THE UNIVERSITY OF CHICAGO

HETEROGENEOUS CONSUMER DYNAMICS AND THE FINANCING GAP

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE UNIVERSITY OF CHICAGO
BOOTH SCHOOL OF BUSINESS
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

BY
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CHICAGO, ILLINOIS
AUGUST 2023

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ACKNOWLEDGMENTS

I am profoundly indebted to my advisor Jean-Pierre Dubé for his unwaivering guidance, support, and friendship throughout this journey. My heartfelt thanks go to my dissertation committee members, Anita Rao, Giovanni Compiani, and Ali Hortaçsu, for investing time in me and providing invaluable feedback.

I have also received tremendous kindness and guidance from other faculty members at the Booth School of Business, especially Pradeep Chintagunta, Sanjog Misra, Günter Hitsch, Brad Shapiro, Avner Strulov-Shlain, Oleg Urminsky, and Abby Sussman, who provided constructive feedback to the project, gave me confidence to navigate the job market, and were instrumental to my development as a researcher. A special tribute to Øystein Daljord, whose exemplary research, mentorship, and friendship have left a lasting impact on me. I cherish the privilege of having crossed paths with him, albeit too briefly. I think of him often.

I am truely fortunate to be part of a wonderful community of students who always give me joy, comfort, and the strength to carry on. To Xilin Li, Olivia Natan, Jane Li, Ningyin Xu, Jiarui Liu, Walter Zhang, Ali Goli, my friends from the Booth marketing PhD program, and many others – becoming friends with all of you has been a highlight of this journey.

My heartfelt gratitude extends to Eric Anderson, Anna Tuchman, and Brett Gordon for their encouragement and belief in my potential, without which this journey would not have been possible.

To my husband, Yinxi Xie, for his love, companionship, and patience even during the challenging moments of this endeavor; to my parents and friends, for their love and support; to cats from Feline Friends Chicago, whose presence contributed to my well-being immensely.

Lastly, I acknowledge the thoughtful feedback received from participants at the Booth Marketing Brown Bag and various seminars. I thank TransUnion for providing access to the data. I acknowledge research support from the Juan Manuel de la Torre Memorial Fellowship, the Joseph A. and Susan E. Pichler Fellowship, and the ISMS Early-stage Research Grant. Any remaining errors are my own.

ABSTRACT

This paper studies heterogeneity in consumer myopia and its role in creating a gap in financing cost across consumers in consumer credit markets. Using a unique data set of the US automobile and auto loan market, I find that consumers in the lowest income quartile tend to pay more for auto financing. In particular, they are less likely to accelerate car purchases with an interest rate hike in sight, acting as more myopic agents. I build a structural model to test and quantify the extent to which the financing gap arises from myopia, as opposed to differences in price sensitivities and automobile preferences. I find that consumers are considerably more impatient than would be implied by the real rate of interest, and socio-economically disadvantaged consumers are more myopic and more price sensitive. A decomposition analysis quantifies the amount myopia contributes to the predicted financing gap. Counterfactual analysis further shows that strategic dealers could exacerbate the financing gap by gaining market power from more myopic consumers.

CHAPTER 1

HETEROGENEOUS CONSUMER DYNAMICS AND THE FINANCING GAP

1.1 Introduction

Resolving unequal access to credit markets, especially amongst the most socio-economically disadvantaged segments of society, has become a central matter of public policy concern for such agencies as the Consumer Financial Protection Bureau [CFPB, 2013, 2020, 2022] and the Federal Trade Commission [FTC, 2020a,b]. Consumers make many critical and high-stakes product purchases, such as homes and automobiles, with the help of financing, yet face a sizable gap in the financing rate they receive for similar loan products [Bhutta et al., 2019, Argyle et al., 2020]. Existing literature focuses almost entirely on lender or dealer practices in the consumer credit market, especially in examining disparate treatment related to protected classes [Charles et al., 2008, Cohen, 2012, Lanning, 2021, Butler et al., 2022, Bartlett et al., 2022].

I take a demand-side approach, looking for aspects of consumer behavior that might cause unequal access to affordable credit. In particular, I focus on a consumer's ability to find more favorable rates, especially in markets that are exposed to the inherent inter-temporal variation in interest rates as the central bank adjusts its monetary policy. If consumers consider potential short and medium-term changes in the interest rate, they may be able to find a more favorable rate by timing their purchases. Since such forward-looking behavior requires both "sophisticated" decision-making and a degree of literacy regarding financial markets, consumer myopia amongst socio-economically disadvantaged segments, i.e., consumers acting as if they put less weight on future utility, could be a cause of unequal access to affordable finance. Further, to the extent that sellers, on the supply side, can segment consumers based, in part, on their myopia, sellers' incentives to pass through rate changes to consumers could exacerbate unequal access to affordable finance.

To assess the extent to which consumer myopia causes unequal access to consumer finance, I conduct an empirical case study of the auto loan market, the third largest consumer credit market in the United States after mortgages and student loans. I use a unique database that matches the Booth TransUnion Consumer Credit Panel[1] with the IHS Markit vehicle data to determine the exact car purchased and financing terms for a sample of 16 million consumers along with their credit profiling features. I use the Federal Funds Futures contract prices to determine both the current interest rate and the market consensus beliefs of future interest rate evolution. I also use the Michigan Survey of Consumers (MSC) to calibrate consumer beliefs of future interest rate evolution across household income percentiles. An interesting feature of the loan market is that the Fed communications often focus on influencing the public's expectation about the future direction of monetary policy, which potentially shocks consumers' expectations without changing current financing rates.

1. The results in this paper are calculated (or derived) based on credit data provided by TransUnion, a global information solutions company, through a relationship with the Kilts Center for Marketing at the University of Chicago Booth School of Business. No personally identifiable information was provided to me by TransUnion at any time for this paper. TransUnion (the data provider) has the right to review the research before dissemination to ensure it accurately describes TransUnion data, does not disclose confidential information, and does not contain material it deems to be misleading or false regarding TransUnion, TransUnion's partners, affiliates or customer base, or the consumer lending industry.

In a descriptive analysis of the data, I document a financing gap that consumers in the lowest income quartile on average pay 45 basis point more for financing than consumers in the highest income quartile for the same type of car loan after controlling for borrower creditworthiness. Consumers in the lowest income quartile are also more likely to have smaller mortgage balance, smaller monthly scheduled loan payment, higher credit card utilization, and more public bankruptcy records, suggesting a lack of experience in the consumer credit market and potentially a lack of financial literacy. In an event study of a sudden increase in future interest rate expectation, I find that consumers in the lower income quartiles are 2.2% less likely to accelerate purchase of an automobile to lock in lower rates. These findings indicate that the socio-economically disadvantaged consumers not only pay more for financing, but also seem less sophisticated about timing their purchases to save money. Further, this does not appear to be an indirect effect of differential price pass-through on the supply side. Of course, the descriptive analysis is inconclusive as to whether the financing gap is due to heterogeneous discount factors, heterogeneous price sensitivities, or other possible explanations.

To test between various aspects of consumer behavior that might cause the financing gap, I use a structural approach that models the joint demand for automobiles and financing as a finite-horizon dynamic discrete-choice problem, relaxing the assumptions on both homogeneous beliefs and a known, homogeneous discount factor. To test between car preferences, price sensitivity and discounting, I use the variation in beliefs about the evolution of future interest rates as an exclusion restriction to identify the discount factor and preference parameters, since expected future interest rates do not enter current flow utilities.

I show that this exclusion restriction is sufficient for identification following theorem 3 in Abbring and Daljord [2020]. This approach to estimate the discount factor is novel given that most of the extant literature on dynamic discrete-choice demand has assumed that consumers discount the future according to the common real rate of interest (e.g., Erdem and Keane, 1996, Erdem et al., 2003, Sun, 2005, Hendel and Nevo, 2006, Nair, 2007, Gowrisankaran and Rysman, 2012, Copeland, 2014). One of the key identifying assumptions is rational expectations. Unlike most of the extant literature on dynamic discrete-choice demand, where beliefs are assumed to be stationary Markov and identified from observed state transitions [Rust, 1994, Magnac and Thesmar, 2002], I use the observed, market-implied transitions of future interest rates and the MSC to calibrate heterogeneous household beliefs of future interest rates. Under the rational expectation assumption, the model can exploit the frequent changes in heterogeneous consumer beliefs that closely tracks market-implied beliefs and less frequent changes in car and loan prices to identify consumers' heterogeneous discount factors. The identified heterogeneous discount factors reflects the various degree of discounting across consumers that is not explained by heterogeneous beliefs. Like the extant quantitative marketing literature, I do not dig into the behavioral mechanisms of discounting (Urminsky and Zauberman [2015]).

My estimates indicate that consumers are on average quite myopic, with a population average discount factor of 0.063 per period, equivalent to 0.033 per annum. Automobile consumers discount future utilities at a much higher rate than the commonly-assumed real interest rate. I also find substantial heterogeneity in the discount factor, ranging from 0 to 0.287 per period. If the more myopic consumers were endowed with the discount factor of the most forward-looking consumers' discount factor, they would have paid \$48 to \$151 more for the total financed cost of a car. The magnitude is equivalent to 0.22% of the average car price and 0.62% of the total credit card limit for the most myopic segment. Zooming into the cross-sectional financing gap, a decomposition exercise shows that heterogeneity in consumer behavior between the most and least myopic consumers can drive a two-basis-point predicted difference in auto loan rates, of which 137% would be attributed to myopia, 2% would be attributed to price sensitivity, and −39% would be attributed to car preferences and time fixed effects. This gap reflects myopic consumers' inability to delay purchase in anticipation of lower future interest rates. I show that the cross-sectional gap in the discount factor is associated with heterogeneity in consumer credit profiling, including total monthly loan payment, non-mortgage loan balance, credit card balance, number of credit inquires, and the vintage of the last auto loan. The heterogeneity pattern uncovers an unequal degree of myopia across socio-economic factors, suggesting those with lower wealth, lower financial literacy, and less activity in the credit market are the most myopic.

Turning to the supply side of the market, I study the hypothetical scenario if dealers were to set prices that price in future interest rate paths, and targeted at observed consumer characteristics. I use the demand estimates to understand the potential for discount rate heterogeneity to affect market pricing and its potential impact on unequal access to affordable credit. I compute the Markov Perfect equilibrium prices and quantities in a model where forward-looking dealers set automobile and loan prices for heterogeneous, forward-looking consumers. I conduct several simulations in a calibrated counterfactual case study with anticipated interest rate decrease. As a benchmark, I first compare the financing gap between lower- and higher-income consumers under an optimal uniform pricing policy. I find that lower income consumers, who also appear to be more myopic, on average pays 0.229 basis points more for financing than higher-income consumers. The difference comes entirely from demand heterogeneity under the uniform pricing policy. I then analyze equilibrium prices when the firms can price target based on observed characteristics that are known to firms in practice at the point of sale. Recall that observed characteristics are correlated with income, and hence, the degree of myopia. I find that the financing gap between lower- and higher-income consumers increases to 0.231 basis points. The counterfactual analysis suggests that when firms can target indirectly on the basis of patience, the financing gap is exacerbated, but the magnitude of additional financing gap is minimal when compared to the gap driven by demand heterogeneity.

This paper contributes to a growing literature on consumer financial decision making [Lynch Jr, 2011, Greenberg and Hershfield, 2019, Sussman et al., 2022]. Past empirical work has examined how time preferences may help explain important financial outcomes such as credit worthiness [Meier and Sprenger, 2012] and mortgage choice [Atlas et al., 2017]. I study the seemingly myopic behavior in the auto loan uptake, a highly consequential borrowing decision which has received less attention. Adding to the recent research that suggests best practices for eliciting discount rates from surveys [Antonia Krefeld-Schwalb and Johnson, 2021], I develop identification strategies for estimating discount factors from observational data. My findings on the systematic relationship between social-economic status and the degree of myopia suggest that inequality can influence financial decisions through a different channel from risk taking [Payne et al., 2017] or conspicuous consumption [Ordabayeva and Chandon, 2011].

This paper also contributes to a growing literature estimating consumer discount factors in dynamic discrete choice models. Recent work has devised empirical strategies to estimate a consumer discount factor in such markets as cellphone usage [Yao et al., 2012], mortgage default [Bajari et al., 2016, Daljord et al., 2019a], stockpiling [Ching and Osborne, 2020], book [Daljord, 2021], and habitual brand loyalty in consumer-packaged goods [Kong et al., 2022]. I devise a novel approach based on incorporating auxiliary data on belief variation from Fed Funds futures, applied to one of the highest-stakes consumer purchase decisions [FTC, 2012] where the magnitude of the discount factor has economically meaningful impact on the cost of adopting financing products. In contrast with earlier works that assume both known common beliefs and a deterministically-known, common discount factor, I use auxiliary data to construct heterogeneous beliefs, and find that consumers have heterogeneous discount rates that are much lower than the real rate of interest. I also document a systematic relationship between the heterogeneity in discount factors and the heterogeneity in consumers' credit profiling.

While I do not study protected classes herein, my findings nevertheless contribute to the literature on disparate treatment in the consumer finance market. Past empirical work has uncovered disparate treatment across demographic groups under the current practice of the consumer finance product suppliers and intermediaries [Charles et al., 2008, Cohen, 2012, Lanning, 2021, Butler et al., 2022, Bartlett et al., 2022, Fuster et al., 2022]. I demonstrate herein how consumer myopia can lead to higher loan prices for the most socio-economically disadvantaged groups without any explicit price discrimination on the supply side of the market. Moreover, I show that sellers could exacerbate the financing gap by setting optimal segmented pricing, since they gain more pricing power from myopic consumers than from forward looking ones, but the extent of seller-driven financing gap could be second order.

