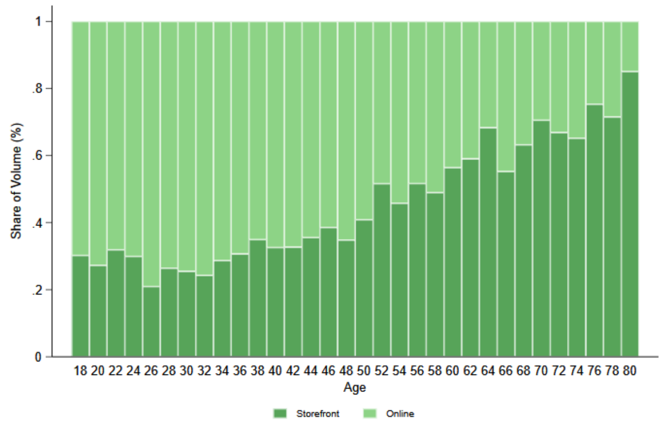
(a) Loans up to $550



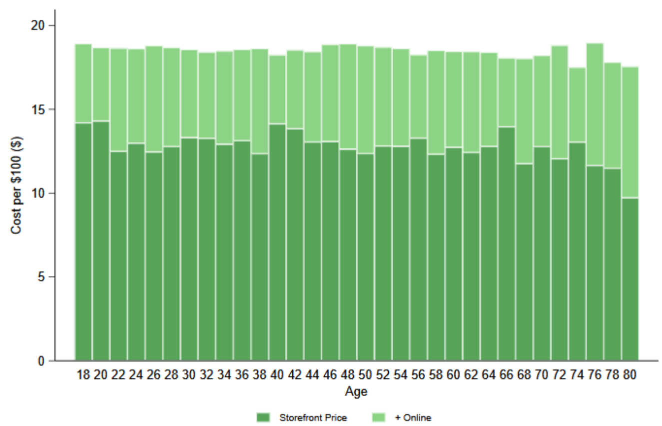
(b) All loans

Note: The figure presents binscatter plots of repayment amounts versus loan amounts, for storefront loans (blue) and online loans (red). The lines represent the lines of best fit with the slope indicating, on average, one plus the gross profit margin of each business model.

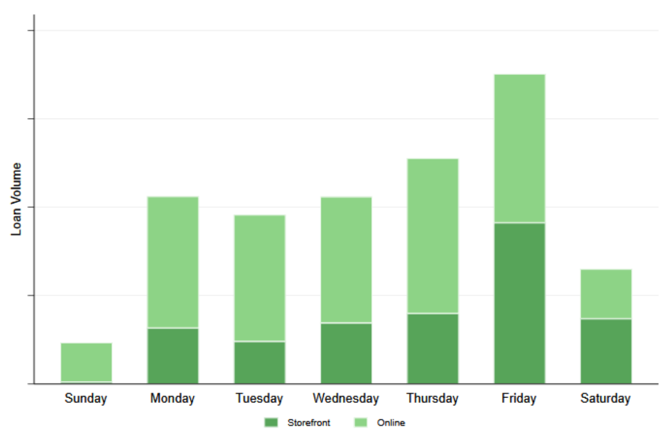
Figure 10: Online Payday Loan Convenience



