Designing Dealer Compensation in the Auto Loan Market: Implications from a Policy Change

Zhenling Jiang, Yanhao 'Max' Wei, Tat Chan, and Naser Hamdi*

Abstract

We study dealer compensation in the indirect auto lending market, where most lenders give dealers the discretion to mark up interest rates and the markup constitutes a dealer's compensation. To protect consumers from potential discrimination by this dealer discretion, several banks adopted a policy that removes dealer discretion and compensates dealers by a fixed percentage of the loan amount. We document that this policy decreased (increased) the interest rates for low-credit (high-credit) consumers; however, the market share of these banks also decreased (increased) in low-credit (high-credit) segments — a reversal of the usual demand curve. This reversal highlights a significant influence of auto dealers on consumer choices. Accordingly, we develop an empirical model that features dealer–consumer bargaining. Our estimation results show systematically different levels of bargaining power across consumer groups. We use the model to explore alternative compensation schemes that remove dealer discretion. We find that a lump-sum compensation scheme obtains the most market share. In addition, the optimized lump-sum scheme improves consumer welfare compared to the adopted policy. Our study highlights the importance of accounting for the incentives and bargaining power of middlepersons.

Keywords: auto loan, interest-rate markup, dealer compensation, consumer protection, Nash bargaining.

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1 Introduction

In many consumer markets, products are sold not directly from firms to consumers but through middlepersons, who typically receive compensation from the firms for each completed transaction. For example, car dealers act as the middlepersons for arranging auto loans in indirect auto financing. Typically, banks specify an interest rate ("*bank-receiving rate*" hereafter) based on the consumer credit profile and loan characteristics. Dealers impose a markup ("*dealer rate*" hereafter) on top of the bank-receiving rate as their compensation for arranging loans. The final interest rate that consumers pay ("*consumer rate*" hereafter) is the sum of the bank-receiving rate and the dealer rate. Needless to say, such a layered setting has important implications for pricing from banks' perspective; changes in the bank-receiving rate must pass through dealers before they can affect the consumer demand.

This layered setting creates an even more complex landscape for auto lenders when it comes to consumer protection. In 2013, the Consumer Financial Protection Bureau (CFPB) issued statements that the dealership's discretion to vary the dealer rate on a loan-by-loan basis resulted in certain consumers (e.g., minority consumers) paying higher interest rates than others with similar credit scores, violating the Equal Credit Opportunity Act. The Act prohibits creditors from discriminating against credit applicants on the basis of race, color, religion, national origin, sex, and marital status. Even though the bank-receiving rate is set based on consumer credit profile and loan characteristics, the dealer's markup is at the discretion of the dealer. As a result, this discretionary markup and consequently the consumer rate can vary systematically by protected characteristics such as gender and race. Nevertheless, the CFPB and the Department of Justice held banks (rather than dealers) accountable and fined several of them for alleged discriminatory consumer rates.

To protect consumers, policy makers advocated *non-discretionary compensation schemes*, where banks directly set the consumer rate as well as the dealer compensation instead of leaving them up to the dealer discretion. Under this regulatory environment, several banks switched to a non-discretionary compensation scheme, offering *3 percent of the loan amount* as the dealer compensation. For each loan, the consumer rate then equals the bank-receiving rate plus the dealer rate equivalent to this 3-percent compensation. From the banks' perspective, in addition to whether this policy eliminates discriminatory consumer rates, a key question is how the policy affects their market share. The involvement of dealers complicates this question. For example, lower consumer rates do not necessarily translate to a larger market share if they require a reduction in the compensation for dealers, who often have a significant influence on consumers' bank choices (i.e., choosing which bank to finance the loan).

In this paper, we study the design of dealer compensation in the auto loan market. We leverage the above policy change at several banks. First, we empirically document the impact of the policy on consumers as well as banks. In particular, we show how consumers' bank choices are influenced by the incentives of not only the consumers but also the dealers. Second, we use a bargaining model to capture how the dealer and consumer incentives may jointly determine the loan outcomes, i.e., the bank choice and consumer rate. Particularly, we focus on the choice between banks with discretionary vs. non-discretionary compensation schemes. Third, with the estimated model, we explore alternative non-discretionary compensation schemes that eliminate discriminatory consumer rates while minimizing the potential negative impact on the market share of banks that adopt these schemes.