The findings of this paper also add to the substantial existing empirical literature on the automobile and auto loan market. Although revenue from financing arrangement is substantial for dealers [Cohen, 2012], the literature on auto markets has largely abstracted away from joint pricing of cars and loans [Berry et al., 1995, Morton et al., 2001, 2003], as well as the dynamic aspects of loan rate fluctuations [Esteban and Shum, 2007, Schiraldi, 2011, Copeland et al., 2011, Chen et al., 2013, Copeland, 2014]. The literature on the auto loan market typically focuses on intermediaries selling products to consumers who have misperception for financial charges [Grunewald et al., 2020, Jiang, 2021], who are credit constrained [Attanasio et al., 2008, Argyle et al., 2021], or face search costs [Argyle et al., 2020]. I model the joint vehicle and loan adoption decisions, on the demand side, introducing rational consumers with heterogeneous degree of myopia that could explain the dispersion in the transaction price of auto financing products. Understanding how heterogeneous consumer myopia explains the financing gap also contribute to understanding wealth inequality in the US, as there is widespread belief that equal access to consumer credit products is at the forefront in shaping economic opportunities [Demirgüç-Kunt and Levine, 2009, Fourcade and Healy, 2013, Quadrini and Ríos-Rull, 2015].

1.2 Institutional Background and Data

1.2.1 Institutional Background

Auto loans are the third largest consumer credit market in the United States, behind mortgage and student loans, with over 100 million auto loans at over 1.47 trillion dollars outstanding [Fed, 2022]. The majority of new car purchases are financed with fixed-rate auto loans. For a consumer who does not purchase a home, an auto loan might be the largest debt a consumer needs to pay back. According to Experian, over 80% of new car purchases were financed with auto loans in 2020 [Experian, 2020].

Consumers usually go through several stages to buy a car with financing. Typically, consumers and sellers negotiate on vehicle specifics and the price. Once the price of the car is determined, financing is addressed at the Finance & Insurance office. Auto financing can be arranged with either direct or indirect lending. With the former, consumers get an interest rate quote directly from a financial institution before going to a dealership. With the latter, which accounts for the majority of auto finance transactions [Grunewald et al., 2020], consumers obtain financing through the dealership they purchase the car from. Dealers solicit financing offers for their car buyers from various third-party finance companies (e.g. banks, credit unions, captive financing, among others). Dealers typically have discretion to add a margin to the interest rate offered by the third party finance companies, and most consumers think they could not negotiate interest rates [FTC, 2020a].

Most auto loan borrowers are locked into a fixed interest rate at the time of purchase. The auto loan rates are indirectly impacted by the Federal Funds rate, a benchmark rate on which auto loan lenders base their rates. A 0.5% rate difference on a 72-month auto loan (the dominating new car loan type) for an average $46,000 car means $800 difference in total financing cost, or $10 difference in monthly payment. Auto loan refinancing is possible, but it is a small segment of the auto finance market. According to a recent survey by TransUnion, awareness of auto loan refinancing is greatly lagged behind that of mortgage [TransUnion, 2021].

1.2.2 Data

I leverage multiple data sets from the Booth TransUnion Consumer Credit Panel, daily market prices of Fed Funds futures contracts, and the consumer interest rate expectations elicited in the MSC to study the dynamic demand for financed vehicles. I combine vehicle purchases in the IHS Markit data with auto loan records along with individual credit profiling features in the Booth TransUnion Consumer Credit Panel. I use the market prices of Fed Funds futures contracts to construct market-consensus beliefs for future risk-free interest rate evolution. By examining the correlation between household beliefs in the MSC and market-implied beliefs, I calibrate heterogeneous consumer beliefs across income percentiles. These constructed beliefs are then linked to individual vehicle purchases via the open date of auto loan accounts.

Booth TransUnion Consumer Credit Panel

The Booth TransUnion Consumer Credit Panel provides an anonymized 10% sample of all its credit records from 2001 to 2021. Individuals who were in the initial sample in 2000 have their data continually updated monthly, and each month 10% of new first-time individuals in the credit panel are added to the sample.[2] The data set provides monthly records for all auto loans opened by the panelists. Each loan observation contains the open date, loan amount, term length, scheduled payments, the most recent payment, current balance, payment history, the borrower identifier, and the lender identifier. TransUnion does not provide the auto loan rates, but I back them out using the amortization formula with scheduled payments and loan balances.[3]

The data set also has a rich set of consumer credit profiles updated at a monthly frequency, which allows me to control for observed consumer heterogeneity in the demand estimation. The credit profiling dimensions include credit score, zip code, months since the last auto loan account open date, total monthly payment of all loans, number of credit inquiries in the past 12 months, delinquency status, and various measures of the number, balance, utilization rate and credit line of all types of loan accounts, including mortgage, home equity, auto loans, credit cards and student loans. These dimensions could indicate current car vintage, commute zone migration, credit worthiness, disposable income, home ownership status, financial

2. Keys et al. [2020] and Yannelis and Zhang [2021] provide more details about the Booth TransUnion Consumer Credit Panel.

3. $A = \frac{B*r}{1-(1+r)^{-M}}$ where A is the monthly payment, B is the loan balance, r is the loan rate, and M is the maturity in months.

sophistication, experience with consumer credit products, and activeness in the credit market.

IHS Markit Vehicle Data

I obtain the vehicle information from IHS Markit to supplement the auto loan records. The vehicle data set contains car features, including new or used, model year, vehicle type, vehicle segment, manufacturer, make, model, series and vehicle registration date for prime and above auto loans opened in 2015 to 2020 in all states except California, Pennsylvania, South Carolina and New Hampshire. TransUnion conducted the match between vehicle data and auto loan data by linking name, address and vehicle registration date from the vehicle registration record to name, address and loan origination date in the credit file. Approximately 50% of the loans are matched with vehicle information. Loan records may be unmatched due to how every state handles their DMV data or the mismatch between the co-applicant registered to the vehicle versus to the auto loan record. The causes of unmatched records appear to suggest that vehicle features are missing at random rather than due to selection. The resulting match rate is also confirmed to be within the typical range of similar data merging exercises with the Consumer Credit Panel.

Bloomberg World Interest Rate Prediction (WIRP) Function

The Bloomberg WIRP function provides daily market-implied unconditional expectation of federal funds rates at each future Federal Open Market Committee (FOMC) meeting dates. The market-implied expectation is constructed from the Fed Funds futures contract prices that would expire within a year. Based on the unconditional expectations, I create a binary decision tree to construct the non-stationary transition probabilities of risk-free interest rates.[4] Each branch of the binary decision tree represents a 0 or 25bps federal funds rates change since the Fed usually adjust rates by 25bps at a time during the sample period.

Michigan Survey of Consumers

The Michigan Survey of Consumers [Armantier et al., 2017] elicits consumer expectation of future interest rates on a monthly basis. More specifically, respondents of the survey are asked *"No one can say for sure, but what do you think will happen to interest rates for borrowing money during the next 12 months — will they go up, stay the same, or go down?"* The survey collects individual respondent's answers, as well as their income and demographics information. The survey aggregates individual answers to an overall measure of consumer interest rate expectation, which equals to the percentage of consumers who anticipate an increase in interest rates minus the percentage who anticipate a decrease.

Estimation Sample

For my analysis, I use the consumer credit panel of individuals whose credit scores are above 660, from September 2015 to August 2019, and in all states except California, Pennsylvania, South Carolina and New Hampshire that matches with the scope of

4. The use of a binary decision tree follows common practices among Central Bank watchers, for example the CME FedWath Tool (`https://www.cmegroup.com/education/demos-and-tutorials/fed-funds-futures-probability-tree-calculator.html`)

the vehicle data. The sample period ends before the 2020 model year when pandemic started. I focus on new car purchases of the current model-year with standard loan terms including 72, 60, 84, 36 and 75 months contracts. The choice set is defined to be 40 top-selling vehicle models plus the outside option.[5] The outside option is defined to be no purchase, all-cash purchase, or a financed purchase outside of the choice set, such as buying used cars, buying a previous model-year new car, or buying a less popular new car model. A vehicle model is considered to be top-selling if its quantity sold is among the top 75% in a year for all four years. The resulting inside options account for 60% of all current model-year, standard terms, new car purchases with financing in the sample.

To construct the final sample, I further dropped individuals whose auto loan records are not matched with vehicle information. To accommodate the missing matches between loan and vehicle data, I down weight the panelists who did not open any auto loans by randomly dropping individuals according to the state specific matching rate. Finally, for car purchases with more than one loan applicants, I count them as multiple independent purchases since I do not observe household compositions in my data. The final estimation sample contains 16.24 million individuals and 979,558 car purchases made from Sep 2015 to Aug 2020.

5. A vehicle model in different model years, for example Ford F150 in 2017 and 2018 model years, are considered to be the same product.

1.3 Stylized Facts of the Financing Gap

In this section, I document a financing gap that lower-income consumers pay higher rates for the same type of auto loan products after controlling for borrower credit-worthiness in my data. I then show suggestive evidence for the role of heterogeneous consumer myopia in creating the financing gap, via an event study that compares how lower- and higher-income consumers adjust timing of purchases in anticipation of an interest rate hike in the near future.

1.3.1 The Financing Gap

I begin by presenting a gap in the financing rate paid by consumers in different income quartiles with similar credit worthiness for the same type of loan products. I use total credit card line as a proxy for a consumer's income level, and regress the financing rate on income quartiles, as well as loan characteristics (size, term duration and lender), car characteristics (model and year), market characteristics (state), and borrower creditworthiness (credit score in bins of 50).

Table 1.1 shows that consumers in the lowest income quartile tend to pay 45 basis points more for auto financing compared to consumers in higher income quartiles after accounting for a rich set of controlling factors. Further more, a correlation analysis in Table A4.2 shows that individuals with lower income are also more likely to have lower credit score, smaller mortgage balance, smaller monthly scheduled payment, higher credit card utilization, and more public bankruptcy records. This suggests that low-income consumers potentially suffer from higher financing rate

	Dependent variable:
	r_{ijt}
Income Quartile 1	–
Income Quartile 2	-0.425^{***}
	(0.016)
Income Quartile 3	-0.455^{***}
	(0.016)
Income Quartile 4	-0.454^{***}
	(0.017)
log(Loan amount)	-0.706^{***}
	(0.017)
Observations	1,121,378
R^2	0.101
Adjusted R^2	0.098
Residual Std. Error	5.563 (df = 1116982)
Note:	*p<0.1; **p<0.05; ***p<0.01

This table summarizes the gap in auto loan rates across consumer income quartiles. Additional controls include car model, model year, loan term duration, credit score bins, lender identifier, and state. The sample includes car models beyond the top 40 best selling models.

Table 1.1: The financing gap across income quartiles

related to a lack of experience in the consumer credit market and a lack of financial literacy.

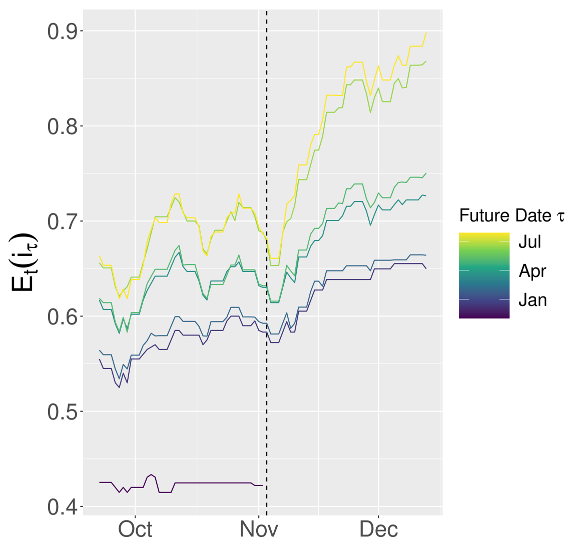
1.3.2 Descriptive Evidence of Heterogeneous Consumer Dynamics

To further explore the explanation that heterogeneous ability to adjust purchase timing could account for the financing gap, I conduct an event study to show how consumers time car purchases when an interest rate hike is suddenly in sight. In particular, I test whether lower-income consumers are less likely to accelerate purchase when an interest rate hike is anticipated, acting as if they are more myopic.

I examine an event - an FOMC meeting announcement that induced sudden exogenous changes in consumer beliefs - and show the corresponding changes in the number of vehicle purchases are significant and coherent with belief changes. A similar event study on the supply side shows that the dealer pricing responses around the event are muted, hence the demand side responses are likely caused by belief shocks rather than price changes. The event study demonstrates that consumers seem to accelerate automobile purchases in anticipation of higher future interest rates, and even lower-income consumers adjust timing of purchases, but to a lesser extent compared to higher-income consumers.

The Event

I study the event of FOMC meeting on November 1 - 2, 2016. At this meeting, the FOMC voted not to raise interest rates, keeping the target range for the federal funds rate at 0.25 to 0.5 percent. However, the Fed signaled in its statement that a rate hike could come "relatively soon" if the U.S. labor market continues to strengthen. Market-implied beliefs of future interest rate paths confirmed that this event triggered an increasing belief on interest rate hikes in the future periods. Figure 1.1 shows the daily market-implied federal funds rates expectation $\mathbb{E}_t(i_\tau)$ six weeks before and after the event, marked by the vertical dashed line. On each date t, the market forms beliefs for federal funds rates $\mathbb{E}_t(i_\tau)$ for a series of future dates τ ranging from Nov 2, 2016 to July 27, 2017. The expectations are relatively stable before the event for all future dates τ, but start climbing up after the event. This



This figure summarizes daily market-implied federal funds rate expectation. The x-axis represents the dates on which market-implied rate expectations are recorded. The y-axis represents the expected federal funds rate. The colors indicate various future FOMC dates τ of which the market-implied expectations are calculated for. Each line depicts the daily change in market-implied expected federal funds rate for a future date τ.

Figure 1.1: Belief Shocks around the November 2, 2016 FOMC Meeting

reflects that the event caused the market to expect a higher likelihood of increasing i_τ in the near future.