(a) Market Shares by Age



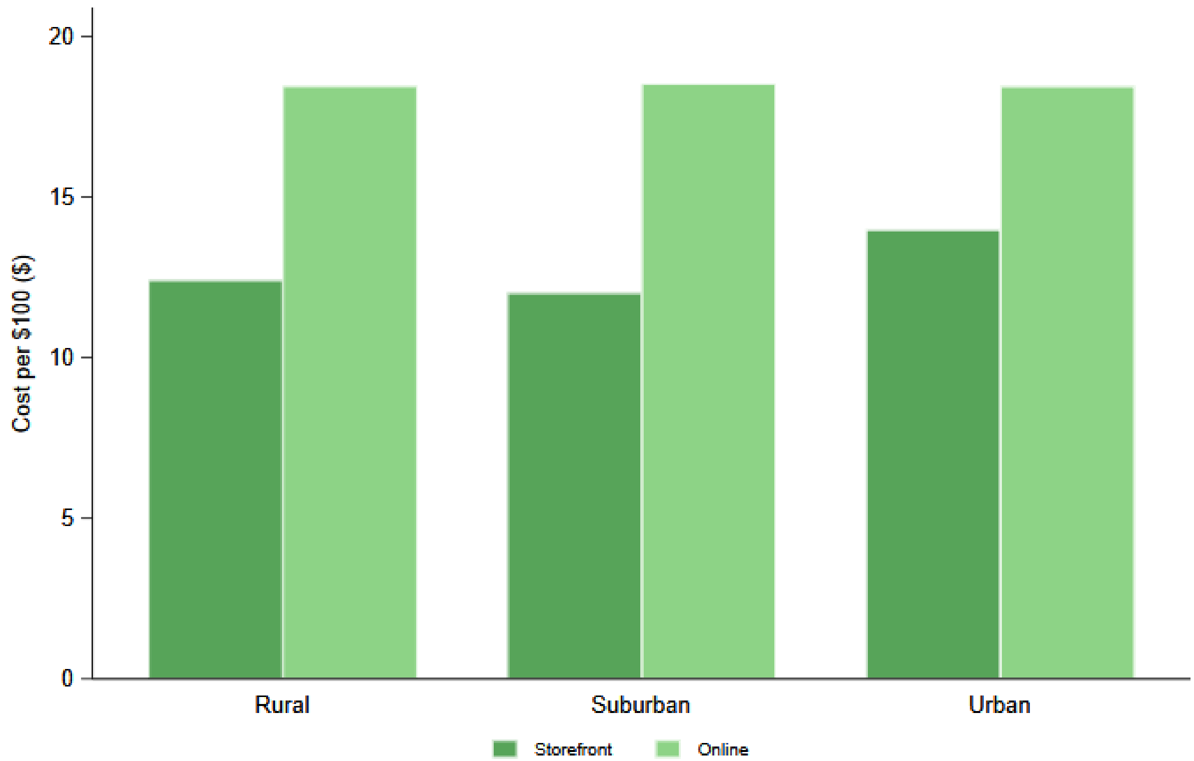
(b) Prices by Age



(c) Loan Volume by Day of Week

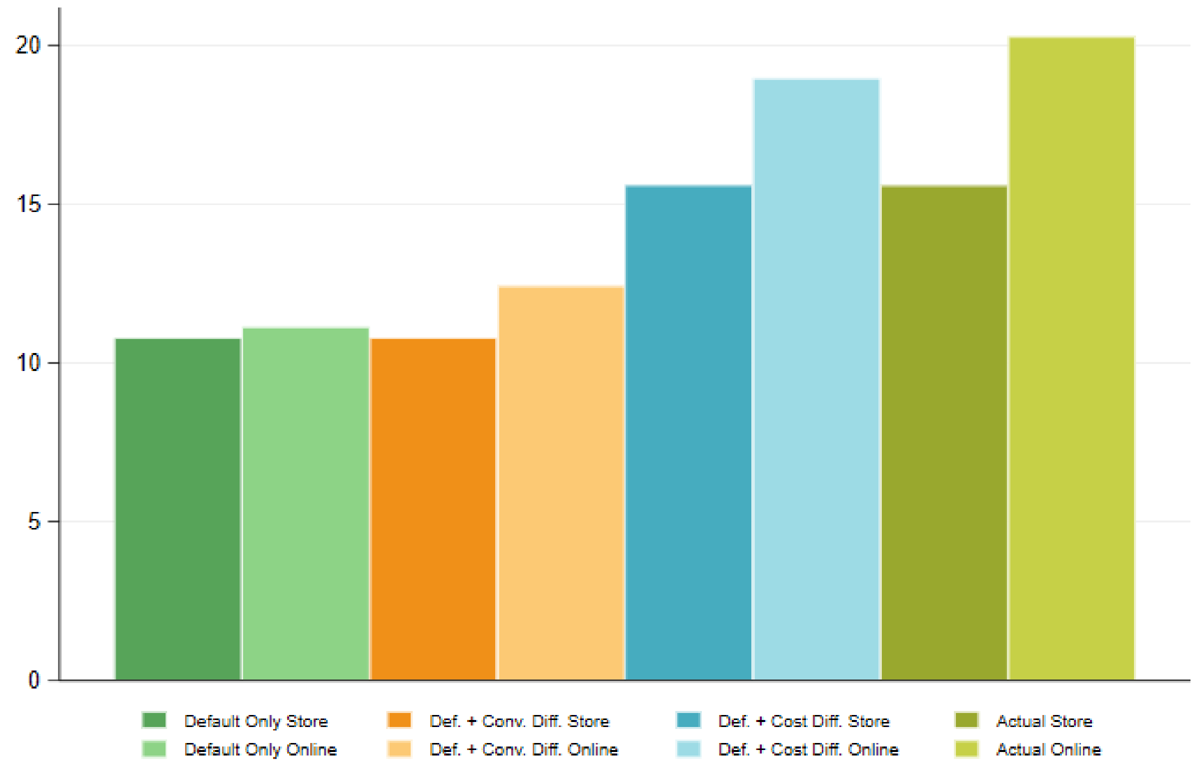
Note: This figure presents descriptive information of online and storefront market shares by age in panel (a), loan prices by age in panel (b), and loan volumes by day of week in panel (c).

Figure 11: Rural, Suburban, and Urban Payday Loan Prices



Note: This graph reports payday loan prices in rural, suburban, and urban areas, for online and storefront loans.

Figure 12: Counterfactual estimation



Note: The figure presents loan prices for storefront and online, under three counterfactual scenarios. Scenario 1: actual default, $\phi_O = \phi_S$, and $\kappa_O = 0$; Scenario 2: actual default, and $\phi_O = \phi_S$. Scenario 3: actual default, and $\kappa_O = 0$. The seventh and eighth bars correspond to actual observed values.

Table 1: **Summary Statistics**

Panel A: Random Clarity Sample (2013-2017)						
Subsample:	All			Non-imputed	Online	Storefront
	Mean	Median	SD	Mean	Mean	Mean
Loan Characteristics						
Loan Amount ($)	365	260	265	344	316	456
Repayment Amount ($)	403	307	293	397	351	498
Loan Maturity (days)	20	15	9	19	20	19
Default	7%	0%	26%	0%	9%	4%
Cost per $100 ($)	16.6	17.3	6.3	16.1	18.9	12.4
APR	373%	322%	217%	363%	416%	295%
Online Loan	65%	100%	48%	62%	100%	0%
Self-Reported Information						
Owns Home	15%	0%	35%	13%	19%	5%
Age	42.5	41.0	14.0	43.1	39.9	47.3
Months at Address	29.1	24.0	23.9	28.6	29.5	25.6
Net Monthly Income	2545	2200	1490	2533	2849	1970
# of Loans		336,690		272,220	217,596	119,094
# of Unique Borrowers		65,733		46,010	49,877	17,484

Panel B: Credit Visible Sample (2013-2019)						
Subsample:	All			Non-imputed	Online	Storefront
	Mean	Median	SD	Mean	Mean	Mean
Loan Characteristics						
Loan Amount ($)	370	255	284	342	332	460
Repayment Amount ($)	409	301	313	396	367	505
Loan Maturity (days)	19	15	9	19	19	19
Default	7%	0%	26%	0%	8%	4%
Cost per $100 ($)	16.9	17.5	5.8	16.4	18.5	13.3
APR	382%	336%	208%	372%	417%	300%
Vantage score	510	538	113	512	500	535
Unscoreable	18%	0%	38%	18%	21%	10%
Online Loan	70%	100%	46%	68%	100%	0%
Self-Reported Information						
Owns Home	16%	0%	36%	14%	20%	6%
Age	42.1	41.0	13.5	42.4	40.1	46.6
Months at Address	30.5	24.0	24.2	30.0	31.0	26.0
Net Monthly Income	2578	2244	1514	2576	2844	1956
# of Loans		188,913		149,458	132,520	56,393
# of Unique Borrowers		35,550		24,654	27,473	9,097

Note: Table contains summary statistics for two samples of online and storefront payday loans from Clarity. The random Clarity sample presented in Panel A consists of a random sample of 1 million unique borrowers that submitted loan inquiries in Clarity's full database between 2013-17. Only inquiries resulting in originated payday loans are included in the analysis sample. The credit visible sample shown in Panel B consists of payday borrowers who are matched to a random 1% sample of all consumers in the Experian credit bureau database in 2018. All inquiries and loans originated by matched borrowers between 2013 and 2019 are included in this sample. The two samples are drawn independently. Each panel shows statistics for the full set of loans, 'non-imputed' loans where prices are calculated directly from loan-level terms instead of imputed based on loans with similar characteristics (see text for details), online payday loans, and storefront payday loans.