More specifically, we start with important patterns in the data related to the policy change. Our data include 0.18 million auto loans in the U.S. within a 20-week window that equally covers the pre- and post-policy periods. For data privacy reasons, we combine together the data of several banks that implemented the non-discretionary scheme (more details given in Section 2). We refer to them jointly as "*target banks*," and the competing banks that kept the discretionary compensation scheme as "*general banks*." We find that at the target banks, the policy *decreased* consumer rates for low-credit consumer segments and *slightly increased* the rates for high-credit segments. This is consistent with studies showing that, under the discretionary compensation scheme, dealers typically charge a higher dealer rate on low-credit consumers (e.g. Salz et al., 2020).

What is counter-intuitive, however, is that the market share of target banks *decreased* in low-credit segments and *increased* in high-credit segments — a reversal of the usual demand curve. While this result is implausible in the eyes of standard demand models where brand choices are made solely by consumers, it would be consistent with a model that accounts for dealers' incentives. The target banks will lose low-credit consumers if dealers can obtain higher compensations by pushing consumers to the general banks that allow for dealer discretion. In this sense, though the policy was intended to help disadvantaged consumers with lower bargaining power, the intended effect of the policy did not fully pass-through due to the incentives of dealers. Overall, reduced form analysis of the data highlights us the important role of the dealers in this market.

We specify a model for auto loan demand based on Nash bargaining between consumers and dealers (Nash, 1953; Zhou, 1997). We take a consumer's need for a specific auto loan (amount and length) as given, and focus on how both (i) the consumer rate and (ii) the bank choice are determined. Under the discretionary compensation scheme, the consumer rate is a bargaining outcome between the dealer and consumer. On top of this, the choice between target banks vs. general banks to finance the loan is also a bargaining outcome. Under the non-discretionary scheme, the consumer rate is no longer bargained but set by banks. In practice, consumers may or may not engage in explicit bargaining with dealers. Nevertheless, Nash bargaining serves as a useful model to capture the key tension between consumers and dealers in this market.

We apply the model to data. The estimation isolates the role of bargaining power from the role of bank-receiving rates in explaining the consumer rate at the individual loan level. Based on the estimates, we calculate that at the target banks before the policy, about 50% of the dispersion in observed consumer rates comes from the heterogeneity in bargaining power across consumers (with the rest of the variation coming from bank-receiving rates). Higher bargaining power rests with consumers who have: (i) higher credit scores,[1] (ii) loans with shorter lengths, and (iii) loans with larger amounts to be financed. These results are consistent with the findings in Davis and Frank (2011), a consumer report based on surveys of auto loan lenders. Further, we use the estimated model to back out the part of each consumer's bargaining power that cannot be explained by credit profile and loan characteristics. This "residual" bargaining power explains about 37% of the dispersion in observed consumer rates. We relate the residual bargaining power to demographics at the zip code level. Results show that consumers who live in zip codes with higher African American or Hispanic population, lower median income, or lower college education tend to have lower residual bargaining power, implying that they face higher dealer rates for the same credit profile and loan characteristics.

We use counterfactuals to study alternative non-discretionary compensation schemes that eliminate discriminatory consumer rates for the target banks.[2] We consider three types of non-discretionary compensation schemes: (i) paying the dealer a fixed percentage of loan amount, (ii) paying the dealer a fixed dealer rate, and (iii) paying the dealer a fixed lump sum amount for each loan. Note the policy adopted by target banks in our data falls under (i). For each type of compensation schemes, we take the bank-receiving rates as given, and search for the optimal percentage, dealer rate, or lump-sum amount that maximizes the market share of target banks. We find that the lump-sum compensation scheme results in the highest market share for target banks. Compared to the implemented 3%-of-loan-amount scheme, the lump-sum compensation scheme leads to a 4.4% increase in the market share for the target banks. The optimal lump-sum also leads to an improvement in consumer welfare.