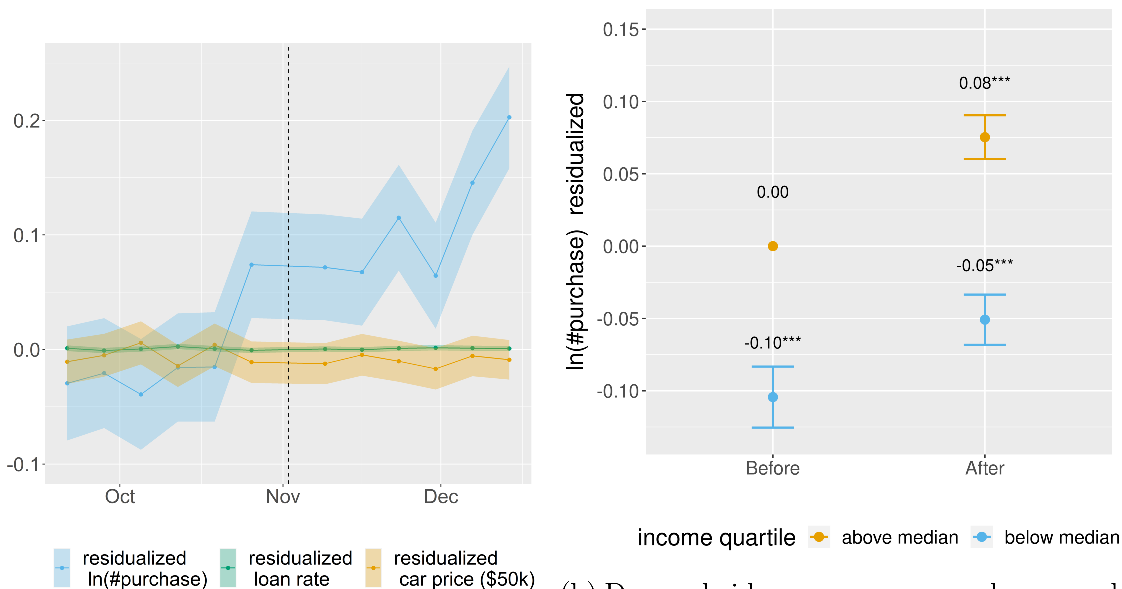
Demand and Supply Side Responses Around the Event

I next conduct an event study analysis for the demand and supply side responses in the financed car market around the time of the event. I regress weekly average demand and supply side actions on a set of distance-to-the-event dummy variables, controlling for covariates X_{ij}, including loan term duration, state, and vehicle segment fixed effects as in (1.1). For the demand side analysis, the outcome variable of interest is weekly log number of car purchases. For the supply side analysis, I focus on weekly average car prices and weekly average car loan rates (APR). All outcome variables are aggregated at vehicle - state - type-of-loan level.

$$y_{ijt} = \alpha + \beta_\tau \sum_{\tau=-6}^{6} \mathbb{I}\{t = \tau\} + X_{ij} + \epsilon_{ijt} \tag{1.1}$$

Figure 1.2a shows the estimates and 95% confidence intervals of β_τ for all three outcome variables. The blue line shows that the number of financed vehicle purchases is relatively flat before the event, but starts increasing significantly after the event. This is coherent with the beliefs of increasing future interest rates - in anticipation of higher future interest rates, consumers have incentives to advance their purchases today to lock in more favorable car loan rates. The demand side responses are likely not caused by supply side adjustments in car and loan prices. The yellow and green bars show that the average car prices and car loan rates (APR) are flat through out the event with no significant changes.

I further compare the demand-side response between lower- and higher-income consumers during the event. Figure 1.3b and Table 1.2 present the comparison. Using a diff-in-diff regression, I find that both lower- and higher- income consumers accelerated car purchases when an interest rate hike comes in sight, but lower-income consumers responded to a less extent. Starting from one week before the FOMC announcement, when the belief of future interest rate hikes started to pick up and the demand side responses started to show, lower-income consumers are on average 2.2% less likely to accelerate automobile purchases than higher-income consumers. The difference is marginally significant. The comparison suggests that both lower- and higher- income consumers are strategically responding to future interest rate



(a) Demand- and supply-side responses

(b) Demand-side responses among lower- and higher- income consumers

This figure summarizes demand- and supply-side responses in the financed car market around the November 2, 2016 FOMC announcement. The left figure plots estimated aggregated changes in log number of purchases, loan rates, and car prices for each week in the $\pm$ six-week window around the announcement, after controlling for loan characteristics, state, and vehicle segments. The right figure plots the estimated changes in demand-side responses between lower- and higher-income consumers before and after the announcement, using the same time window and controlling for the same covariates.

Figure 1.2: Event analysis of the November 2, 2016 FOMC meeting

	Dependent variable:
	log(# purchases)
income below median × after event	-0.022^{*}
	(0.013)
after event	0.075^{***}
	(0.008)
income below median	-0.104^{***}
	(0.011)
Observations	23,754
R^2	0.261
Adjusted R^2	0.258
Residual Std. Error	0.450 (df = 23666)
Note:	*p<0.1; **p<0.05; ***p<0.01

This table summarizes the differences in demand side responses to the FOMC event among consumers of lower- and higher- income quartiles. Consumers are split by the median total credit card line in the year. After event is defined as weeks beyond week -1 – a point in time when belief for higher future interest rates start to emerge and purchase acceleration started to show effects. Additional controls include loan duration, state, and vehicle segment.

Table 1.2: Demand side response to the event by income quartiles

changes in a forward-looking manner, but there might be heterogeneity in the degree of their strategic responses.

The event study is an example of how my data could inform consumer forward looking behavior in financed vehicle purchases. There are many more events of similar nature in my data. Such data pattern carries information about whether consumers adjust their car purchasing probability in anticipation of future changes in risk-free interest rates, holding current car prices and loan rates fixed. However, with the reduced form analysis alone, is inconclusive as to whether the differences in demand responses is due to heterogeneous price sensitivities, or heterogeneous weight that consumers put on future streams of utility. Therefore, I will resort to structural estimation to jointly estimate heterogeneous consumer discount factor and utility parameters.

1.4 A Demand Model for Financed Vehicle

Stylized facts show that the financing gap could be attributed to a difference in timing of purchase across consumers. In this section, I use a structural approach to test and quantify the extent to which heterogeneity in discount factors – a measure for the weight consumers put on future utility that affects timing of purchases – contribute to the financing gap, as opposed to other demand-side heterogeneity such as price sensitivities and automobile preferences.

This section builds a finite-horizon dynamic discrete choice demand for financed vehicles within a model-year. Each consumer enters into the year and faces an optimal stopping problem about when to adopt a vehicle and conditional on adopt, which car to choose. Once the consumer adopts, she drops out from the market and never returns.

Consumer faces a finite-horizon problem of length T. In each period t, the consumer faces a choice set $\mathcal{J} = \{1, .., J, J+1\}$, including J car choices of the current model year, and a no-purchase option, $J+1$. Car choices $1, ..., J$ are grouped into M sets $\mathcal{J}_1, ..., \mathcal{J}_M$ corresponding to the vehicle segments they belong to (e.g., Non-luxury Full Size Half-ton Pickup Truck, Non-luxury Mid Size SUV, etc.), whereas the no-purchase option forms a standalone set $\mathcal{J}_{M+1} \equiv \{J+1\}$. Once the consumer purchase a car $j \in \{1, ..., J\}$, she drops out from the market and never returns.

The span of horizon starts from September and ends in August of the next year, corresponding to a vehicle model year in which most car manufacturers release new car models every fall and clear up inventory to make room for new models at the end of the horizon. The finite-horizon nature of the problem assumes consumers do not explicitly consider substitution across model-year, which is found to be little in the literature,[6] although such substitution could be captured by the outside option.

Consumer demand in each period is characterized by states $s_t = (p_t, i_t) \in \mathcal{S}$, where $p_t \equiv (p_{1t}, ..., p_{Jt})$ is the vector of car prices and $i_t \in \mathcal{I} \equiv \{i_1, .., i_L\}$ is the risk-free interest rate set by the Fed. When purchasing a car j, consumer forms dis-utility of payment from both the car price p_{jt}, and the financing cost $r_{jt} = \rho_j(p_{jt}, i_t)$, where $\rho_j(\cdot, \cdot)$ is a known auto loan rate setting process. The dis-utility of payment occurs at the time of purchase, although loan repayment may be scheduled for future periods. I assume no sequential negotiation of car prices and loan prices, such that both are presented to consumers simultaneously.

A consumer in state $s = (p, i)$ receives flow utility $u_{jt}(s) + \epsilon_{jt}$ from purchasing a car j and receives a normalized utility $u_{J+1,t}(s_t) = 0$ when she chooses to not purchase. I assume that random utility shocks ϵ_t are i.i.d. drawn from a generalized extreme value (GEV) distribution, which is a convention in the literature that studies car demand [Goldberg, 1995, Ivaldi and Verboven, 2005, Goldberg and Verboven,

6. Copeland 2014 and Copeland, Dunn and, Hall 2011 find car prices of the older model-years have little impact on the car purchases of the current model-year.

2001, Silva-Risso and Ionova, 2008]. The error distribution takes the form

$$G(\epsilon) = \exp\left[-\sum_{m=1}^{M+1}\left(\sum_{j\in\mathcal{J}_m}\exp\left(-\epsilon_j/\lambda_m\right)\right)^{\lambda_m}\right]$$

where errors within the same vehicle segment m are correlated with coefficient λ_m, and errors between vehicle segments m and m' are independent.

I assume that consumers have perfect foresight for car prices p_t, hence the belief for car prices is degenerate. I assume that loan rates r_t are set by a known function $\rho_j(p_{jt}, i_t)$. Consumers have full information for the loan rate setting process ρ_j and rational expectation for the evolution of i_t, hence they have rational expectation for r_t as well. The uncertainty in r_t comes from the fact that car loan rates depend on the current interest rate environment i_t, and there's inherent uncertainty in whether the Fed might announce hikes or cuts in i_t that consequently affect car loan rates r_t. I do not assume that ρ_j is optimal in the demand estimation, but will solve for an optimal pricing strategy in the counterfactual analysis.

The risk-free interest rate i_t is set by the Fed in each period, and it evolves according to a non-stationary Markov process summarized by a series of transition probabilities $\{\mathbf{F}_\tau\}_{\tau=t}^{T}$, where

$$F_\tau(i) \equiv \left[Pr_\tau\left[i_{\tau+1} = i_1 | i_\tau = i\right], ..., Pr_\tau\left[i_{\tau+1} = i_L | i_\tau = i\right]\right]$$

Therefore, the evolution of car loan rate, governed by the car prices p_t and the interest rate environment i_t, follows the transition probabilities below

$$Pr\left[r_{\tau+1} = \rho(p_{\tau+1}, i')|i_\tau = i\right] = Pr\left[i_{\tau+1} = i'|i_\tau = i\right] \quad \text{for } i' \in \mathcal{I}$$

The consumer solves a finite-horizon optimal stopping problem. Since the belief for prices and income is degenerate due to perfect foresight, the belief for interest rate evolution $\{\mathbf{F}_\tau\}_{\tau=t}^T$ summarizes the uncertainty in the transition of the entire state vector s_t. Denoting a shorthand $\mathbf{F}$ for a series of beliefs $\{\mathbf{F}_\tau\}_{\tau=t}^T$. The ex-ante value function is

$$V_t\left(s;\mathbf{F}\right) = \mathbb{E}_\epsilon\left[\max_j\left\{v_{jt}\left(s;\mathbf{F}\right) + \epsilon_{jt}\right\}\right]$$

the choice-specific value functions are defined as the solutions to

$$v_{jt}\left(s;\mathbf{F}\right) = \begin{cases} \beta\sum_{i'\in\mathcal{I}} F_t(i_{t+1}|i_t)V_{t+1}\left(s_{t+1};\{\mathbf{F}_\tau\}_{\tau=t+1}^T\right) & \text{for } j = J+1 \\ u_{jt}(s) & \text{for } j = 1, ..., J \end{cases}$$

The consumer's utility maximizing choice probability for option j in vehicle segment m is

$$\sigma_{jmt}\left(s;\mathbf{F}\right) = \frac{\exp\left[\lambda_m \ln\left(\sum_{k\in\mathcal{J}_m}\exp\left(v_{kt}(s;\mathbf{F})/\lambda_m\right)\right)\right]}{\sum_{m'=1}^{M+1}\exp\left[\lambda_{m'}\ln\left(\sum_{l\in\mathcal{J}_{m'}}\exp\left(v_{lt}(s;\mathbf{F})/\lambda_{m'}\right)\right)\right]} \cdot \frac{\exp\left(v_{jt}\left(s;\mathbf{F}\right)/\lambda_m\right)}{\sum_{k\in\mathcal{J}_m}\exp\left(v_{kt}\left(s;\mathbf{F}\right)/\lambda_m\right)} \tag{1.2}$$

Taking log of odds ratio based on product choice propensities relative to the outside option, I get

$$\ln\left(\frac{\sigma_{jmt}(s;\mathbf{F})}{\sigma_{J+1,t}(s;\mathbf{F})}\right) = (\lambda_m - 1)\ln\left(\sum_{k\in\mathcal{J}_m}\exp\left(u_{kt}(s)/\lambda_m\right)\right) + \frac{1}{\lambda_m}u_{jt}\left(s\right) - \beta\mathbf{F}_t(s)\mathbf{V}_{t+1}(\mathbf{F}) \tag{1.3}$$

1.4.1 Identification of the Discount Factor

In the financed vehicle purchasing context, I show that a source of variation in consumer beliefs allows me to construct intuitive exclusion restrictions like those discussed in Abbring and Daljord [2020]. My exclusion restrictions provide additional identification moments for the discount factor beyond the time-homogeneity of utility function and the finite horizon structure of the problem.