Table 2: **Online Payday Loan Premium**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Random Clarity Sample (2013-2017)								
Outcome:		Cost / 100			APR			Default	
Storefront mean:		12.4			295			0.041	
Online dummy	4.35	4.65	6.52	98.4	110.3	141.2	0.030	0.026	0.084
	(2.20)	(2.52)	(3.07)	(36.0)	(41.7)	(54.3)	(0.026)	(0.032)	(0.038)
	[0.053]	[0.071]	[0.039]	[0.009]	[0.011]	[0.012]	[0.253]	[0.422]	[0.032]
R^2	0.582	0.663	0.812	0.534	0.615	0.775	0.139	0.202	0.511
N	336,690	332,937	305,775	336,690	332,937	305,775	336,690	332,937	305,775
	Panel B: Credit Visible Sample (2013-2019)								
Outcome:		Cost / 100			APR			Default	
Storefront mean:		13.3			300			0.044	
Online dummy	3.36	3.70	4.91	91.9	103.1	127.1	0.036	0.034	0.060
	(1.48)	(1.78)	(2.38)	(25.8)	(33.7)	(54.2)	(0.020)	(0.027)	(0.028)
	[0.027]	[0.042]	[0.045]	[0.001]	[0.004]	[0.023]	[0.080]	[0.202]	[0.041]
R^2	0.543	0.623	0.757	0.531	0.605	0.743	0.121	0.167	0.320
N	188,913	186,687	171,518	188,913	186,687	171,518	188,913	186,687	171,518
	Panel C: Credit Visible Sample with Vantage								
Online dummy	3.37	3.71	4.91	91.9	103.1	127.2	0.036	0.035	0.060
	(1.48)	(1.78)	(2.38)	(25.8)	(33.7)	(54.2)	(0.020)	(0.027)	(0.029)
	[0.027]	[0.042]	[0.044]	[0.001]	[0.004]	[0.023]	[0.077]	[0.199]	[0.041]
R^2	0.544	0.623	0.757	0.531	0.605	0.743	0.125	0.171	0.320
N	188,913	186,687	171,518	188,913	186,687	171,518	188,913	186,687	171,518
State FE	Yes	No	No	Yes	No	No	Yes	No	No
Zip FE	No	Yes	No	No	Yes	No	No	Yes	No
Consumer FE	No	No	Yes	No	No	Yes	No	No	Yes

Note: The table presents coefficient estimates of the online loan dummy from regressions of payday loan prices, default probability, and late payment probability for the random Clarity sample in Panel A and the credit visible sample in Panels B and C. All regressions include fixed effects for either state, ZIP code, or customer; fixed effects for day of week, day of month, month of year, and calendar year; and controls for deciles of loan duration, loan size, age, and income, categorical variables for housing status and pay frequency, and number of inquiries per week. Panel C additionally includes controls for decile of Vantage score. Robust standard errors clustered at the state level are in parentheses, and p-values are in brackets.

Table 3: **Online Payday Loan Premium - Binned Regression**

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:		Cost / 100			APR	
Online dummy	4.7	4.2	4.1	87.5	97.8	120.0
	(0.0)	(0.1)	(0.0)	(1.5)	(2.0)	(1.7)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Bins	Age-Income	Age-Income	Credit Score	Age-Income	Age-Income	Credit Score
Sample	Stand-Alone	Credit Visible	Credit Visible	Stand-Alone	Credit Visible	Credit Visible
R2	0.570	0.544	0.544	0.290	0.295	0.270
N	303,183	155,795	155,795	303,183	155,795	155,795
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Bin FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table presents coefficient estimates of the online loan dummy from regressions of payday loan prices. The unit of observation is a bin of similar borrowers, in a given week. Bins are defined as 25 age-income cross quintiles, in columns (1),(2), (4), and (5), or credit score quintiles in columns (3) and (6). All regressions include state, week, and bin fixed effects and controls for averages of loan duration, loan size, age, income, number of inquiries per week, and lagged default rates and lagged percentage of late payments in the market. Robust standard errors are in parentheses, and p-values are in brackets.

Table 4: **Statewide Payday Loan Database - Difference in Differences**

	(1)	(2)	(3)	(4)
	Panel A: Random Clarity Sample (2013-2017)			
Outcome:	Cost per $100 ($)		APR (p.p.)	
Online x Database	- 4.9	- 3.6	- 46.6	- 49.0
	(1.6)	(1.5)	(50.6)	(38.3)
	[0.002]	[0.016]	[0.357]	[0.202]
Online	5.8	5.2	122.4	109.1
	(1.5)	(1.4)	(36.6)	(26.5)
	[0.000]	[0.000]	[0.001]	[0.000]
Controls	No	Yes	No	Yes
FE	No	Yes	No	Yes
R2	0.545	0.573	0.199	0.520
N	336,690	336,690	336,690	336,690
	Panel B: Credit Visible Sample (2013-2019)			
Outcome:	Cost per $100 ($)		APR (p.p.)	
Online x Database	- 4.1	- 2.5	- 39.2	- 34.1
	(1.3)	(1.4)	(36.7)	(31.1)
	[0.001]	[0.072]	[0.287]	[0.274]
Online	4.8	4.1	120.7	101.5
	(1.2)	(1.1)	(27.3)	(20.3)
	[0.000]	[0.000]	[0.000]	[0.000]
Controls	No	Yes	No	Yes
FE	No	Yes	No	Yes
R2	0.486	0.530	0.207	0.518
N	188,913	188,913	188,913	188,913

Note: The table presents coefficient estimates of loan-level regressions of prices, in APR and cost per $100 borrowed, and loan amounts, on a dummy variable that indicates whether the loan is an online loan, and a dummy variable that indicates whether the state where the tradeline originated has a statewide payday loan database, and their interaction. Columns (2), (4), and (6) contain loan and customer-level controls, and time fixed effects. The samples used are in Panel A and the random Clarity sample, in Panel B the credit visible sample. Robust standard errors clustered at the state-year level are in parentheses, and p-values are in brackets.

Table 5: **State Payday Loan Fee Caps**

State	Fee Cap (per $100)	# Online Loans	# Storefront Loans	Online Premium	Citation (as of 2019)
AL	$17.50	9,222	3,488	0.193	AL Code §§ 5-18A-12
AK	$5 admin fee + $15	776	186	0.655	AK Stat § 06.50.460
CA	15% of check amount	52,621	3,149	0.112	CA Code, FIN § 23036
FL	10% of check amount	5,666	145	-1.926	FL Statute 560.404 (6)(a)
ID	No Limit	374	370	3.292	ID Code § 28-46-412
IL	$15.50	1,880	87	0.732	815 ILCS 122 (e-5)
IN	Depends on loan amount	1,108	2,505	2.671	IN Code §§ 24-4.5-7-201
KS	$15	1,027	447	-0.499	KS Stat. Ann. §§ 16a-2-404 (c)
KY	$15	147	1,061	0.883	KY Rev. Stat. Ann. §§ 286.9-100 (1)
LA	16.75% of check amount	8,165	1,035	-2.462	LA Rev. Stat. 9:3578.4
MI	Depends on loan amount	4,978	449	1.261	MI Comp L § 487.2153
MS	Depends on loan amount	3,841	657	-0.523	MS Code § 75-67-519 (4)
MO	75%	1,605	1,005	1.018	MO Rev Stat § 408.505 (3)
NE	15% of check amount	71	145	7.685	NE Code § 45-918
NV	No Limit	1,661	1,092	5.000	NRS 604A
OH	60%	5,851	33,720	10.332	OH Rev Code § 1321.403
OK	Depends on loan amount	3,816	327	1.266	OK Stat § 59-3108
TN	15% of check amount	4,075	525	-0.012	TN Code § 45-17-112 (b)
TX	No Limit	15,835	1,729	4.572	TX Fin. Code §§ 393 + §§ 342.004
UT	No Limit	380	137	6.14	UT Code § 7-23-401
WA	Depends on loan amount	1,229	1,871	0.237	WA Rev Code § 31.45.073 (5)

Note: This table summarizes the state laws on fee caps as of 2019 for all states for which we have at least 50 observations of both online and storefront payday loans.