The key reason that the lump-sum scheme outperforms the other two schemes in gaining market share for the target banks lies in how dealers' compensation aligns with the consumer bargaining power. Intuitively, to attract loans, banks should offer a lower dealer rate (and thus a lower consumer rate) to consumers with a higher bargaining power. Conforming with this intuition, the lump-sum scheme introduces a significant negative correlation between the dealer rate and consumer bargaining power. This negative correlation comes from two facts. First, note that the lump-sum payment does not vary with loan amount, thus the equivalent dealer rate decreases with the loan amount. Second, our estimates suggest that consumers with a larger loan amount tend to have a higher bargaining power. Thus, the lump-sum scheme effectively uses a smaller dealer rate in cases of higher consumer bargaining power, which helps banks achieve a higher market share.

This paper makes contributions on two fronts. From a substantive perspective, we provide

[1] The credit score used in this paper is VantageScore 3.0, developed by the three major credit bureaus in the U.S. (Equifax, Experian, and TransUnion). For details, please see https://your.vantagescore.com/.

[2] One might wonder what would happen if there is an industry-wide regulation of eliminating discretionary dealer compensation. But such a regulatory change would be hard to pass given auto dealers' high lobbying power. See, for example, "With 6 car dealers in Congress, industry revs up horsepower on Capitol Hill," *Center for Public Integrity*, April 2011.

insights on how dealer incentives play an important role in the loans consumers get. This speaks directly to the potential discriminatory issues that have caught sizable attention in the indirect auto lending market. The CFPB sued auto lenders with settlements of hundreds of millions of dollars (see McDonald and Rojc 2016 and Taylor 2018). These actions put banks under pressure to change their dealer compensation practice. We show that by adopting a lump-sum compensation scheme, a bank not only provides consumer protection but also minimizes the impact to its market share. More broadly than auto loans, our insights speak to policy efforts to resolve lending disparity.[3] From a methodology perspective, this paper extends Nash bargaining to the demand estimation of auto loans to capture the role played by dealers. Dealers can heavily influence borrowers' bank choices. We use Nash bargaining to model the joint decision making of both dealers and borrowers. Our modeling framework can be applied to other settings where middlepersons play a substantial role in shaping the consumer demand.

1.1 Literature

This paper is related to several streams of literature. First, it speaks to the literature that investigates potential discrimination in the indirect auto lending market. Previous studies have found that disadvantaged consumers, such as minority consumers, pay a higher dealer markup (e.g., Charles et al. 2008; Hudson et al. 1999; Cohen 2012). Our result that the bargaining power is lower for consumers from regions with larger minority presence is consistent with this finding. Related to auto loans, discriminatory outcomes have also been found in car prices (e.g., Ayres and Siegelman, 1995; Goldberg, 1996). More broadly, our paper is related to prior works that study price negotiation in car dealership (Atefi et al., 2020; Scott Morton et al., 2011). In light of the discriminatory outcomes that arise from the negotiation practices, our paper focuses on non-discretionary compensation schemes that protect consumers. Our structural approach allows us to evaluate the alternative designs of non-discretionary schemes.

Second, this paper bridges the literatures on empirical bargaining and demand estimation. Empirical studies have applied Nash bargaining to model outcomes that arise under the tension of interests between two parties, such as price negotiation (Chen et al. 2008; Jiang 2022; Zhang and Chung 2020; Jindal 2022) and contractual terms in B2B transactions (Draganska et al. 2010; Grennan 2014; Gowrisankaran et al. 2015).[4] A few studies have examined the impact of intermediaries on consumer demand, focusing on salesperson effort (Yang et al. 2019; Roussanov et al. 2021) and quality of service (Kim 2021). However, they neither focus on nor explicitly model the tension between consumers and intermediaries. Our paper contributes to these literatures by extending

[3] See "Fed, Biden Administration Float New Lending Rules for Lower-Income Areas," *Wall Street Journal*, May 2022.

[4] There have been studies extending the theory of Nash bargaining to incomplete information settings (e.g., Myerson 1984). However, we are not aware of empirical applications of the extension.

the application of Nash bargaining to demand estimation where firms' prices must pass through middlepersons to reach consumers.

Third, this paper is related to the literature on retail channel management. Channels can lead to inefficiencies such as double marginalization. A large theoretical literature has studied how to improve the economic efficiency in this setting (e.g., Jeuland and Shugan 1983; Lee and Staelin 1997; Taylor 2002; Cachon and Lariviere 2005). The empirical research is relatively thin, with a handful of papers evaluating vertical price restraints with resale price maintenance (Bonnet et al. 2013; De los Santos and Wildenbeest 2017), two-part tariff contracts (Bonnet and Dubois 2010), and revenue-sharing contracts (Mortimer 2008). Our paper differs from the typical retail channel setting, where the same price or price schedule applies to all consumers. Under the discretionary dealer compensation, the dealer markup and thus the final consumer rate vary across consumers depending on the consumer-dealer negotiation.