Suppose there is at least one pair of beliefs $\{\mathbf{F}_\tau\}_{\tau=1}^T$ and $\{\mathbf{F'}_\tau\}_{\tau=1}^T$ under some state s_t. That is, consumers face the same time period, car prices, Fed rates, loan rates, and income, but differs in their beliefs of future interest rate environment. The change in beliefs could only affect the value of current choices through continuation value. Therefore, I could construct a set of moment conditions by differencing the log-odds conditions (1.3) to isolate the discount factor,

$$\ln\Big(\frac{\sigma_{jmt}\left(s_t;\mathbf{F}\right)}{\sigma_{J+1,M+1,t}\left(s_t;\mathbf{F}\right)} - \ln\left(\frac{\sigma_{jmt}\left(s_t;\mathbf{F'}\right)}{\sigma_{J+1,M+1,t}\left(s_t;\mathbf{F'}\right)}\right) \qquad \textit{units}$$

$$= \beta\left[\mathbf{F'}_t(s_t)\mathbf{V}_{t+1}(\mathbf{F'}) - \mathbf{F}_t(s_t)\mathbf{V}_{t+1}(\mathbf{F})\right] \tag{1.4}$$

where

$$\mathbf{V}_t(\mathbf{F}) = \mathbf{m}_t(\mathbf{F}) + \sum_{\tau=t+1}^{T} \beta^{\tau-t} \left[\prod_{q=t}^{\tau-1} \mathbf{F}_q \right] \mathbf{m}_\tau(\mathbf{F}) \tag{1.5}$$

$\mathbf{m}_t = \big(\gamma - \ln(\sigma_{J+1,M+1,t}(s_1; \mathbf{F})), ..., \gamma - \ln(\sigma_{J+1,M+1,t}(s_L; \mathbf{F}))\big)$, and $s_1, ..., s_L$ are the support points of the state space. Abbring and Daljord [2020] (Theoreom 3) shows that the moment condition (1.4) set identifies the discount factor β, and there are no more than $T - t$ points in the identified set under mild rank conditions. If one could form the moment condition with $t = T - 1$, β could be point identified.

The intuition is that the pair of beliefs leads to different ways for consumers to integrate the future, holding current utility fixed. As an example, holding everything else fixed, if a forward-looking consumer believes that the probability of the Fed announcing an interest rate cut in the future has drastically increased under $\mathbf{F}'$ than under $\mathbf{F}$, the consumer should have stronger incentive to postpone her purchase of any vehicle until later when loan rates might be more favorable.

1.4.2 Observations of the Beliefs $\{\mathbf{F}_\tau\}_{\tau=t}^{T}$

One key factor for forming the identifying moment in (1.4) is that the researcher observes the series of beliefs $\{\mathbf{F}_\tau\}_{\tau=t}^{T}$, as well as any "surprise" changes in the beliefs. The auto financing market has a novel feature that a market-consensus belief on the evolution of i_t, i.e. $\{\mathbf{F}_\tau\}_{\tau=t}^{T}$, can be directly observed from the financial market at high frequency. The observed frequent changes in market-implied beliefs reflect "surprise" elements that I can use for identifying the discount factor.

Market-Consensus Beliefs

There is an active financial market trading Fed Funds futures contracts, the prices of which is defined as 100 - $\mathbb{E}_t[i_\tau|i_t]$, i.e., 100 minus the expected future risk-free interest rate i_τ for some $\tau > t$ at current period t. It is the current state of art to use the prices of Fed Funds futures contracts to back up the market consensus belief of the future course of monetary policy. The resulting market-implied belief follows a non-stationary first-order Markov process.[7] Such construction of market consensus beliefs is widely used in the financial press, by Fed watchers (e.g., the CME Group FedWatch Tool[8]), by central banks (e.g., Robertson et al., 1998, Owens and Webb, 2001, Fisher and Robertson, 2016) and in the academic literature (e.g., Krueger et al., 1996, Rudebusch, 1998, Bernanke and Kuttner, 2005, Gürkaynak, 2005). I use the market-implied belief constructed by Bloomberg's World Interest Rate Prediction (WIRP) function as auxiliary data to form observed state transition process as a binary decision tree, as well as for observing exogenous changes in beliefs.

Calibrated Household Beliefs

Due to the lack of data on consumer's individual belief formation, belief homogeneity is a prevailing assumption in a slew of papers studying dynamic consumer demand. I improve this practice by using the MSC to examine whether consumer beliefs are homogeneous and how distant they are from market-implied beliefs. I then use the

7. For example, $\mathbb{E}_t[i_{t+1}|i_t] = Pr_t(\text{hike at } t+1|i_t) \cdot (i_t + \Delta) + (1 - Pr_t(\text{hike at } t+1|i_t))i_t$, where Δ is the prevailing magnitude of the Fed's adjustment of the federal funds rate.

8. https://www.cmegroup.com/education/demos-and-tutorials/fed-funds-futures-probability-tree-calculator.html

MSC in conjunction with market-implied expectations to calibrate heterogeneous beliefs among different income groups.

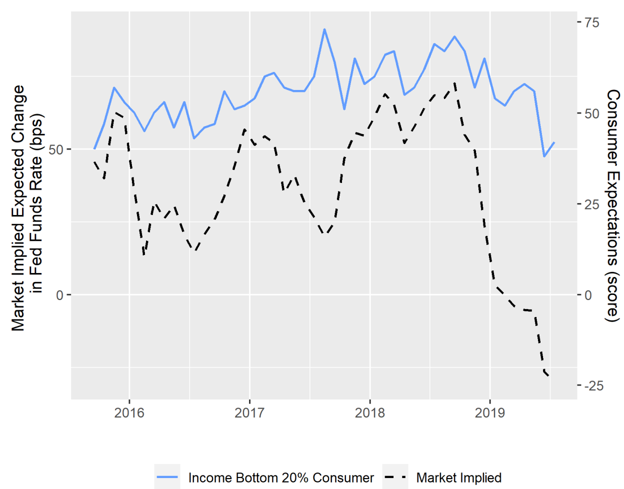
To my knowledge, there has not been a systematic elicitation of consumer beliefs of future risk-free interest rate paths. The closest documentation is from Question A11 in the Michigan Consumer Survey, which asks respondents *"No one can say for sure, but what do you think will happen to interest rates for borrowing money during the next 12 months — will they go up, stay the same, or go down?"* The survey collects individual answers as well as income and demographics information. It also constructs an overall measure of household interest rate expectation, derived by calculating the percentage of consumers who anticipate an increase in interest rates minus the percentage of consumers who anticipate a decrease.

The MSC captures one moment of the household belief process, with data collected on a monthly basis. These household beliefs can be compared to an analogous measure derived from market-implied beliefs, providing insights into the alignment or divergence between consumer expectations and market expectations. More specifically, I compare the monthly MSC survey measure to the monthly average market-consensus expected interest rate changes in 12 months from now. Figure 1.3 illustrates the temporal evolution in market beliefs and consumer beliefs for individuals in the bottom and top 20% percentiles of income. It shows a strong co-movement in market-implied beliefs and household beliefs across the income percentiles. A correlation test between the market expectation and MSC measure aggregated over all survey respondents from September 2015 to August 2019 shows a significant correlation of 0.75 (p-value = 0.000). Table A4.4 shows that the significant correlation is also consistent across consumer income percentiles, ranging from 0.52 among consumers in the bottom 20% of income to 0.77 among those in the top 20 % of income.

Despite the close co-movement between household beliefs and market-implied beliefs regarding interest rate changes in 12 months, households across different income percentiles may perceive interest rate changes with varying magnitudes. I calibrate heterogeneous household beliefs in the following steps. I first compute MSC survey measure aggregated at the household-income percentile level. I then use the measure to calibrate household beliefs as a fixed proportion of market expectation for the future time periods not surveyed. Table A4.5 shows that when market expects a 25 basis points increase in future interest rate (equivalent to 100% chance of Fed announcing a rate hike), the share of consumers expecting interest rate increase ranges from 31.05% to 36.58% across income percentiles. Finally, I use the calibrated magnitude to impute household beliefs for time periods without an MSC survey. The calibrated heterogeneous consumer beliefs are paired with consumers in the estimation sample based on percentiles of their total debt payment, which serves as a proxy for income percentiles.

The observation that household beliefs closely tracks market-consensus beliefs may not be a surprising result. As non-experts, consumers may still have access to information about expert opinion of future interest rate paths from news articles [Lamla and Vinogradov, 2019, Kryvtsov and Petersen, 2021], or Twitter [Ehrmann and Wabitsch, 2022]. The literature on household expectation formation has also found evidence of households adjusting expectation on future interest rates following information treatment of various kinds [De Fiore et al., 2022, Coibion et al., 2022,

(a) Market vs Consumers of Top 20% Income



(b) Market vs Consumers of Bottom 20% Income

This figure describes the market-implied expected changes in federal funds rate a year from now, and the aggregate score of household expectation of changes in borrowing rate a year from now. The market-implied expectation is calculated as a monthly average of the Bloomberg WIRP function, while household beliefs are surveyed in the MSC. The MSC survey scores are constructed as the percentage of consumers who anticipated an increase in interest rates minus the percentage who anticipate a decrease. The scores are constructed among consumers who belong to top 20% income for the top figure, and bottom 20% income for the bottom figure.

Figure 1.3: Temporal evolution of market-implied beliefs and MSC consumer beliefs

2023].

To the extent that the MSC survey do not fully capture the deviation from consumer beliefs from market-implied beliefs, my assumption on the belief process will have implication on the discount factor estimates. If a consumer is inadequately informed of future monetary policies, a lack of response in vehicle adoption due to inadequate change in beliefs could be interpreted as impatience by my model.

1.4.3 Exclusion of the Changes in Beliefs in Flow Utilities

Another key factor for forming the identifying moment in (1.4) is that the "surprise" changes in beliefs – those caused by FOMC announcements in the auto financing context, are excluded from flow utilities. The supply side event analysis in 1.3.2 shows one example that belief could change without changing current car prices and financing rates. In Appendix A2, I use the entire data period to estimate a reduced-form loan rate setting process, taking car loan rates as a function of the loan amount and market-consensus interest rate beliefs. The estimates help verify if changes in beliefs are more frequent than changes in loan prices, as we've seen in the example of the event analysis. I find that concurrent changes in the risk-free interest rate are almost transmitted one-to-one to car loan rates, while auto loan rates are not significantly responsive to changes in belief. I interpret this result as evidence for existence of loan rate states being invariant to changes in belief, which facilitates the strategy of identifying the discount factor.

1.5 Structural Estimation of the DDC Model

I now turn to estimating the finite-horizon DDC model and the empirical magnitude of consumers' discount factors. To implement the model, I parameterize the flow utility to be

$$u_{gjt}(s) = \gamma_{gj} + \eta_{gt} - \alpha_g p_j[1 + \rho_{gj}(p_j, i)]$$

where γ_j is the vehicle model FE, η_t include quarter FE and model-year FE, p_j is the vehicle price and $\rho_{gj}(p_j, i)$ is obtained from the reduced form loan rate setting process estimated from Table A4.3. The utility function takes into account observed heterogeneity across consumers by carrying subscript g - i.e., preference parameters as well as the loan rate setting process are cluster-specific. Consumers within a cluster are assumed to be homogeneous.

I define $T = 8$ per model year, and the beginning of each period is marked by the pre-scheduled date of an FOMC meeting where the central bank has a chance to reset the risk-free interest rate i_t. To accommodate high frequency changes in consumer beliefs of future risk-free interest rates, I further split each period into two sub-periods that differs in beliefs but are otherwise identical.

Consumer have perfect foresight of car prices and the belief is assumed to be the same as the evolution of average observed car prices. Car prices are not directly observed in the data set, therefore I use the amount of auto loan as a proxy. In months close to the beginning of a model year when some car models are not available yet, I set car prices to be $100,000, twice as expensive as the highest average loan amount for any car models in my sample. Figure A4.3 shows the expected car price evolution summarized in Törnqvist index across years.

To control for heterogeneity, I pre-cluster individuals based on census block, credit score, commute zone mover, presence of mortgage, home equity (HE) or home equity line of credit (HELOC) as an approximation for home ownership, total scheduled monthly payment of all loan accounts, average balance, utilization and credit various loan accounts, number of auto loans opened in the past 24 months, months since the last auto loan account, number of credit inquiries, and number of past due loan accounts in 90 days. Of the 11 clusters, one consists all the consumers who moved to a different commute zone within $\pm$ 6 months from the beginning and the end of the current model year, and the rest are formed by k-means clustering on the observed individual credit profiles discussed above. Table A4.6 summaries the cluster mean of each credit profiling feature.

I use a maximum likelihood estimator for each cluster separately. The MLE estimator is a full solution estimator that already bears the product-level log odds identifying moments in its structure. The addition parametric structure of the model, e.g., additively separable linear utility index, adds efficiency to the estimation. Moreover, since many states in my model are not visited due to the unique realization of risk-free interest rate in each period, the parametric assumption of the utility function is useful for extrapolating value functions in un-visited states.

Let $\Gamma_g = \left(\beta_g, \theta_g, \lambda_g\right)$ denote all the structural parameters for consumer cluster g. I define an cluster-specific MLE estimator as

$$\Gamma_g^\star = \underset{\Gamma}{\text{argmax}} \sum_{j=1}^{J+1} \sum_{t=1}^{T} \left[N_{gjt}^{(1)} \ln \sigma_{gjmt}(s_t; \mathbf{F}_t^{(1)}) + N_{gjt}^{(2)} \ln \sigma_{gjmt}(s_t; \mathbf{F}_t^{(2)}) \right] \tag{1.6}$$

where $N_{jt}^{(1)}$ and $N_{jt}^{(2)}$ are the total number of choices for option j in the two sub-periods within period t, and $\mathbf{F}_t^{(1)}$ and $\mathbf{F}_t^{(2)}$ are the two corresponding different beliefs per each sub-period. The product specific choice probability is defined in (1.2). I also provide the analytical gradient to improve the robustness and speed of the optimization. For details, please see Appendix A3.1.