Table 6: **Quantitative Model Estimates**

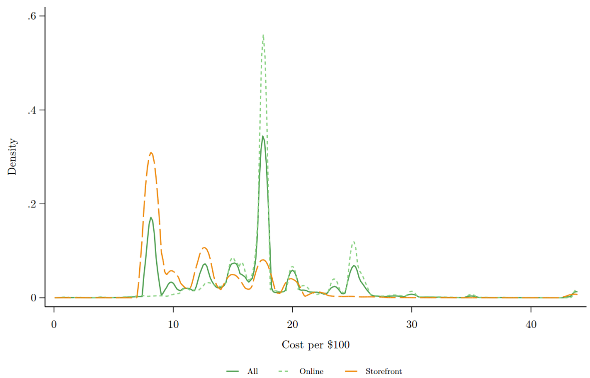
Parameter	Average Across States	CI Lower Bound	CI Upper Bound
α	0.297	0.249	0.346
κ_S	0.042	0.027	0.058
ϕ_O/F	9.641	9.272	10.011
ϕ_S/F	6.108	6.110	6.805

Note: This table contains estimates for averages across states for the parameters we estimate, based on our quantitative model. The first row refers to α estimates using online prices and market shares, and the second row refers to α estimates using storefront prices and market shares. The third and fourth columns are bounds for 95% confidence intervals. We use only states with substantial presence of both lenders ($s_l > 0.05,\ \forall l$).

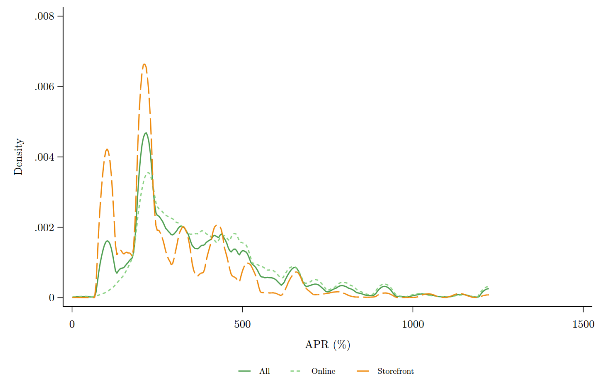
Internet Appendix

Figure A1: Online and Storefront Price distributions

Panel A: Random Clarity sample

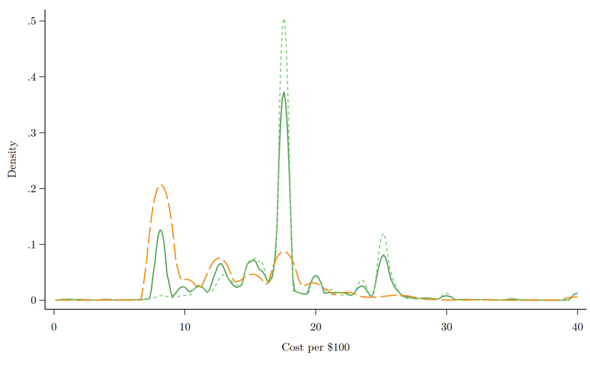


(a) Cost per $100

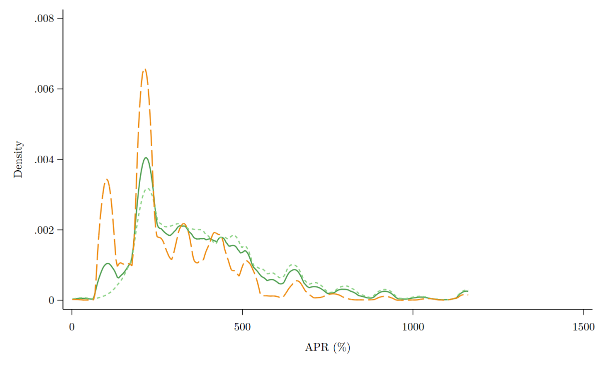


(b) APR

Panel B: Credit visible sample



(c) Cost per $100

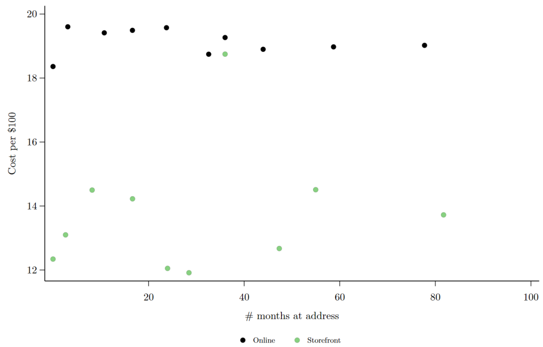


(d) APR

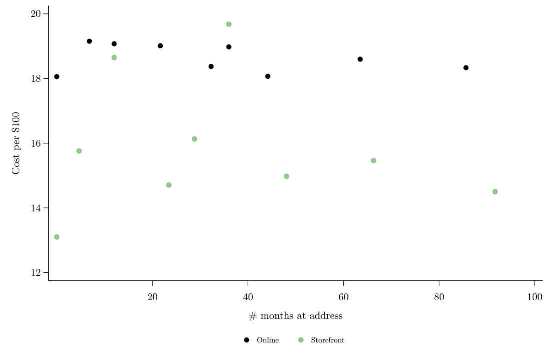
Note: This figure shows the distributions of prices for online and storefront payday loans. The random Clarity sample presented in Panel A consists of a random sample of 1 million unique borrowers who submitted loan inquiries in Clarity's full database between 2013 and 17. Only originated payday loans from this sample of consumers are included in the analysis sample. The credit visible sample shown in Panel B consists of payday borrowers that are matched to a random 1% sample of all consumers in the Experian credit bureau database in 2018. All loans originated by matched borrowers between 2013 and 2019 are included in this sample.