The rest of the paper is organized as follows. Section 2 presents the industry background, data and model-free analysis. Section 3 describes the model and the estimation. Section 4 presents the model estimates. Section 5 presents the counterfactuals on dealer compensation. Section 6 concludes.

2 Industry Background and Reduced-Form Data Analysis

2.1 Industry background

We study indirect auto financing where consumers get auto loans from a lender through an auto dealer. In a typical transaction at the auto dealer, the consumer first chooses a car and negotiates on the car price. After that, she will be brought to the finance manager's office to arrange auto financing. The finance manager acts as an intermediary where he submits the consumer information such as the credit score to one or multiple banks (In this paper, we use "banks" in a broad sense to refer to all auto lenders.) A bank quotes an interest rate (i.e., the bank-receiving rate) based on the consumer credit profile and loan characteristics. This bank-receiving rate is also known as the "bank buy rate" since this is the rate that the bank will "buy" the loan from the dealer. Auto dealers get compensated by banks for arranging the loan. The traditional way for banks to compensate dealers is by allowing the latter to add a *discretionary* markup (i.e., the dealer rate) on top of the bank-receiving rate. This markup is added to the final interest rate that the consumer pays (i.e., the consumer rate). In this setting, the final consumer rate is up to the negotiation between the consumer and the finance manager. Note that consumers may or may not actually engage in back-and-forth bargaining with the finance managers at dealers. Price dispersion can come in the form of third-degree price discrimination where the finance managers at dealers make different offers to different types of consumers. See Jiang (2022) who rationalizes price dispersion in loans with heterogeneity in bargaining power.

The above discretionary compensation scheme will inevitably lead to consumers receiving different interest rates even conditional on the same observed credit profile and loan characteristics. Lawsuits were filed claiming this practice resulted in a disparate impact on African American and Hispanic borrowers – a violation of the Equal Credit Opportunity Act. Such lawsuits have a long history, starting in relatively small-scale, sporadic class action lawsuits (e.g., see Munro et al., 2005). The situation changed with the creation of the Consumer Financial Protection Bureau (CFPB) in 2011, by the Dodd-Frank Act after the 2007-2010 financial crisis. The CFPB has jurisdiction over indirect auto lending. CFPB and the Department of Justice had several high-profile cases where they fined or sought restitution from several large auto lenders, alleging that the companies had discriminated in their lending.[5] The CFPB gave several recommendations to indirect auto lenders, including imposing controls on dealer markup and eliminating dealer discretion by using a flat fee per transaction.[6] Under this regulatory environment, industry participants considered alternative dealer compensation schemes.[7] While there was no industry-wide policy banning discretionary dealer markup, several banks (which we refer to as the "target banks") changed how they compensate dealers in response to the regulatory environment. This "limited-scale" policy change at the target banks is the focus of our study.

2.2 Sample construction

Our data covers the periods before and after the change in dealer compensation. We leverage anonymized auto loan data from Equifax Inc., one of the three major credit bureaus in the United States. For data privacy reasons, we cannot report statistics from any single lender. In our empirical application, we mix data from three lenders that switched their dealer compensation scheme (i.e., the "policy change") during the mid 2010s. We refer to them as "target banks." After this policy change, these banks directly set the dealer compensation and thus the consumer rates. Specifically, they adopted a non-discretionary compensation scheme that offers 3 percent of the loan amount to dealers. The exact date of the policy change is different across the three banks. We collect data over a 20-week horizon, 10 weeks before and 10 weeks after the policy for each bank. We denote the time of the loan relative to the date of policy change for that bank (instead of using calendar dates) when combining the data from the three banks together.

Given the 20-week window, we construct a data sample of the target banks and their competing

[5] E.g., "CFPB and DOJ Reach Resolution with Honda to Address Discriminatory Auto Loan Pricing," CFPB (2015). "CFPB and DOJ Order Ally to Pay $80 Million to Consumers Harmed by Discriminatory Auto Loan Pricing," CFPB (2013). "CFPB and DOJ Reach Resolution With Toyota Motor Credit To Address Loan Pricing Policies With Discriminatory Effects," CFPB (2016).