1.5.1 Empirical Results

Table 1.3 column (1) reports the estimates assuming all consumers are homogeneous, and column (2) reports the population average of heterogeneous estimates conditional on clustering on observed consumer credit profiling. The discount factor estimates in both columns reject complete myopia, although suggesting that consumers are on average quite myopic in the inter-temporal trade-off of financed car purchases. For the homogeneous model estimates, a per-period discount factor of 0.234 is equivalent to an annual discount factor of 0.037. For the heterogeneous model estimates, the discount factor ranges from 0 to 0.287, with a population average ,weighted by size of each cluster, of 0.063, equivalent to an annual discount factor of 0.008.

Diving into the heterogeneous parameter estimates, Table 1.4 presents the discount factor estimates within each cluster, and Table A3.1 presents the full set of preference estimates across clusters. Albeit consumers being myopic overall, there is

	Parameters	(1) Homogeneous	(2) Heterogeneous *population avg*
	discount factor β	0.234	0.063
		(0.009)	(0.016)
	price	-0.497	-0.016
		(0.006)	(0.008)
quarter FE	fall	-0.721	-8.142
		(0.006)	(0.014)
	winter	-0.174	-9.559
		(0.006)	(0.012)
	spring	0.029	-0.797
		(0.005)	(0.011)
model year FE	2016	-0.087	-0.230
		(0.004)	(0.010)
	2017	-0.022	-0.035
		(0.003)	(0.009)
	2018	0.030	-0.031
		(0.003)	(0.009)

This table reports the estimated primitives of the structural model of financed car demand. Column 1 reports the estimates of a homogeneous demand model, and column 2 reports the population average of estimates demand model with observed heterogeneity. The population average is weighted by size of each cluster.

Table 1.3: Parametric Estimates of the DDC Model

substantial heterogeneity in the discount factor, ranging from 0 to 0.287 per period, or equivalently 0 to 0.044 per annum. While the single largest cluster (group 1) are myopic with a discount factor 0, about 51.1% of the population has significant non-zero discount factor significantly greater than zero.

The size of the discount factor, ranging from 0 to 0.287, may seem quite small to economists as it is at odds with the usual assumption that consumers discount future utilities at 0.95 per annum. But a large literature (see surveys by Frederick et al. [2002], Urminsky and Zauberman [2015]) documented heterogeneous and predominantly discount factors across various choice contexts using both lab studies and real outcomes, even after controlling for other factors that may confound the discount factor elicitation. There is a dramatic range of annualized discount factors

Group	Share of population	$\hat{\beta}$	S.E.
1	0.261	0.000	(0.000)
2	0.080	0.031	(0.019)
3	0.158	0.041	(0.014)
4	0.142	0.045	(0.025)
5	0.063	0.053	(0.022)
6	0.006	0.053	(0.069)
7	0.145	0.122	(0.015)
8	0.029	0.122	(0.030)
9	0.056	0.196	(0.019)
10	0.013	0.287	(0.078)
11	0.047	0.177	(0.029)

This table reports the estimated discount factor and their standard errors across clustered consumer groups.

Table 1.4: Heterogeneous Discount Factor Estimates

estimated in previous studies about consumer choices despite little discussion about the instability of discount factors across choice contexts. For example, ranging from 0.01 to 0.95 in Kong et al. [2022], 0.045 in Ching and Osborne [2020], 0.15 in Yao et al. [2012], 0.7 in Dubé et al. [2014], and 0.87 in De Groote and Verboven [2019]. My findings are in line with the range presented in the literature. In addition, since my discount factor estimates speak to the inter-temporal trade-offs in the car loan rate dimension, it's magnitude may be a combination of both the consumer patience, and the perceived importance of this single dimension. If a behavioral consumer is obfuscated by the loan price, or under-informed by the future rate paths, my discount factor estimates could be downward biased.

To understand the heterogeneity in the discount factor across consumer clusters, Figures A3.1 to A3.2 plot the relationship between the heterogeneous discount factor estimates and the cluster-average credit profiles among the non-movers. Among the various dimensions of credit profiling, the discount factor appears to be correlated with monthly loan payment, total loan balance excluding home equity and mortgage, total credit card balance, years since last auto loan opened, and number of credit inquiries in 12 months. Factors of credit profiling that does not seem to explain the heterogeneity in discount factor include whether the individual is a homeowner, the total balance of mortgage, and credit score. The discount factor among commute zone movers is close to the higher end of the range among all individuals.

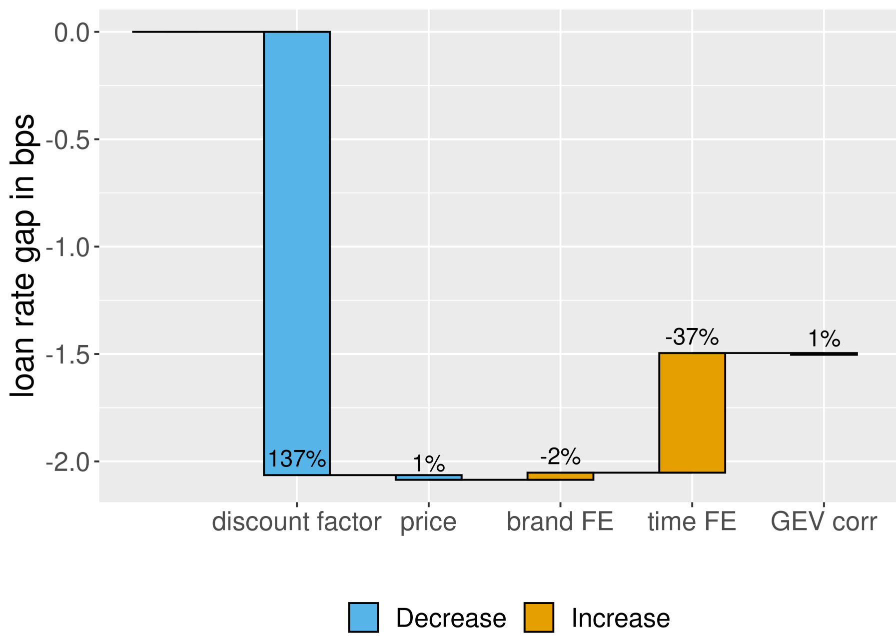
The most forward-looking cluster (group 10) features a cluster with prime credit scores, mostly homeowners, with highest monthly loan payment (around $7,900), highest loan balance of both mortgage and non-mortgage, moderate credit card balance, and about six year since last financed vehicle purchase. Meanwhile, the most myopic cluster (group 1) features a cluster of individuals with prime credit scores, without a home or mortgage, with the least loan balance from all type of loan accounts, credit inactive, and those whose last financed vehicle purchase is more than 10 years ago.

To quantify the importance of heterogeneity in myopia, I then use a decomposition analysis to quantify how much myopia, as opposed to price sensitivities and other preferences, could explain predicted differences in loan rates and total price paid for the vehicle among lower- and higher-income consumers. More specifically, I assume all consumers have the same market-implied beliefs, and compare the predicted loan rates paid by lower-income consumers with what they would have paid ex-ante, defined by (1.7), had they been assigned the discount factor, price sensitivity, brand preferences, time preferences, and GEV correlation parameters of higher-income consumers one on top of another one. This measure in equation (1.7) captures the expected loan rate paid by group g, conditional on purchasing the same car model under a set of counterfactual demand parameters Γ.

$$P_g(\Gamma) = \sum_{j \neq J+1} \sum_{t} \frac{\sigma_{gjt}(\Gamma)}{\sum_{\tau} \sigma_{gj\tau}(\Gamma)} r_{jt} \tag{1.7}$$

As an example, Figure 1.4 shows the decomposition results for consumers in group 1, the most myopic group, had they been assigned the demand parameters of group 10, the most forward looking group in the model year of 2018. Heterogeneity in consumer behavior between the two groups can drive a two-basis-point differences in auto loan rates, of which 137% would be attributed to myopia, -37% explained by time fixed effects, and the rest account for less than 1%. In other words, if the most myopic consumers are endowed with the discount factor of the most forward looking consumers, they would pay a much lower loan rate that not only closes the gap but even reverse it. If we look at total financed cost of the automobile instead of the loan rate, myopia alone leads to \$40 less had group 1 been as forward-looking as group 10. If we further accounts for the cross-vehicle substitution by looking at the ex-ante price paid for any vehicle conditional on buying, myopia alone can save car buyers \$48 to \$151 across all 10 groups over the four years of my data. The amount of saving is larger for more myopic groups, who also tend to be more price inelastic groups.

The discount factor estimates reveals economically meaningful heterogeneity among consumers despite consumers on average being very myopic. Although investigating the cause of discount factor heterogeneity is beyond the scope of this paper, esti-



This figure reports the decomposition of predicted loan rate gap. It starts from the most myopic consumer group on the left, shows changes in the predicted loan rate gap if the group were endowed with a different set of demand primitives, until the group looks the same as the most forward looking gropu on the right.

Figure 1.4: Decomposition of predicted loan rate gap

mation results pointed out a few plausible directions, including wealth, disposable income, activeness in the credit market, knowledge spillover from other consumer credit products (e.g. mortgage, previously opened auto loans), or financial literacy.

1.6 Counterfactual Analysis

The structural estimation and the comparative statics of varying the discount factor shows that holding everything else fixed, myopic consumers would pay more for a financed vehicle conditional on purchase. The cost of myopia is positively associated with consumers who rent, haven't bought a car in a long time, inactive in credit markets, and have lowest monthly payment and loan balances across credit products.

Notably, the predicted financing gap by the dynamic demand model is derived under the observed firm conduct that does not price expected changes in future interest rates into either loan rates or car prices, or in any targeted fashion. A natural follow up question is that in the full equilibrium, if firms were to explicit set targeted price to consumers according to their observed characteristics including the degree of myopia, how would the hypothetical firm conduct change the distributional impact on consumer car adoption by pricing in beliefs of future interest rate paths. Will targeted prices set by the firms further exacerbate the differences in how much consumers pay for a financed vehicle?

To answer the distributional impact of price targeting on consumer timing of vehicle purchase, I study the optimal joint pricing strategy of vehicle price and loan rates when both firms and consumers are strategic, and the resulting consumer adoption timing across demographic groups. I focus on two scenarios, whereas firms set an optimal uniform pricing policy in one and an optimal targeted pricing policy in another. I evaluate the additional harm to consumers brought by explicit price targeting by the firms. In the counterfactual analysis, the objects of interest are the optimal car prices, and the loan rate setting functions ρ_j which are observed in the data for estimation, but will be optimized in the counterfactual analysis.

In the full equilibrium, firms are the dealers who sell a portfolio of vehicles and arrange financing for consumers in this market. Since my data does not allow separation of manufacturers, lenders and dealers, I will assume that firms are manufacturers who sell their own car models and provides auto loans at the same time, an example of which could be auto manufacturers and their captive lending arms. With richer data that reveals the dealership and their product portfolio that involves cars of difference manufacturers, the counterfactual analysis could be easily adapted. I also assume that it is equally costly to supply vehicles and financing to different consumers for simplicity, although the assumption could be easily adapted with more input for the cost function calibration.

1.6.1 Dealers' Problem

A firm (dealer) sets car prices $\mathbf{p}_{dt}$ and loan rates $\mathbf{r}_{dt}$ for consumers in each cluster $g \in \mathcal{G}$. The firm's per-period profit function is

$$\pi_{dt}(\mathbf{p}_{dt}, \mathbf{r}_{dt}, \mathbf{p}_{-dt}, \mathbf{r}_{-dt}, i_t, R_t) = \sum_{j \in \mathcal{J}_d} \sum_{g \in \mathcal{G}} R_{gt} \sigma_{gjt}(\mathbf{p}_t, \mathbf{r}_t) \cdot \left[p_{gjt} - c_{jt} + p_{gjt} \cdot (r_{gjt} - i_t) \right]$$

where c_{jt} is the wholesale price of the vehicle, i_t is the firm's cost of funding, and R_{gt} is the residual demand among the consumers in cluster g at the beginning of period t. The expected present value of profits to firm d in period t is

$$\mathbb{E}_t \left[\sum_{\tau=t}^{T} \delta^{\tau-1} \pi_{d\tau}(\mathbf{p}_{d\tau}, \mathbf{r}_{d\tau}, \mathbf{p}_{-d\tau}, \mathbf{r}_{-d\tau}, i, \mathbf{R}_\tau) | \mathbf{p}_t, \mathbf{r}_t, \mathbf{R}_t \right] \tag{1.8}$$

where δ is the firm's discount factor assumed to be known and homogeneous across firms.