Figure A2: Prices and Default Rates by Months at Address

Panel A: Cost per $100

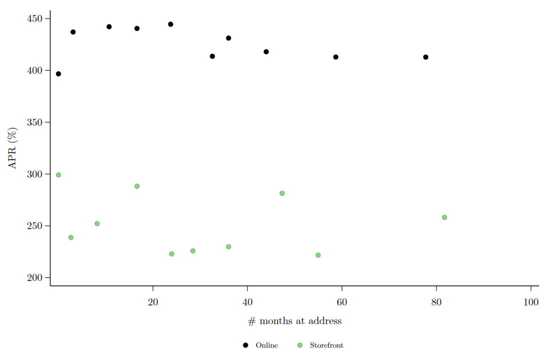


(a) Random Clarity sample

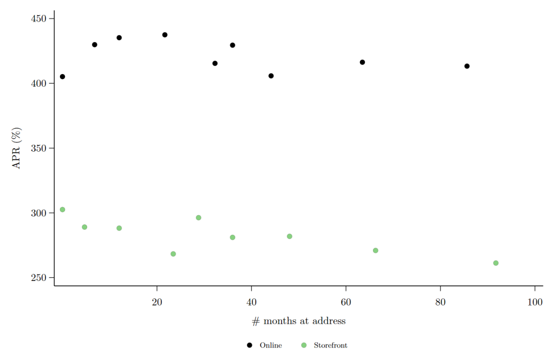


(b) Credit visible sample

Panel B: APR

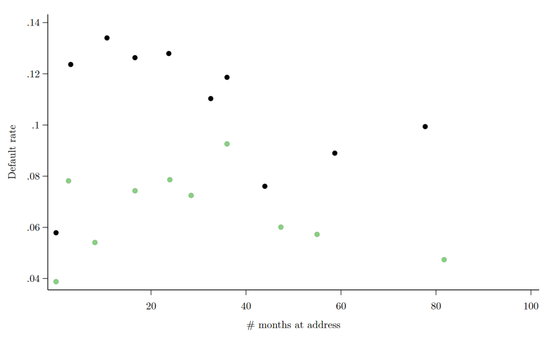


(c) Random Clarity sample

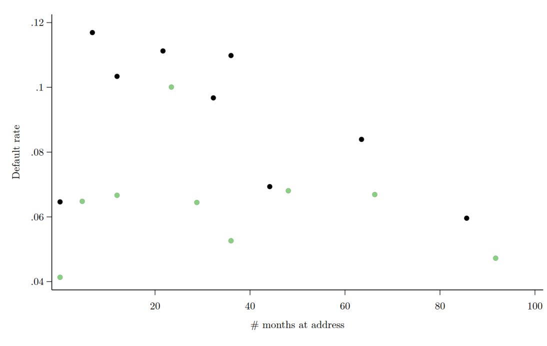


(d) Credit visible sample

Panel C: Default



(e) Random Clarity sample

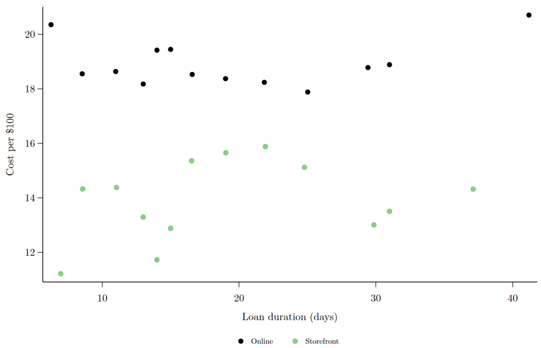


(f) Credit visible sample

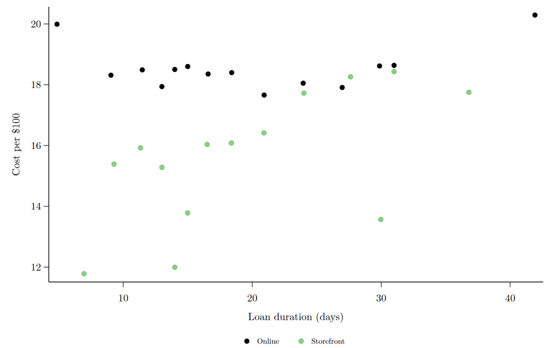
Note: The figure presents binscatter plots of cost per $100 borrowed, APR, and default rates in the credit visible sample in graphs (b), (d), and (f), and in the standalone sample in graphs (a), (c), and (e). The x-axis contains the number of months living at the same address for the loan applicant, at the application date.