[6] See: files.consumerfinance.gov/f/201303_cfpb_march_-Auto-Finance-Factsheet.pdf

[7] See, e.g., "Some Dealers Prep for Flat Fees," Automotive News (2015).

banks, who did not change their compensation scheme. We refer to these competing banks as the "general banks." The inclusion of general banks is important to characterize the competitive landscape for the target banks. Since we do not directly observe the menu of bank choices for each loan, we rely on geography and pricing to determine the set of general banks. Specifically, we seek to find a group of lenders which operated in the same geographic area and had similar pricing patterns as the target banks before the policy.

For each target bank, we first select the primary counties that it operates in. Specifically, we select counties with at least 5000 loan originated (by all banks) in the pre-policy period, and then select the top counties in terms of the target bank's loan origination so that the resulting data contains at least 30% of the target bank's loans. This relatively small cutoff of 30% ensures that the target bank has a substantial market share in each selected county (also see Appendix A.2 for a robustness check). We combine the selected data across the three target banks.[8] We end up with data from 13 counties, with one target bank in each of these counties.

Next, we identify general banks that are close competitors to the target banks. Generally, banks differ in the consumer segments that they focus on and the pricing strategy across segments. We include in the set of general banks any bank for which: (i) both the average consumer rate and the slope of consumer rate to credit score (in a regression of consumer rate against credit score) are within +/-20% margin of those of the target banks, and (ii) the market share is at least 20% of that of the target banks. This matching process gives us five general banks, all of which are present in all selected counties in our sample. In this sense, we can view each county as a local market, where the target bank in that county competes with the general banks that operate in the same county adopting a similar pricing strategy. We note that ideally, one would want to match on other variables as well (e.g., loan amount and loan length). We choose not to do so for a practical reason: the number of matched general banks is already fairly small. Therefore, we focus on the dimensions that we think are most important (i.e., average consumer rate as well as the slope of consumer rate to credit score).

Finally, because the target banks mainly serve the consumer segments with credit scores above 600, we restrict our analysis to these consumer segments.[9] Ultimately, our data sample includes a total of near 0.18 million loans. For each loan in our sample, we observe loan characteristics including the consumer's credit score, loan amount, loan length, and annual percentage rate (APR). The APR is what we refer to as the consumer rate. Table 1 shows descriptive statistics for the loans over the 20-week period. On average, a consumer borrows about $26.7K for 5.5 years with a 3.4% interest rate. Table 2 breaks down the statistics by the target banks and general banks as well as the credit scores. The overall market share of the target banks is 16.6 percent. Their

[8] Note that we select counties for each target bank before combining data across the target banks. The reason is that the target banks vary in size; selecting counties based on the combined presence of the target banks in each county would drop counties where the smaller target bank has a significant presence.

[9] At the target banks, the share of loans from consumers with below-600 credit scores is only 3.7%.

market share is larger among consumers with prime credit scores, and decreases as we move to the lower-credit segments.[10]

Table 1: Descriptive Statistics

	Mean (1)	25 Percentile (2)	Median (3)	75 Percentile (4)
Credit score	742	699	748	793
Interest rate (i.e., consumer rate)	3.4%	2.6%	3.2%	4.0%
Loan amount ($)	26,678	17,619	24,330	32,873
Loan length (year)	5.5	5.0	6.0	6.0