A pricing strategy profile is a set of vehicle prices and loan rates

$$\boldsymbol{\rho}_t = [\boldsymbol{\rho}_{it}(i, R), ..., \boldsymbol{\rho}_{Dt}(i, R)]$$

for all $i \in \mathcal{I}$, where $\boldsymbol{\rho}_{dt}(i, R) = (\boldsymbol{\rho}_{p,j_1 t}(i, R), ..., \boldsymbol{\rho}_{p,j_d t}(i, R), \boldsymbol{\rho}_{r,j_1 t}(i, R), ..., \boldsymbol{\rho}_{r,j_d t}(i, R))$ is a set of car price $\boldsymbol{\rho}_{p,jt}(i, R)$ and loan rate $\boldsymbol{\rho}_{r,jt}(i, R)$ for all products $j \in \mathcal{J}_d$ in period t under financing cost i and residual demand R. A sequence of strategy profiles is denoted $\boldsymbol{\rho}_\tau = \{\boldsymbol{\rho}_{1t}, ..., \boldsymbol{\rho}_{Jt}\}_{t=\tau}^{T}$ for $\tau = 1, ..., T$. The firm has belief $F_t(\mathbf{R}_{t+1}, i_{t+1} | \boldsymbol{\rho}_t, \boldsymbol{R}_t, i_t) = F_{1t}(\mathbf{R}_{t+1} | \boldsymbol{\rho}_t, \mathbf{R}_t, i_t) \cdot F_{2t}(i_{t+1} | i_t)$ over the evolution of residual market size $\mathbf{R}_t$ and the cost of funding i_t which are profit relevant states. The belief of the evolution of financing cost i_t is exogenous, and the belief of residual demand evolution is deterministic, endogenously decided based on consumer reaction to the firm's pricing strategy, that is,

$$R_{g(t+1)} = R_{gt} \cdot \big(1 - \sigma_{g,J+1,t}(\mathbf{p}_t, \mathbf{r}_t)\big) \quad \text{for all } g \tag{1.9}$$

A firm solves profit maximization problem by jointly optimizing both car prices and loan prices, subject to a constraint that loan rates may not exceed a pre-specified exogenous cap $\bar{m}$. Such cap may feature a usury cap, a state regulated markup cap (e.g., the California Bill of Rights requires dealer's markup be no more than 2% for loans of 60 months or more), or a firm's self-imposed dealer markup cap (e.g., Jiang et al 2021, public comments to FTC's Motor Vehicle Round Table[9]).

$$\begin{aligned}
\max_{\mathbf{p}_{dt}(i),\mathbf{r}_{dt}(i)} & \Pi_{dt}\left(\mathbf{p}_{dt}(i), \mathbf{r}_{dt}(i), \boldsymbol{\rho}_{-dt}(i), i, \mathbf{R}_t\right)\right) \\
& \equiv \pi_{dt}\left(\boldsymbol{\rho}_{dt}(i), \boldsymbol{\rho}_{-dt}(i), i, \mathbf{R}_t\right) + \\
& \qquad \delta \mathbb{E}_{i', \mathbf{R}_{t+1}}\left[\Pi_{t+1}(\boldsymbol{\rho}_{dt+1}(i'), \boldsymbol{\rho}_{-dt+1}(i'), \mathbf{R}_{t+1}) | \rho_{dt}, \rho_{-dt}, \mathbf{R}_t, i\right] \quad (1.10) \\
s.t. \quad & r_{jt}(i) \leq i + \bar{m} \quad (1.11)
\end{aligned}$$

1.6.2 Consumer's Problem

The consumer demand function $\boldsymbol{\sigma}_t(\mathbf{p}_t, \mathbf{r}_t)$ uses the utility parameters and the discount factor estimated in Section 1.5. Unlike in the estimation procedure where I assume consumers hold an exogenous belief for vehicle prices p and loan rate pricing function $r_j = \rho_j(p_j, i)$ estimated from the data, both consumers' and firms' expectation are formed in equilibrium except for the evolution of risk-free rate i_t, which is assumed to be exogeneously set after the central bank's policy announcements.

9. https://www.ftc.gov/sites/default/files/documents/public_comments/public-roundtables-protecting-consumers-sale-and-leasing-motor-vehicles-project-no.p104811-00105/00105-82872.pdf

1.6.3 Equilibrium

The set of pay-off relevant states to both firms and consumers are the residual market sizes, costs of vehicles, and the cost of financing. The pay-off relevant beliefs include commonly shared beliefs of an endogenously determined residual market sizes evolution $F_1(\mathbf{R}_{t+1}|\boldsymbol{\rho}_t, \mathbf{R}_t, i_t)$ and exogeneously determined cost of funding evolution $F_2(i_{t+1}|i_t)$.

The equilibrium concept is a Markov Perfect equilibrium defined by a set of price functions $\mathbf{p}_t(c, i_t, \mathbf{R}_t)$ and $\mathbf{r}_t(c, i_t, \mathbf{R_t})$ that simultaneously satisfy (1.2), (1.9), and (1.11). The equilibrium solution features a fixed point at which (a) the firms' pricing strategies maximize the net present value of profits given the consumer behavior, (b) consumers make purchasing decisions by maximizing inter-temporal utilities, and (c) expectation of the future prices are fulfilled along the realized pricing path.

Since the firms and consumers are playing a finite horizon game, the equilibrium solution can be solved from backward induction. The optimal pricing in each period features a corner solution that $\mathbf{r}_{dt}(i_t, c)^\star \equiv i_t + \bar{m}$ and $\mathbf{p}_{dt}(i_t, c)$ satisfies the first-order condition below for all $d = 1, ..., D$,

$$\begin{aligned}\sum_{k\in\mathcal{J}_d}\sum_{g\in\mathcal{G}} R_{gt}\frac{\partial\sigma_{gkt}(p, r^\star)}{\partial p_{gjt}(i)}\left(p_{gk} - c_k + p_{gk}(r_k^\star - i_t)\right) + \sum_{g\in\mathcal{G}} R_{gt}\sigma_{gjt}(p, r^\star)(1 + r_j^\star - i_t)\\ + \delta\mathbb{E}\Pi_{dt+1}(\boldsymbol{\rho}_{dt+1}, \boldsymbol{\rho}_{-dt+1}, i_{t+1}, \mathbf{R}_{t+1}) = 0\\ s.t.\ \mathbf{R}_t\boldsymbol{\sigma}_{(J+1)t}(\boldsymbol{\rho}) = \mathbf{R}_{t+1} \qquad (1.12)\end{aligned}$$

The presence of the corner solution is due to marginal profits derived from auto loans being higher than marginal profits derived from the vehicle, so that firms will charge the highest loan rate they could and use the vehicle price leverage once loan rates hit the constraint.

In the terminal period, the dealers play a static simultaneous price setting game. The optimal vehicle prices is a fixed point to the system of FOCs in (1.12) with $\mathbb{E}\Pi_{dT+1}(\rho_{T+1}, i_{T+1}, c, R_{T+1}) \equiv 0$ for all d.

In the penultimate period, consumers make choices based on the expectation of future optimal prices at each possible states i_T sovled in the previous step. Firms optimize the expected net present value of two-period profits. Optimal vehicle prices is again a fixed point to a system of FOCs in (1.12) with $\mathbb{E}_{i_T}\Pi_{dT}(\rho^{\star}_{T}, i_T, R_T)$ being the maximized profit under optimal pricing strategies in period T state i_T solved in the previous step.

1.6.4 Optimal Price Paths and Interest Rate Pass Through

The optimal pricing strategy features auto loan rates set at $i + \bar{m}$ and optimal vehicle prices satisfy the first order condition (1.12). Given an ex-ante belief of future risk-free interest rate path, the changes in expected risk-free interest rates over time are pass on to consumers via vehicle prices, and the magnitude of pass through is larger for myopic consumers.

Take a decreasing expected risk-free interest rate path as an example, in which the expected risk-free interest rate i_t decline by 0.332% in the final four periods in a model year. The optimal expected total price for the financed vehicle is downward sloping as well, on average declining by 0.134% across consumer groups. That is, about 40% of the expected changes in interest rates are passed through to consumers via the dealers' optimal pricing schedule. However, if the consumers are more forward looking, for example with a discount factor 0.994 implied by a 5% annual real interest rate, the optimal pass through rate for forward-looking consumers would be smaller than that when consumers are myopic, at a magnitude ranging from 0.002% to 0.097%. In other words, strategic dealers have incentive to infuse its knowledge about future to consumers, but it takes a steeper price path for myopic consumers than for forward looking consumers.

1.6.5 Distributional Impact Due to Purchase Timing Under the Optimal Pricing Policy

I next quantify to what extent does explicit price targeting on the firm's side contribute to the auto loan rate disparity. I consider two scenarios, where firms set an optimal uniform pricing policy in one scenario and set an optimal targeted pricing policy based on observed consumer characteristics in the other scenario. Under the uniform pricing policy, the auto loan rate disparity is entirely driven by heterogeneity in consumer behavior. Under the targeted pricing policy, the disparity would be driven by both heterogeneous demand and heterogeneous prices. The differences in auto loan rate disparity between the two scenarios suggest how much damage could firms bring to consumers by explicit price discrimination.

A preliminary analysis simplifies the counterfactual analysis by creating a hypothetical consumer population constituted by the most myopic and the most forward looking consumer clusters in the data. In the hypothetical consumer population, myopic consumers accounts for the majority with a weight of 95% – the relative weight of the two consumer clusters resembles that in the estimation sample. The preliminary analysis also assumes myopic firms, calibrated vehicle costs (75% of MSRP as estimated in Grunewald et al. [2020]), and calibrated cost of funding as the federal funds rate.

Under optimal uniform pricing, the average financing gap conditional on purchasing a car, as defined by the differences in (1.7) across groups g, amounts to 0.229 bps. That is, the myopic cluster on average pays more for auto financing and the entire gap is caused by demand heterogeneity since the firms set a uniform pricing policy for all consumers. Under optimal targeted pricing, however, the average financing gap slightly increased to be 0.231 bps. This gap reflects a combination of heterogeneity in demand and heterogeneity in pricing for each cluster. Comparing the two scenarios, I find that the magnitude of the financing gap under uniform pricing is 99% of that under targeted pricing. This analysis suggests that explicit discrimination hurt consumers by exacerbating the financing gap, but the magnitude is minimal when compared to the disparity caused by demand heterogeneity alone.

1.7 Conclusion

I documented evidence of consumer forward looking behavior in financed vehicle purchases. Consumers are on average quite myopic, discounting future utility at a much higher rate than the real rate of interest. I also documented substantial heterogeneity in the discount factor, and stronger myopia is associated with lower scheduled loan repayment, lower loan and credit card balance, less activity in the credit market, and less frequent car purchases. Such association of discount factor heterogeneity with credit profiling points to an unequal degree of myopia across across consumers in my sample. The comparative cost of being myopic in the data ranges from $48 to $151 over the sample period. Finally, using a calibrated full equilibrium model, I show that explicit price targeting by the firms would exacerbate the financing gap beyond what has been caused by heterogeneity in consumer behavior, but the magnitude could be minimal when compared to the financing gap driven by heterogeneous consumer behavior.

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A1 The Construction of Non-stationary Transition Probabilities of Risk-free Interest Rates

I construct the non-stationary transition probabilities of risk-free interest rates by creating a binary decision tree to match the market-implied expectation of federal funds rate documented in the Bloomberg WIRP Function.

I first create a time-averaged market-implied expectations of future federal funds rate from the Bloomberg WIRP data as a moment of the market-consensus belief I use for the model. The Bloomberg WIRP data provides daily market-implied expectation of federal funds rate on a series of future dates, $\mathbb{E}_t[i_\mathcal{T}|i_t]$, where t is the report date and τ corresponds to some future FOMC announcement date. For every τ corresponding to the beginning period of a period, and for every set of dates $\tilde{t}$ corresponding to the sub-period $\mathbf{t}$ of my demand model time frame, I construct the following time-averaged market-implied expectations

$$\mathbb{E}_t(i_\mathcal{T}|i_t) \equiv \frac{\sum_{\tilde{t}} \mathbb{E}_{\tilde{t}}(i_\mathcal{T}|i_{\tilde{t}})}{\sum_{\tilde{t}} 1}$$

With such construction, I can collect a series of expectations,

$$\mathbb{E}_t(i_{\mathcal{T}_1}|i_t), \mathbb{E}_t(i_{\mathcal{T}_2}|i_t), ..., \mathbb{E}_t(i_T|i_t)$$

at each sub-period t of the model. Assuming that the Fed would only announce interest rate changes by δ in one direction, I can match the expectations with a set of binary-decision probabilities. For example, for any two adjacent periods t and

$t + 1$,

$$\mathbb{E}_t(i_{t+1}|i_t) = P[i_{t+1} = i_t + \delta] \cdot (i_t + \Delta) + (1 - P[i_{t+1} = i_t + \delta]) \cdot i_t$$

Since $\mathbb{E}_t(i_{t+1}|i_t)$, i_t and δ are known, we can solve for $P[i_{t+1} = i_t + \delta]$, the probability of seeing an interest rate hike next period, and get the probability of no changes in the federal funds rate as $1 - P[i_{t+1} = i_t + \delta]$.

For any two non-adjacent periods, without generality for example t and $t + 2$, I first determine the number of interest rate hikes or decreases k that the market expect to see. I solve for the k with smallest absolute value that satisfy the following equation

$$\mathbb{E}_t(i_{t+2}|i_t) = P[i_{t+2} = i_t + k\delta] \cdot (i_t + k\delta) + (1 - P[i_{t+2} = i_t + k\delta]) \cdot i_t$$

I assume once the Fed reaches k increases or decreases, it won't change the federal funds rate any further. Using $k = 1$ as an example, I can decompose the expectation as follows,

$$\begin{aligned}
\mathbb{E}_t(i_{t+2}|i_t) =& P[i_{t+2} = i_t + \delta, i_{t+1} = i_t + \delta|i_t] \cdot (i_t + \delta) \\
& + P[i_{t+2} = i_t + \delta, i_{t+1} = i_t|i_t] * (i_t + \delta) \\
& + P[i_{t+2} = i_t, i_{t+1} = i_t|i_t] * i_t \\
=& [P[i_{t+2} = i_t + \delta|i_{t+1} = i_t] \cdot P[i_{t+1} = i_t|i_{t+1} = i_t] + \\
& \quad 1 \cdot P[i_{t+1} = i_t + \delta|i_t]] \cdot (i_t + \delta) + \\
& \quad (1 - P[i_{t+2} = i_t + \delta|i_{t+1} = i_t]) \cdot P[i_{t+1} = i_t|i_t] \cdot i_t
\end{aligned}$$

In the decomposition above, we can solve for the only unknown probability $P[i_{t+2} = i_t + \delta|i_{t+1} = i_t]$, which describe the probability of seeing an interest rate hike in period $t + 2$ if there was none in period $t + 1$.

Using forward induction, for any two non-adjacent periods t and $t + k$, we can construct a set of non-Markov transition probabilities starting from $t+1$ to $t+k$. The transition is non-Markov, because the probabilities depend on the entire historical paths of i_t. I use these transition probabilities in the structural model estimation.