Figure A3: Prices and Default Rates by Loan Duration

Panel A: Cost per $100

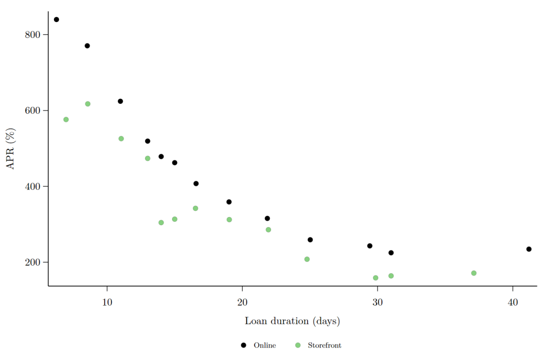


(a) Random Clarity sample

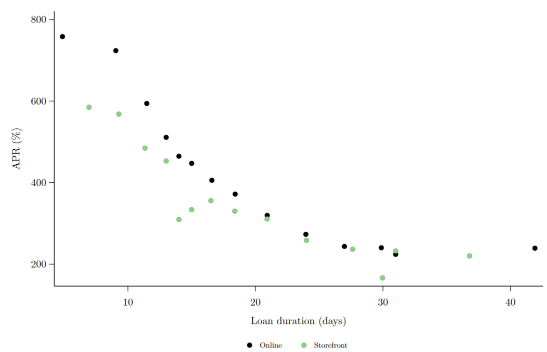


(b) Credit visible sample

Panel B: APR

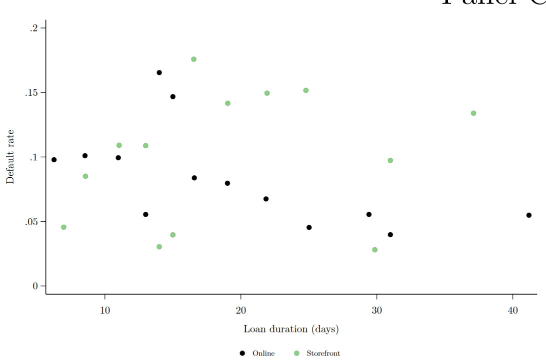


(c) Random Clarity sample

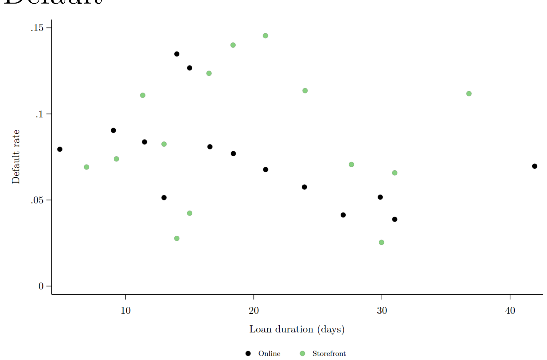


(d) Credit visible sample

Panel C: Default



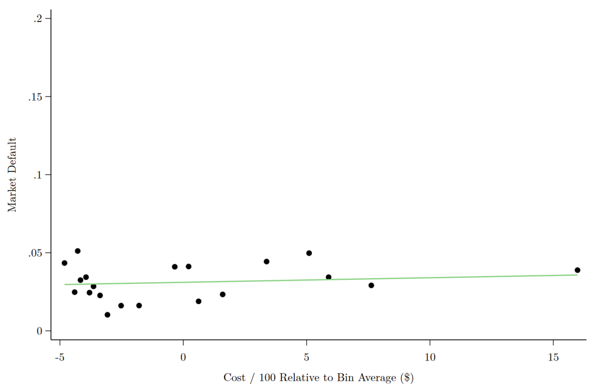
(e) Random Clarity sample



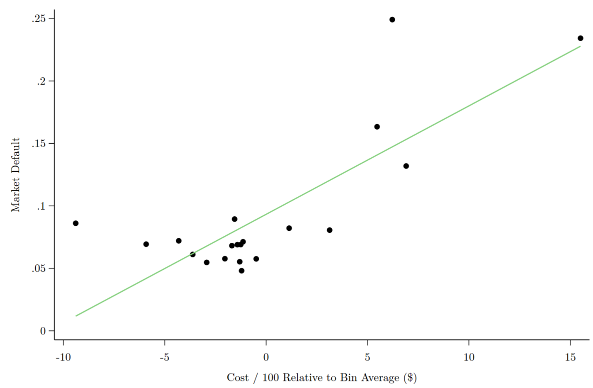
(f) Credit visible sample

Note: The figure presents binscatter plots of cost per $100 borrowed, APR, and default rates in the credit visible sample in graphs (b), (d), and (f), and in the standalone sample in graphs (a), (c), and (e). The x-axis represents the loan maturity.

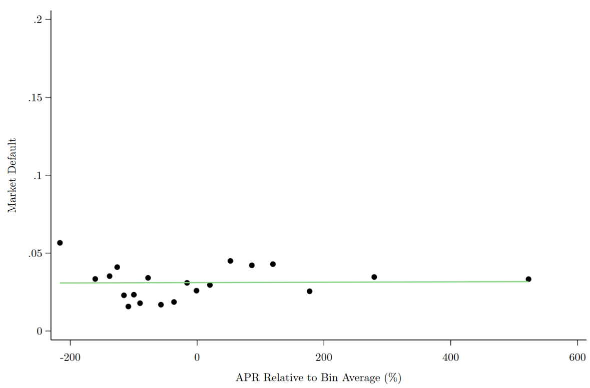
Figure A4: Prices and Default - Random Clarity Sample



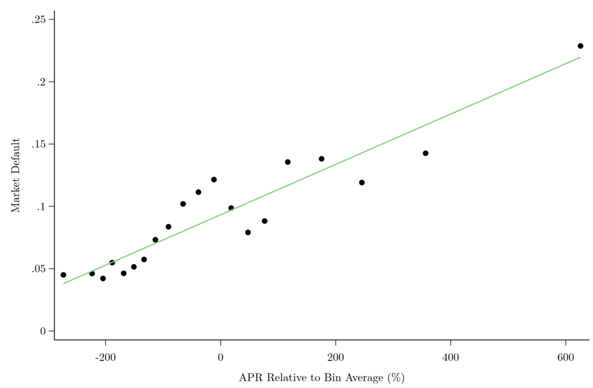
(a) Cost per $100 vs Default, Storefront



(b) Cost per $100 vs Default, Online



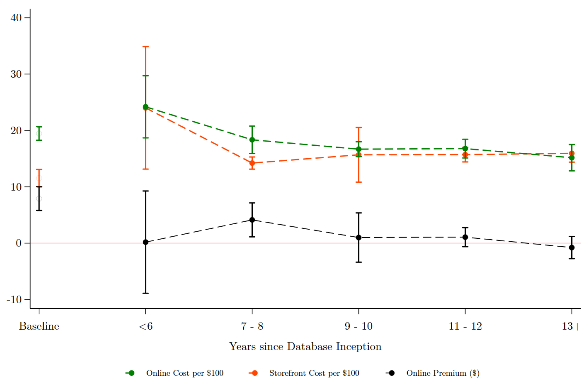
(c) APR vs Default, Storefront



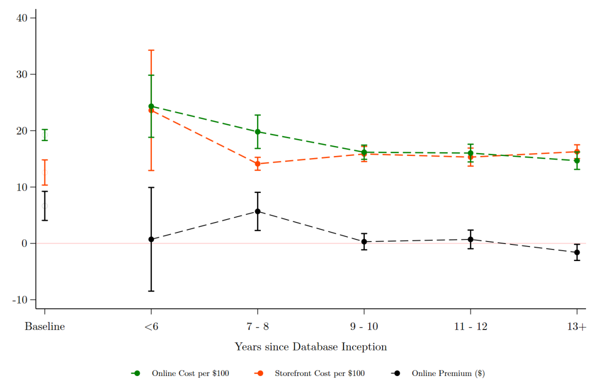
(d) APR vs Default, Online

Note: The figure presents binscatter plots of default by bins of price relative to the bin average price in the stand-alone sample. Prices are expressed as cost per $100 borrower in panels (a) and (b) and APR in panels (c) and (d). Bins are age-income bins.

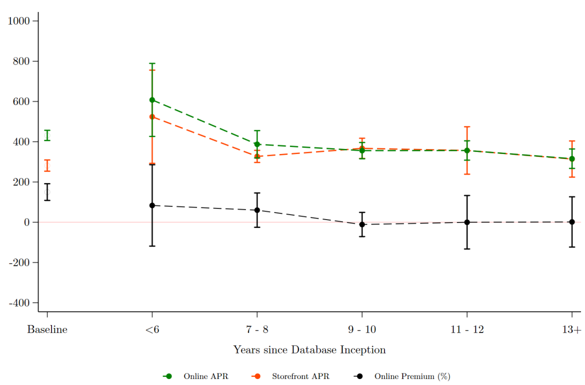
Figure A5: Statewide Payday Loan Database



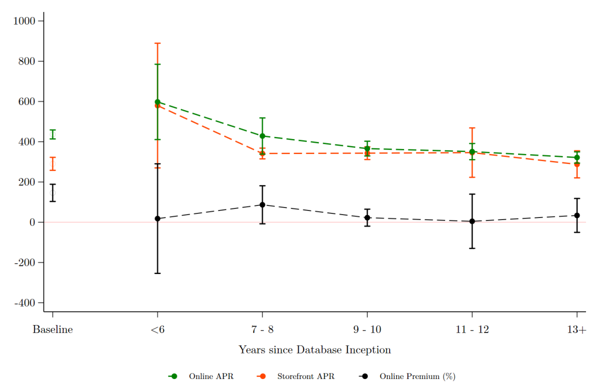
(a) Cost per $100, Random Clarity Sample



(b) Cost per $100, Credit Visible Sample



(c) APR, Random Clarity Sample



(d) APR, Credit Visible Sample

Note: The figure presents coefficients for loan-level regressions of prices and 95% confidence intervals, in APR and cost per $100 borrowed, on a dummy variable that indicates whether the loan is an online loan, and dummy variables for each bin of time since implementation of a statewide payday loan database, and their interaction. Regressions contain loan and customer-level controls, and time fixed effects. Robust standard errors are clustered at the state level.