Table 2: Descriptive Statistics by Banks and Credit Score

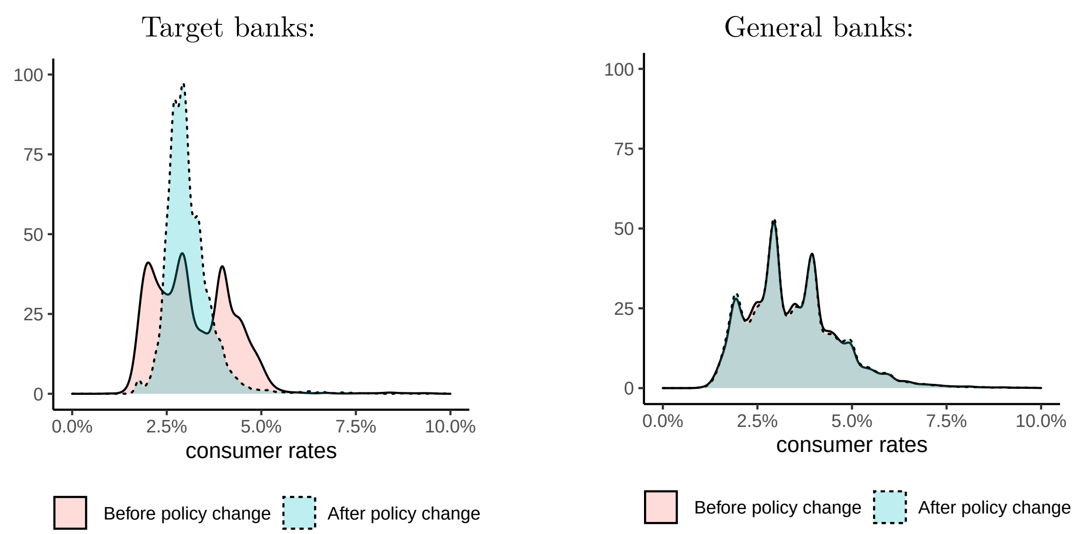
	Number of loans (1)	Market share (2)	Consumer rate (3)	Loan amount ($) (4)	Loan length(year) (5)
Target Banks:					
Overall	30,153	16.6%	3.2%	23,597	5.4
By Credit Score:					
600−650	1,798	12.6%	3.9%	23,945	5.6
651−700	4,757	15.0%	3.5%	24,726	5.6
701−750	7,928	16.9%	3.2%	23,917	5.6
751−800	9,001	17.5%	3.0%	23,330	5.4
801−850	6,669	18.2%	2.8%	22,679	5.2
General Banks:					
Overall	150,950	83.4%	3.5%	27,294	5.5
By Credit Score:					
600−650	12,486	87.4%	4.6%	27,412	5.7
651−700	27,046	85.0%	4.0%	28,155	5.7
701−750	38,974	83.1%	3.5%	27,605	5.6
751−800	42,394	82.5%	3.1%	27,378	5.4
801−850	30,050	81.8%	2.9%	25,947	5.2

[10] One caveat of using the Equifax data is that it does not distinguish indirect auto loans from direct ones that are originated without the dealer involvement. Direct auto loans constitute a relatively small share (estimated to be around 20%; see Cohen (2012)) among all auto loans. Direct auto loans should have a smaller variation in consumer rate (because there is no discretionary dealer markup). To the extent that some direct auto loans are included in our sample, the role of discretionary dealer markup in indirect loans would be even larger than what we have estimated. In this sense, our estimates are conservative in terms of the role of bargaining.

2.3 Reduced-form evidence for dealer incentives

This sub-section presents reduced-form results that motivate our modeling approach (Section 3). We start by showing a direct consequence of the policy: reduction in the dispersion of consumer rates. Before the policy, the target banks gave dealers the discretion over the dealer rate, which could vary across consumers due to not only the observed credit profile and loan characteristics but also other factors unobserved to banks (and researchers), such as race and socio-economic traits. After the policy, dealers no longer had the discretionary power. The left panel of Figure 1 plots the distributions of the consumer rates at the target banks before and after the policy. It shows a substantial drop in the dispersion, a clear demonstration of the impact of the policy. There is no virtually no change in the distribution of consume rates at the general banks (shown in the right panel of Figure 1).

Figure 1: Consumer Rates Distribution before and after Policy



We check whether the result in Figure 1 holds after controlling for covariates that may affect consumer rate. We regress the consumer rate of each loan on the loan amount, loan length, dummies for credit score brackets[11], and county-day fixed effects. Results are shown in Table 3. A larger loan amount and shorter loan length imply a lower consumer rate at both the target and general banks. Importantly, the standard deviation of the residuals from the regression for the target banks is 0.54% after policy, substantially smaller than the 0.97% before the policy. This difference is not seen at the general banks. These results are consistent with Figure 1. We note that the standard deviation of the residuals at the general banks is higher than that at the target banks before policy. This is because general banks are a larger set of banks, and banks always differ somewhat in their

[11]Results are qualitatively unchanged if the credit score is included as a linear term rather than dummies.

pricing strategies. We also note that the coefficients for the loan amount and loan length for the target banks differ considerably before and after policy. The differences can be explained by the impact of the policy change on the dealer compensation. The directions of the coefficient changes are in fact consistent with our later estimates of how the consumer bargaining power relates to the loan amount and loan length (Section 4).