A2 Reduced-form Loan Rate Setting Process

I use the entire data period to estimate a reduced-form loan rate setting process, taking car loan rates as a function of the loan amount and market-consensus interest rate beliefs. The estimates help verify if changes in beliefs are more frequent than changes in loan prices, as we've seen in the example of the event analysis. I will later also use the reduced-form loan rate process for estimating the structural model.

To estimate the loan rate setting process, I implement the following linear regression,

$$
\begin{aligned}
r_{ijt} = \beta_0 i_t + \beta_{1M}\mathbb{E}_t[i_{t+1} - i_t] + \beta_{3M}\mathbb{E}_t[i_{t+3} - i_t] + \\
\beta_{6M}\mathbb{E}_t[i_{t+6} - i_t] + \beta_{9M}\mathbb{E}_t[i_{t+9} - i_t] + \beta_{12M}\mathbb{E}_t[i_{t+12} - i_t] + X_{ijt} + \epsilon_{ijt}
\end{aligned}
$$

where r_{ijt} is the car loan rate (in annual percentage rate) of individual i who purchased vehicle j on date t. The current federal funds rate i_t and a series of moments of market consensus beliefs $\mathbb{E}_t[i_{t+k} - i_t]$ depicts the expected changes in risk-free interest rate i_{t+k} in $k = 1, 3, 6, 9, 12$ months ahead of date t. The covariate X_{ijt} controls for the vehicle, loan and individual characteristics, including log of vehicle price, vehicle model, state, lender, loan term duration, super prime credit score, model year, aggregated time period, day of week, and month end fixed effects. To avoid sparsity in lender-specific loan origination, I use a sub-sample of loans originated from lenders whose monthly loan origination is top 66% (at least 200 loans per month). To control for heterogeneity of of the $\rho_j(\cdot)$ function across consumers, I add consumer cluster fixed effects. The result is robust if consumer cluster FEs interact with the expected interest rate path $\mathbb{E}_t[i_{t+k} - i_t]$. Car loans with 0% APR are excluded from the regression since these loans does not respond to current rate and belief changes by design.

Parameters of interest are β_0 and β_{kM} for $k = 1, 3, 6, 9, 12$, where the former reflects the response in car loan rates r_{jt} to the concurrent risk-free interest rate

i_t, and the latter reflect the responses in car loan rates to expected future changes in i_τ for some $\tau > t$. Table A4.3 shows the regression results. The coefficient β_0 is positive and not significantly different from one, indicating concurrent changes in the risk-free interest rate i_t are almost transmitted one-to-one to car loan rates. However, coefficients β_{kM} for all k are not significantly different from 0, so that car loan rates are not significantly responsive to changes in belief. Despite the rather noisier estimates on the belief coefficients, many can be rejected to be of similar sizes as the car loan rate's responses to concurrent i_t. Therefore, I interpret this result as evidence for existence of car price and loan rate states being invariant to changes in belief. I will plug in such empirical relationship into the structural model to form a known ρ_j function for estimation in the next section. In the counterfactual analysis, the loan rate setting process will be endogenously optimized.

A3 Estimation Details and Results

A3.1 MLE Estimator with Observed Heterogeneity

In the empirical data, I observe a choice vector $Y_{it} = (Y_{i1t}, ..., Y_{i(J+1)t})$ per individual in each choice occasion, in which $Y_{ijt} \in \{0, 1\}$ denote whether the consumer i chooses option j in period t. From the parametric DDC model from Section 1.5, the choice specific values for a consumer i who belongs to cluster g are

$$v_{gjt}(s;\Gamma_g) = \begin{cases} \gamma_{gj} + \eta_{gt} - \alpha_g p_j \left[1 + \rho_{gj}(p_j, i)\right] & \text{if } j = 1, ..., J \\ \beta_g \mathbf{F}_t(s) \ln \left[\exp\left(v_{g,J+1,t+1}(\mathbf{F})\right)\right. & \\ \quad \left. + \sum_{m=1}^{M} \exp\left(\lambda_{gm} \ln \sum_{k\in\mathcal{J}_m} \exp\left(\mathbf{v}_{gk,t+1}/\lambda_{gm}\right)\right)\right] & \text{if } j = J+1 \end{cases}$$

where $\theta_g = (\gamma_g, \eta_g, \alpha_g)$ is the vector of cluster g-specific taste parameter, β_g is the discount factor, λ_g is the nested-logit parameter, $\mathbf{F}$ is the non-stationary Markov state transition matrix. Let $\Gamma_g = (\beta_g, \theta_g, \lambda_g)$ denote all the structural parameters.

I define the cluster g-specific MLE estimator as

$$\Gamma_g^\star = \underset{\Gamma}{\operatorname{argmax}} \sum_{j=1}^{J} \sum_{t=1}^{T} \left[N_{gjt}^{(1)} \ln \sigma_{gjmt}(s_t; \mathbf{F}_t^{(1)}) + N_{gjt}^{(2)} \ln \sigma_{gjmt}(s_t; \mathbf{F}_t^{(2)})\right] \tag{13}$$

where $N_{gjt}^{(\tau)} = \sum_{i:a(i)=g} \mathbb{1}[Y_{ijt}^{(\tau)} = j]$ is the total number of purchases of option j made in the sub-period $\tau = 1, 2$ of period t, by consumers belong to cluster g. I also provide gradients to improve the robustness and speed of the optimization in the MLE estimator. The gradient elements are

$$
\begin{aligned}
\frac{\partial}{\partial \beta} \ln \sigma_{jmt}(s) =& \mathbb{1}[j=0] \cdot \left[\frac{\partial v_{0t}(s)}{\partial \beta}\right] - \sigma_{0t}(s)\frac{\partial v_{0t}(s)}{\partial \beta} \\
\frac{\partial}{\partial \theta} \ln \sigma_{jmt}(s) =& \frac{1}{\lambda_m}\frac{\partial v_{jt}(s)}{\partial \theta} + (\lambda_m - 1)\frac{\partial IVS_{mt}}{\partial \theta} \\
& - \left[\sigma_{0t}(s)\frac{\partial v_{0t}(s)}{\partial \theta} + \sum_{m'=1}^{M} \lambda_{m'}\sigma_{m't}(s)\frac{\partial IVS_{m't}}{\partial \theta}\right] \\
\frac{\partial}{\partial \lambda_m} \ln \sigma_{jmt}(s) =& \mathbb{1}[j \neq 0] \left[-\frac{v_{jt}(s)}{\lambda_m^2} + IVS_{mt} + (\lambda_m - 1)\frac{\partial IVS_{mt}}{\partial \lambda_m}\right] + \mathbb{1}[j=0]\left[\frac{\partial v_{0t}(s)}{\partial \lambda_m}\right] \\
& - \left[\sigma_{0t}(s)\frac{\partial v_{0t}(s)}{\partial \lambda_m} + \sigma_{mt}(s)\left(IVS_{mt} + \lambda_m \frac{\partial IVS_{mt}}{\partial \lambda_m}\right)\right] \\
\frac{\partial}{\partial \lambda_n} \ln \sigma_{jmt}(s) =& \mathbb{1}[j=0]\left[\frac{\partial v_{0t}(s)}{\partial \lambda_n}\right] - \left[\sigma_{0t}(s)\frac{\partial v_{0t}(s)}{\partial \lambda_n} + \sigma_{nt}(s)\left(IVS_{nt} + \lambda_n \frac{\partial IVS_{nt}}{\partial \lambda_n}\right)\right] \\
\frac{\partial IVS_{mt}}{\partial \theta} =& \frac{1}{\lambda_m}\sum_{k \in \mathcal{J}_m} \sigma_{k|mt}(s)\frac{\partial u_{kt}(s)}{\partial \theta} \\
\frac{\partial IVS_{mt}}{\partial \lambda_m} =& -\frac{1}{\lambda_m^2}\sum_{k \in \mathcal{J}_m} \sigma_{k|mt}(s) u_{kt}(s) \\
\frac{\partial}{\partial \beta} v_{0t}(s) =& F_t(s)\gamma + F_t(s)\ln\left[\exp\left(\mathbf{v}_{0t+1}\right) + \sum_{m'} \exp(\lambda_{m'}\mathbf{IVS}_{m't+1})\right] \\
& + \beta F_t(s)\sigma_{0t+1}\frac{\partial \mathbf{v}_{0t+1}}{\partial \beta} \\
\frac{\partial}{\partial \theta} v_{0t}(s) =& \beta F_t(s) \cdot \left[\sigma_{0t+1}\frac{\partial v_{0t+1}}{\partial \theta} + \sum_m \sigma_{mt+1}\lambda_m \frac{\partial \mathbf{IVS}_{mt+1}}{\partial \theta}\right] \\
\frac{\partial}{\partial \lambda_m} v_{0t}(s) =& \beta F_t(s) \cdot \left[\sigma_{0t+1}\frac{\partial \mathbf{v}_{0t+1}}{\partial \lambda_m} + \sigma_{mt+1}\left(\mathbf{IVS}_{mt+1} + \lambda_m \frac{\partial \mathbf{IVS}_{mt+1}}{\partial \lambda_m}\right)\right] \\
\frac{\partial}{\partial \beta} v_{0T}(s) =& \frac{\partial}{\partial \theta} v_{0T}(s) = \frac{\partial}{\partial \lambda_m} v_{0T}(s) = 0
\end{aligned}
$$

To control for the heterogeneity in consumer tastes, I use a vector of individual specific credit profiling moments to classify consumers into discrete clusters. The assumption is that conditional on the observables, consumers are homogeneous within the cluster. The moments consist of a rich vector of individual credit profile characteristics, including credit score, census block, total scheduled monthly payment for all trades verified in past 12 months, average balance of open trades verified in past 12 months, average balance/utilization/credit line of open trades verified in past 12 months (excluding mortgage and home equity), homeowner status (informed by number of mortgages, HE and HELOC accounts), total balance of open HE and HELOC trades verified in past 12 months, total balance of open mortgage trades verified in past 12 months, total balance of open credit card trades verified in past 12 months, utilization for open credit card trades verified in past 12 months, total credit line of open credit card trades verified in past 12 months, number of auto trades opened in past 24 months, months since most recent auto trade opened, number of 90 or more days past due ratings in past 12 months, and number of credit inquiries in 12 months. I classify all consumers who moved to a different commute zone within six months before the beginning of the model year and after the end of the model year to a single "mover" cluster, and cluster the rest of the consumers based on the above moments using the k-means clustering algorithm. Given the size of my panel and the sparsity of purchases, I use $K = 10$ groups.

A3.2 Selected Structural Estimation and Results

Table A3.1 presents the estimation results for the discount factor, preference, and nested logit correlation parameters for each cluster. Model intercepts are not reported

		group 1	group 2	group 3	group 4	group 5	group 6	group 7	group 8	group 9	group 10	group 11
	discount factor β	0.000	0.031	0.041	0.045	0.053	0.053	0.122	0.122	0.196	0.287	0.175
		(0.000)	(0.019)	(0.014)	(0.025)	(0.022)	(0.069)	(0.015)	(0.030)	(0.019)	(0.078)	(0.029)
	price	-0.279	-0.264	-0.263	-0.298	-0.248	-0.190	-0.279	-0.243	-0.233	-0.264	-0.256
		(0.008)	(0.009)	(0.007)	(0.010)	(0.007)	(0.024)	(0.007)	(0.012)	(0.009)	(0.023)	(0.009)
quarter FE	fall	-0.698	-0.814	-0.787	-0.738	-0.713	-0.827	-0.957	-0.946	-1.075	-0.530	-0.792
		(0.011)	(0.013)	(0.009)	(0.016)	(0.014)	(0.048)	(0.011)	(0.022)	(0.016)	(0.073)	(0.022)
	winter	-0.178	-0.243	-0.223	-0.187	-0.164	-0.299	-0.331	-0.281	-0.389	-0.041	-0.247
		(0.009)	(0.010)	(0.008)	(0.014)	(0.012)	(0.039)	(0.010)	(0.019)	(0.014)	(0.070)	(0.020)
	spring	-0.013	-0.038	-0.042	-0.024	-0.030	-0.066	-0.054	-0.084	-0.104	0.114	-0.042
		(0.008)	(0.010)	(0.007)	(0.013)	(0.012)	(0.038)	(0.009)	(0.018)	(0.013)	(0.060)	(0.019)
model year FE	2016	-0.085	-0.000	-0.005	-0.119	0.032	-0.078	0.020	-0.007	0.007	0.024	0.082
		(0.010)	(0.010)	(0.007)	(0.012)	(0.011)	(0.034)	(0.007)	(0.014)	(0.009)	(0.022)	(0.012)
	2017	0.021	0.012	0.014	-0.025	0.091	-0.017	0.028	0.021	-0.018	-0.064	0.061
		(0.009)	(0.009)	(0.006)	(0.011)	(0.010)	(0.031)	(0.007)	(0.013)	(0.008)	(0.026)	(0.012)
	2018	0.057	0.044	0.046	0.015	0.120	0.004	0.067	0.051	0.012	-0.033	0.094
		(0.009)	(0.009)	(0.006)	(0.011)	(0.010)	(0.031)	(0.007)	(0.013)	(0.008)	(0.025)	(0.012)
nested logit corr.	NON LUXURY TRADITIONAL COMPACT	0.531	0.434	0.473	0.518	0.372	0.547	0.557	0.480	0.406	0.563	0.385
		(0.053)	(0.060)	(0.041)	(0.062)	(0.071)	(0.355)	(0.038)	(0.111)	(0.048)	(0.223)	(0.054)
	NON LUXURY TRADITIONAL MID SIZ	1.000	1.000	1.000	1.000	1.000	0.950	1.000	1.000	0.838	1.000	1.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.535)	(0.000)	(0.000)	(0.083)	(0.000)	(0.000)
	NON LUXURY FULL SIZE HALF TON	1.000	1.000	0.967	1.000	1.000	1.000	1.000	1.000	0.967	1.000	1.000
		(0.000)	(0.000)	(0.059)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.070)	(0.000)	(0.000)
	NON LUXURY FULL SIZE 3QTR TO 1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	NON LUXURY COMPACT CUV	1.000	0.967	0.963	1.000	1.000	0.989	0.857	0.972	0.750	0.978	1.000
		(0.000)	(0.043)	(0.031)	(0.000)	(0.000)	(0.190)	(0.033)	(0.077)	(0.042)	(0.136)	(0.000)
	NON LUXURY MID SIZE PICKUP	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	NON LUXURY MID SIZE SUV	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.913	1.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.131)	(0.000)
	NON LUXURY MID SIZE CUV	0.720	0.688	0.686	0.707	0.655	0.560	0.707	0.700	0.624	0.739	0.642
		(0.053)	(0.047)	(0.034)	(0.064)	(0.043)	(0.131)	(0.044)	(0.070)	(0.049)	(0.129)	(0.060)

Table A3.1: Heterogeneous Preference Estimates

total credit card limit	credit score	monthly scheduled loan payment	total mortgage balance	credit card utilization	number of public bankruptcy
1	0.337^{***}	0.227^{***}	0.279^{***}	-0.156^{***}	-0.136^{***}

This table summarizes the correlation between income, approximated by total credit card limits, and other consumer credit profile features.