Table A1: **Online Payday Loan Premium: Excluding 2013**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Random Clarity Sample (2014-2017)								
Outcome:		Cost / 100			APR			Default	
Storefront mean:		12.4			294			0.041	
Online dummy	4.13	4.48	6.17	92.2	106.4	133.0	0.026	0.020	0.062
	(2.14)	(2.47)	(3.10)	(37.0)	(42.7)	(56.0)	(0.026)	(0.031)	(0.036)
	[0.060]	[0.076]	[0.052]	[0.016]	[0.016]	[0.021]	[0.320]	[0.528]	[0.091]
R^2	0.613	0.698	0.825	0.538	0.627	0.779	0.099	0.129	0.398
N	312,298	309,186	286,945	312,298	309,186	286,945	312,298	309,186	286,945
	Panel B: Credit Visible Sample (2014-2019)								
Outcome:		Cost / 100			APR			Default	
Storefront mean:		13.3			300			0.044	
Online dummy	3.18	3.49	4.56	85.3	96.2	116.4	0.034	0.029	0.042
	(1.42)	(1.68)	(2.30)	(25.4)	(32.3)	(53.5)	(0.020)	(0.025)	(0.027)
	[0.029]	[0.044]	[0.053]	[0.001]	[0.005]	[0.035]	[0.094]	[0.265]	[0.131]
R^2	0.556	0.635	0.764	0.533	0.608	0.746	0.096	0.140	0.287
N	178,953	177,197	163,898	178,953	177,197	163,898	178,953	177,197	163,898
	Panel C: Credit Visible Sample with Vantage								
Online dummy	3.19	3.50	4.57	85.4	96.2	116.5	0.034	0.029	0.042
	(1.42)	(1.68)	(2.30)	(25.4)	(32.3)	(53.5)	(0.020)	(0.025)	(0.027)
	[0.029]	[0.044]	[0.053]	[0.001]	[0.005]	[0.034]	[0.089]	[0.259]	[0.132]
R^2	0.557	0.635	0.764	0.533	0.608	0.746	0.100	0.143	0.287
N	178,953	177,197	163,898	178,953	177,197	163,898	178,953	177,197	163,898
State FE	Yes	No	No	Yes	No	No	Yes	No	No
Zip FE	No	Yes	No	No	Yes	No	No	Yes	No
Consumer FE	No	No	Yes	No	No	Yes	No	No	Yes

Note: The table presents coefficient estimates of the online loan dummy from regressions of payday loan prices and default probability for the random Clarity sample in Panel A and the credit visible sample in Panels B and C, excluding loans made in 2013. All regressions include fixed effects for either state, ZIP code, or customer; fixed effects for day of week, day of month, month of year, and calendar year; and controls for deciles of loan duration, loan size, age, and income, categorical variables for housing status and pay frequency, and number of inquiries per week. Panel C additionally includes controls for decile of Vantage score. Robust standard errors clustered at the state level are in parentheses, and p-values are in brackets.

Table A2: **Online Payday Loan Premium: Non-Imputed Sample**

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Random Clarity Sample (2013-2017)					
Outcome:	Cost / 100			APR		
Storefront mean:	12.4			298		
Online dummy	3.45	3.80	4.80	98.7	111.0	119.2
	(1.88)	(2.27)	(2.94)(33.7)	(40.4)	(47.9)	
	[0.073]	[0.101]	[0.109]	[0.005]	[0.008]	[0.016]
R^2	0.641	0.734	0.870	0.595	0.686	0.823
N	272,220	269,436	252,430	272,220	269,436	252,430
	Panel B: Credit Visible Sample (2013-2019)					
Outcome:	Cost / 100			APR		
Storefront mean:	13.0			300		
Online dummy	2.70	3.13	3.85	87.3	99.8	114.1
	(1.30)	(1.70)	(2.34)	(23.7)	(30.9)	(57.8)
	[0.043]	[0.072]	[0.107]	[0.001]	[0.002]	[0.054]
R^2	0.602	0.692	0.837	0.593	0.671	0.801
N	149,458	148,104	138,710	149,458	148,104	138,710
	Panel C: Credit Visible Sample with Vantage					
Online dummy	2.70	3.13	3.85	87.3	99.9	114.1
	(1.30)	(1.70)	(2.34)	(23.7)	(30.9)	(57.8)
	[0.043]	[0.072]	[0.107]	[0.001]	[0.002]	[0.054]
R^2	0.603	0.692	0.837	0.593	0.672	0.801
N	149,458	148,104	138,710	149,458	148,104	138,710
State FE	Yes	No	No	Yes	No	No
Zip FE	No	Yes	No	No	Yes	No
Consumer FE	No	No	Yes	No	No	Yes

Note: The table presents coefficient estimates of the online loan dummy from regressions of payday loan prices and default probability for the random Clarity sample in Panel A and the credit visible sample in Panels B and C, excluding defaulted loans and those with missing information in the pricing formula in Equation (1). All regressions include fixed effects for either state, ZIP code, or customer; fixed effects for day of week, day of month, month of year, and calendar year; and controls for deciles of loan duration, loan size, age, and income, categorical variables for housing status and pay frequency, and number of inquiries per week. Panel C additionally includes controls for decile of Vantage score. Robust standard errors clustered at the state level are in parentheses, and p-values are in brackets.

Table A3: **Asymmetric Information - APR and Default**

	(1)	(2)	(3)	(4)	(5)	(6)
			Propensities (p.p.)			
Outcome:			Default			
Online Dummy x Cost per $100				0.007	0.061	0.079
				(0.028)	(0.035)	(0.034)
				[0.793]	[0.079]	[0.021]
Cost per $100				0.334	0.185	0.162
				(0.019)	(0.024)	(0.024)
				[0.000]	[0.000]	[0.000]
Online Dummy x APR	0.005	0.003	0.000			
	(0.001)	(0.001)	(0.000)			
	[0.000]	[0.000]	[0.001]			
APR	0.003	0.003	0.000			
	(0.000)	(0.001)	(0.000)			
	[0.000]	[0.000]	[0.000]			
Online Dummy	5.950	5.360	0.054	6.730	5.060	4.760
	(0.286)	(0.380)	(0.004)	(0.566)	(0.692)	(0.684)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R^2	0.094	0.075	0.078	0.095	0.075	0.077
N	304,404	157,400	157,400	304,404	157,400	157,400
Sample	Stand-Alone	Credit Visible	Credit Visible	Stand-Alone	Credit Visible	Credit Visible
Binning Quintiles	Age-Income	Age-Income	Credit Score	Age-Income	Age-Income	Credit Score
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Bin FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table presents coefficient estimates of correlations between payday loan prices and default for the random Clarity sample in Columns (1) and (4) and the credit visible sample in Columns (2)-(3) and (5)-(6). The unit of observation is loan, and bins are defined by quintiles of age and income in columns (1)-(2) and (4)-(5) , and credit score in columns (3) and (6). All regressions include fixed effects for bin and week fixed effects and controls for averages of loan duration, loan size, age, income, number of inquiries per week. Robust standard errors clustered at the market level are in parentheses, and p-values are in brackets.