Table 3: Impact of Policy on Consumer Rate Dispersion

Dependent Variable: Consumer Rate (%)				
	Target Banks		General Banks	
	Before Policy	After Policy	Before Policy	After Policy
	(1)	(2)	(3)	(4)
Loan amount ($1000)	-0.02203***	-0.01070***	-0.01216***	-0.01230***
	(0.00089)	(0.00049)	(0.00033)	(0.00032)
Loan length (years)	0.15296***	0.09443***	0.26011***	0.26876***
	(0.01189)	(0.00614)	(0.00514)	(0.00504)
Credit score FE	Yes	Yes	Yes	Yes
County Day FE	Yes	Yes	Yes	Yes
Std. Dev. of Residuals	0.97224	0.54368	1.12031	1.13423
Observations	15,052	15,101	72,753	78,197
R^2	0.26907	0.39810	0.22944	0.23071

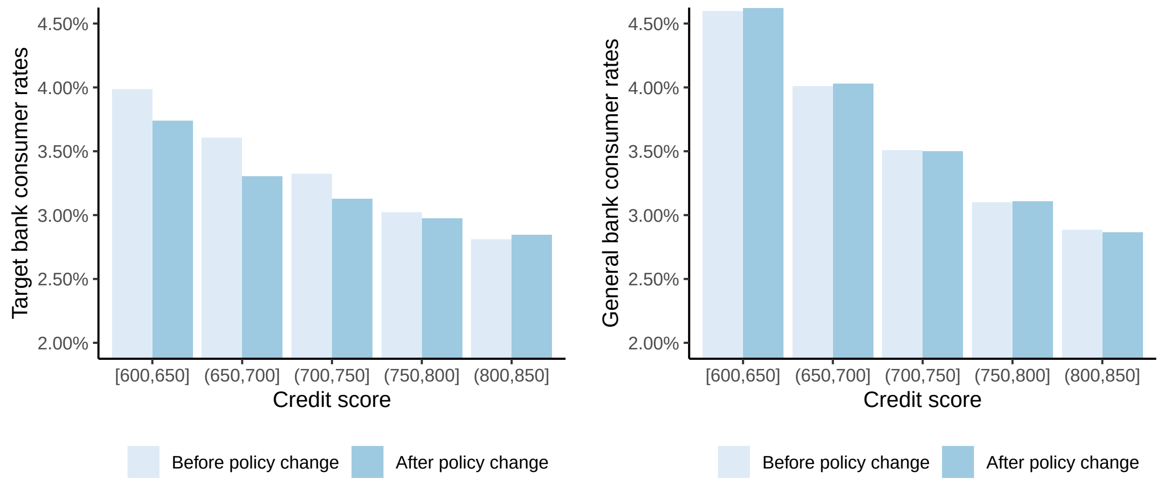
Note: *p<0.1; **p<0.05; ***p<0.01

Next, we look at how the bank choice (i.e. which bank to finance a loan) was affected by the policy. Specifically, we look at the relation between consumer rates and market share of target banks. Because the consumer rate is the "price" that the consumer pays for the loan, this relation essentially represents the demand curve. Figure 2 plots the average interest rate for each credit-score segment before and after the policy. The left plot shows the target banks while the right plot shows the general banks. We see that at the target banks the average interest rate decreased in lower-credit segments (below 750), and increased slightly in higher-credit segments (above 800). This pattern, however, is absent at the general banks – the average interest rate for each credit score segment remained mostly unchanged after the policy. Recall that the policy was implemented only by the target banks. Figure 2 suggests that there were no strategic responses from the general banks, at least during the short period (10 weeks) after the policy. It also suggests that there was no major industry-level or macroeconomic changes that coincided with the time of the policy change.