Table A4.2: Correlation between income and credit profiles

for briefness.

A4 Additional Tables and Figures

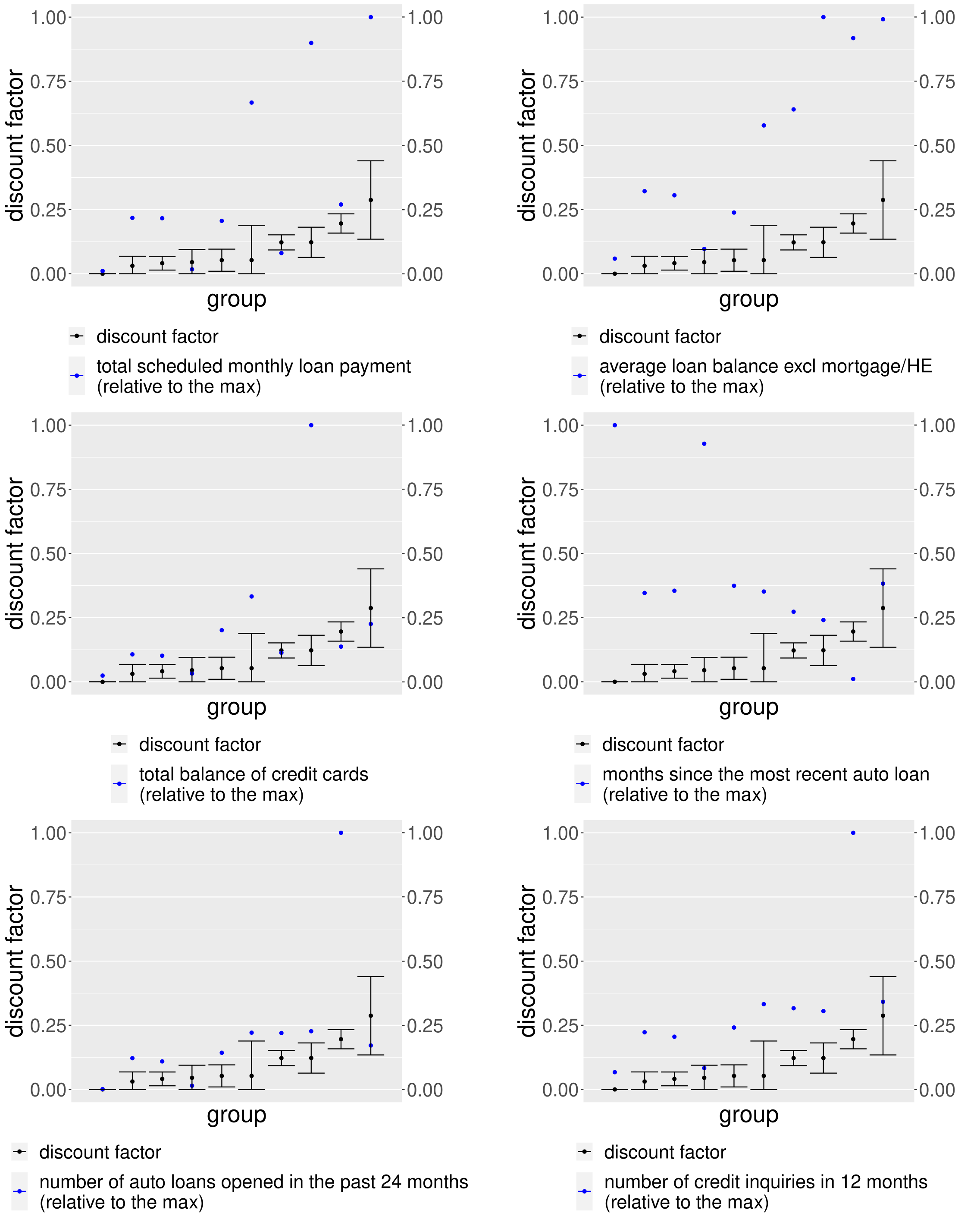


Figure A3.1: Credit profile dimensions that may explain heterogeneous discount factor

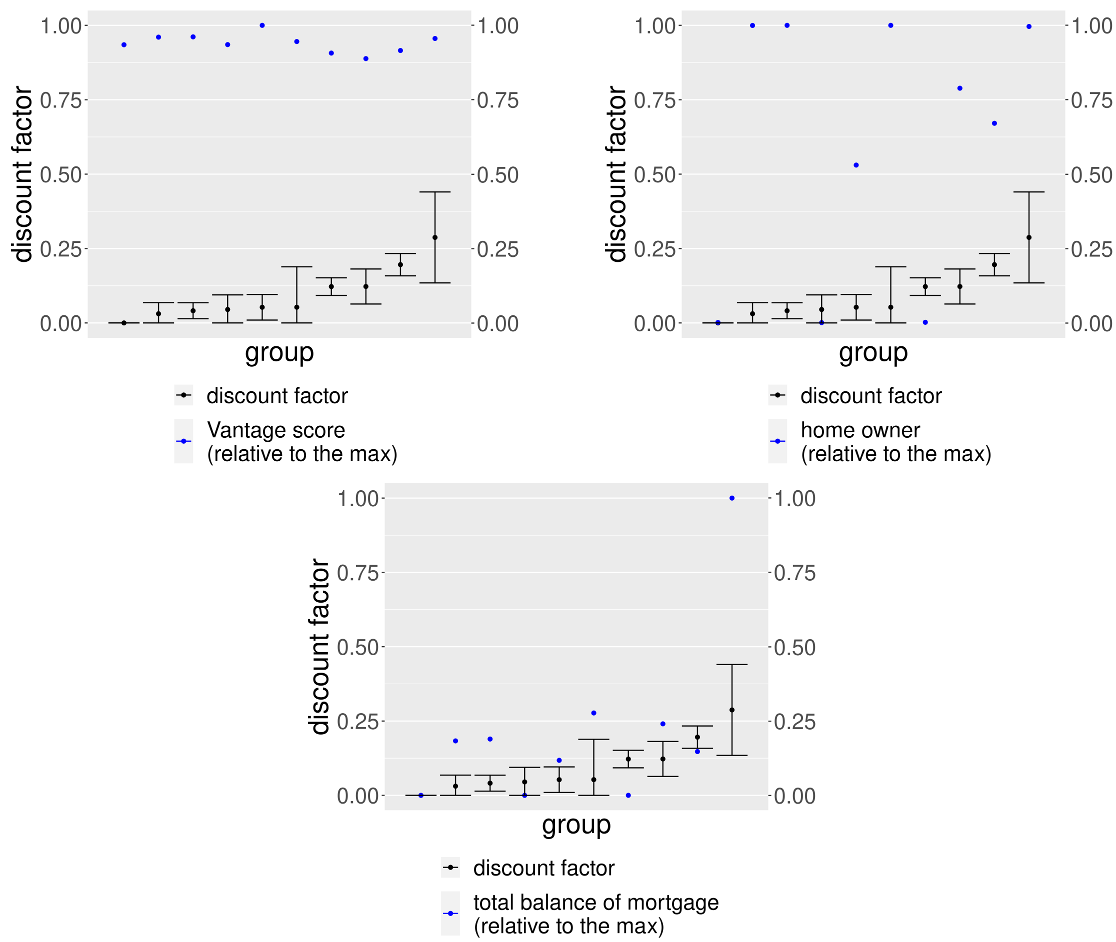


Figure A3.2: Credit profile dimensions that does not explain heterogeneous discount factor

	Dependent variable:
	auto loan rate r_t
i_t	1.182***
	(0.139)
$\mathrm{E}_t[i_{t+1M} - i_t]$	0.137
	(0.210)
$\mathrm{E}_t[i_{t+3M} - i_t]$	−0.253
	(0.382)
$\mathrm{E}_t[i_{t+6M} - i_t]$	0.409
	(0.500)
$\mathrm{E}_t[i_{t+9M} - i_t]$	−0.045
	(0.515)
$\mathrm{E}_t[i_{t+12M} - i_t]$	0.387
	(0.279)
log(loan amount)	−0.305***
	(0.038)
credit score > 780	−0.334***
	(0.027)
Observations	222,345
R^2	0.054
Adjusted R^2	0.053
Residual Std. Error	5.551 (df = 222185)
Note:	*p<0.1; **p<0.05; ***p<0.01

This table summarizes the estimated relationship between auto loan rates and concurrent federal funds rate, as well as an array of market-expected future federal funds rate. The expectations are truncated at 1, 3, 6, 9, and 12 months ahead of today.

Table A4.3: Reduced form loan rate setting process

	Market Implied Expected Change in FFR in 12 Months	Michigan Survey of Consumer Score Among Income Percentiles Bottom 20%	21%-40%	41%-60%	61%-80%	Top 20%
Correlation	1	0.519	0.666	0.683	0.705	0.766
p-value	0	0	0	0	0	0

This table summarizes the correlation test between market implied expected changes in the federal funds rate (FFR) in 12 months and consumer expected changes surveyed from the Michigan Survey of Consumers (MCS) Question A11, during September 2015 to August 2019. The survey measure is shown as a score equal to the percentages of consumers who expect interest rates to increase in the next 12 months minus the percentage that expect interest rate to decrease, constructed per income quartile per month. The market expectation is the monthly average of Bloomberg WIRP expected change (in basis points) in FFR in 12 months.

Table A4.4: Correlation between market-implied expected interest rate changes and MSC surveyed consumer beliefs

	Dependent variable:
	Percentage of consumers who expect interest rate to increase during the next 12 months (%)
Market expected change (bps) × Income Percentiles Bottom 20%	1.242^{***} (0.113)
Market expected change (bps) × Income Percentiles 21-40%	1.290^{***} (0.113)
Market expected change (bps) × Income Percentiles 41-60%	1.306^{***} (0.113)
Market expected change (bps) × Income Percentiles 61-80%	1.404^{***} (0.113)
Market expected change (bps) × Income Percentiles Top 20%	1.463^{***} (0.113)
Observations	275
R^2	0.778
Adjusted R^2	0.773
Residual Std. Error	0.319 (df = 270)
F Statistic	188.732^{***} (df = 5; 270)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

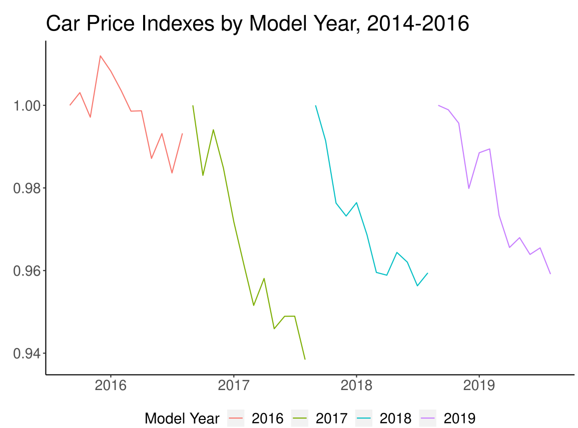
This table summarizes the calibrated heterogeneous relationship between household beliefs and market-implied beliefs of future interest rates. The coefficients of interest translate every basis point of market-expected interest rate changes into the proportion of consumers who expect interest rate to increase during the next 12 months. The translation will be kept for imputing household beliefs during time periods not surveyed by the MSC.

Table A4.5: Consumer expectation as a fixed proportion to market-consensus expectation

Group	Credit score	Monthly loan payment (k)	Loan balance (k) (excl mortgage)	Homeowner (share)	Mortgage balance(k)	Credit card balance (k)	Number of auto loan in 24 months	years since last auto loan	Number of inquiry in 12 months	Mover
1	748	0.09	0.5	0	0	0.9	0.0	15.7	0.2	0
2	769	1.7	2.9	1	131	3.8	0.2	5.4	0.7	0
3	769	1.7	2.8	1	136	3.6	0.2	5.6	0.7	0
4	748	0.1	0.9	0	0	1.1	0.0	14.6	0.3	0
5	800	1.6	2.2	0.53	84	7.1	0.3	5.9	0.8	0
6	757	5.2	5.3	1	198	11.8	0.4	5.5	1.1	0
7	726	0.6	5.8	0	0	4.0	0.4	4.3	1.0	0
8	733	2.1	8.4	0.67	105	4.9	2.0	0.2	3.3	0
9	711	7.1	9.1	0.79	172	35.5	0.4	3.8	1.0	0
10	765	7.9	9.1	1	715	8.0	0.3	6.0	1.1	0
11	743	1.2	4.0	0.29	63	4.3	0.3	8.3	1.2	1

This table presents the group-specific average of consumer credit profiling.

Table A4.6: Group-specific consumer credit profiling



This figure illustrates the observed evolution of car prices in each model year. The evolution is be used for constructing perfect foresight of car prices in the structural model.

Figure A4.3: Törnqvist Car Price Index by Model Year, 2016-2019