Table A4: **Asymmetric Information - Bivariate Probit**

	(1)	(2)	(3)	(4)
	Panel A: Random Clarity Sample (2013-2017)			
	APR > Bin Avg. vs. Default		Cost per $100 > Bin Avg. vs. Default	
Rho (ρ)	0.053	0.222	0.057	0.297
	(0.010)	(0.005)	(0.010)	(0.005)
	[0.000]	[0.000]	[0.000]	[0.000]
N	105,002	199,402	105,002	199,402
Sample	Storefront	Online	Storefront	Online
	Panel B: Credit Visible Sample (2013-2019)			
Rho (ρ)	0.095	0.191	0.029	0.271
	(0.014)	(0.007)	(0.014)	(0.007)
	[0.000]	[0.000]	[0.039]	[0.000]
N	46,937	110,463	46,937	110,463
Sample	Storefront	Online	Storefront	Online
	Panel C: Credit Visible Sample with Vantage			
Rho (ρ)	0.154	0.191	0.012	0.267
	(0.014)	(0.007)	(0.014)	(0.007)
	[0.000]	[0.000]	[0.400]	[0.000]
N	46,937	110,463	46,937	110,463
Sample	Storefront	Online	Storefront	Online

Note: The table presents bivariate Probit coefficient estimates of correlations between payday loan prices and default for the random Clarity sample in Panel A, in Panel B and C the credit visible sample, being Panel C controlled for credit score. In columns (1) and (2) we present correlation estimates for the bivariate distribution of default and a dummy if the loan has an APR larger than the average APR within its bin. In Columns (3) and (4), instead of APR, we use cost per $100 borrowed. Standard errors are in parentheses, and p-values are in brackets.

Table A5: **Statewide Payday Loan Database - Time Series**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Random Clarity Sample (2013-2017)				Panel B: Credit Visible Sample (2013-2019)			
Outcome:	APR		Cost / 100		APR		Cost / 100	
Online × Database 6 or less years ago	- 66.4	- 115.3	- 7.7	- 8.6	- 127.8	- 167.3	- 5.9	- 6.7
	(105.3)	(112.0)	(4.8)	(5.1)	(140.6)	(143.8)	(4.9)	(5.3)
	[0.529]	[0.304]	[0.106]	[0.095]	[0.364]	[0.245]	[0.225]	[0.207]
Online × Database 7 - 8 years ago	- 89.7	- 67.6	- 3.8	- 3.8	- 59.2	- 45.7	- 1.0	- 0.9
	(48.4)	(38.7)	(1.9)	(1.9)	(52.9)	(37.6)	(2.2)	(1.8)
	[0.065]	[0.082]	[0.045]	[0.053]	[0.264]	[0.225]	[0.654]	[0.614]
Online × Database 9 - 10 years ago	- 161.2	- 179.1	- 6.9	- 7.7	- 123.3	- 134.5	- 6.3	- 5.9
	(37.3)	(28.3)	(2.5)	(2.3)	(30.6)	(27.7)	(1.5)	(1.3)
	[0.000]	[0.000]	[0.006]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Online × Database 11 - 12 years ago	- 150.0	- 118.3	- 6.8	- 5.6	- 141.1	- 111.0	- 5.9	- 4.8
	(71.0)	(55.0)	(1.4)	(1.3)	(72.1)	(60.3)	(1.6)	(1.4)
	[0.036]	[0.033]	[0.000]	[0.000]	[0.051]	[0.066]	[0.000]	[0.001]
Online × Database 13 or more years ago	- 148.3	- 136.9	- 8.7	- 6.7	- 112.0	- 95.1	- 8.2	- 6.0
	(67.1)	(59.7)	(1.5)	(1.5)	(48.2)	(46.5)	(1.5)	(1.5)
	[0.028]	[0.023]	[0.000]	[0.000]	[0.021]	[0.042]	[0.000]	[0.000]
Online	149.9	129.1	7.9	7.4	146.0	118.2	6.7	5.7
	(21.2)	(20.8)	(1.1)	(1.1)	(21.8)	(19.3)	(1.3)	(1.1)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Database 6 or less years ago	242.5	228.1	12.5	11.4	289.4	267.8	11.0	9.7
	(119.0)	(127.6)	(5.6)	(5.8)	(158.9)	(159.5)	(5.6)	(6.0)
	[0.043]	[0.075]	[0.027]	[0.052]	[0.069]	[0.094]	[0.048]	[0.107]
Database 7 - 8 years ago	45.6	27.0	2.7	2.0	51.4	39.9	1.5	0.7
	(20.9)	(22.2)	(1.0)	(1.1)	(21.4)	(21.2)	(1.3)	(0.9)
	[0.030]	[0.226]	[0.006]	[0.074]	[0.017]	[0.061]	[0.228]	[0.453]
Database 9 - 10 years ago	85.5	65.5	4.1	3.8	53.0	25.7	3.3	1.9
	(29.3)	(29.5)	(2.6)	(2.4)	(23.0)	(21.7)	(1.3)	(1.2)
	[0.004]	[0.027]	[0.112]	[0.122]	[0.022]	[0.238]	[0.014]	[0.103]
Database 11 - 12 years ago	74.9	62.8	4.2	3.0	55.8	40.2	2.7	1.7
	(61.8)	(48.2)	(1.0)	(0.9)	(64.8)	(54.4)	(1.4)	(1.1)
	[0.226]	[0.193]	[0.000]	[0.002]	[0.390]	[0.460]	[0.052]	[0.109]
Database 13 or more years ago	32.5	59.9	4.4	3.1	- 2.5	7.7	3.7	1.7
	(48.0)	(39.3)	(1.1)	(0.7)	(38.1)	(36.4)	(1.3)	(1.0)
	[0.499]	[0.129]	[0.000]	[0.000]	[0.948]	[0.832]	[0.005]	[0.090]
Controls	No	Yes	No	Yes	No	Yes	No	Yes
FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.111	0.465	0.330	0.401	0.111	0.454	0.256	0.346
N	336,690	336,690	336,690	336,690	188,913	188,913	188,913	188,913

Note: The table presents coefficient estimates of loan-level regressions of prices, in APR and cost per $100 borrowed, on a dummy variable that indicates whether the loan is an online loan, and dummy variables for each bin of time since implementation of a statewide payday loan database, and their interaction. Columns (2), (4), (6), and (8) contain loan and customer level controls, and time fixed effects. The samples used are in Panel A and the random Clarity sample, in Panel B the credit visible sample. Robust standard errors clustered at the state-year level are in parentheses, and p-values are in brackets.