Given the changes in consumer rates shown in Figure 2, one would expect the market share of target banks to increase in lower-credit segments and decrease in higher-credit segments. This, however, is not what we observe in the data. Figure 3 plots the market share of target banks by credit score segments, before and after the policy. The market share actually decreased in lower-credit segments (below 750) and increased for high-credit segments (above 800). In other words,

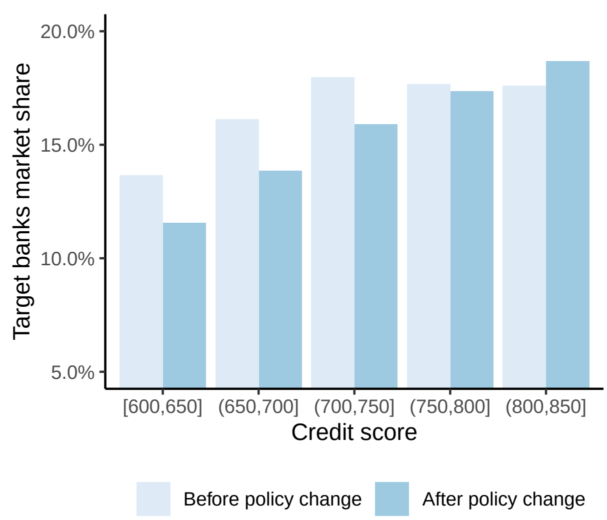
Figure 2: Average Consumer Rate before and after Policy by Credit Score

Target banks: General banks:



the changes in market share had *the same direction* as the changes in price – a reversal of demand curve. Taking all segments together, the target banks' market share decreased from 17.1% to 16.2% after the policy.

Figure 3: Target Banks' Market Share before and after Policy by Credit Score



We further test whether the patterns in Figures 2 and 3 hold if we control for covariates that may affect interest rates and market share. First, we estimate the impact of the policy on consumer rates using the following regression:

$$r_i = \sum_s \eta_s \cdot C_{i,s} \cdot Target_i \cdot Policy_i + \sum_s \rho_s \cdot C_{i,s} \cdot Target_i + \boldsymbol{\beta}' \boldsymbol{X}_i + \epsilon_i,$$

where r_i is the observed consumer rate for loan i, $C_{i,s}$ is a credit-score dummy that equals 1 if the consumer belongs to credit bracket s, $Target_i$ is a dummy indicating whether loan i is financed by target banks, $Policy_i$ is another dummy indicating if loan i is originated after the policy, and finally $\boldsymbol{X}_i$ is a vector of other controls including the credit bracket dummies. Coefficient ρ_s captures the consumer rate difference between the target and general banks in segment s. Coefficient η_s is of our main interest and it captures the consumer rate change at the target banks after the policy in segment s. The left side of Table 4 shows the regression results. We see that η_s is significantly negative for lower-credit segments (below 750) and significantly positive for high-credit segments (above 800). This is consistent with Figure 2.

Table 4: Impact of Policy Change on Consumer Rates and Target Banks' Market Share

	Consumer Rate (%)			Choose Target Banks	
	(1)			(2)	
η_s: Target banks post policy			ϕ_s: Post policy		
Credit 600-650	-0.2178***	(0.0511)	Credit 600-650	-0.0134**	(0.0060)
Credit 651-700	-0.2783***	(0.0317)	Credit 651-700	-0.0167***	(0.0040)
Credit 701-750	-0.1571***	(0.0248)	Credit 701-750	-0.0168***	(0.0033)
Credit 751-800	0.0033	(0.0234)	Credit 751-800	0.0008	(0.0032)
Credit 801-850	0.0847***	(0.0270)	Credit 801-850	0.0144***	(0.0037)
ρ_s: Target banks					
Credit 600-650	-0.6395***	(0.0362)			
Credit 651-700	-0.4424***	(0.0227)			
Credit 701-750	-0.2337***	(0.0180)			
Credit 751-800	-0.1551***	(0.0174)			
Credit 801-850	-0.1245***	(0.0206)			
$\boldsymbol{\beta}$:			$\boldsymbol{\gamma}$:		
Loan amount ($1000)	-0.0465***	(0.0007)	Loan amount ($1000)	-0.0041***	(0.0002)
Loan amount^2	0.0005***	(1e-5)	Loan amount^2	2e-5***	(3e-6)
Loan length (years)	-0.8955***	(0.0219)	Loan length (years)	0.1549***	(0.0073)
Loan length^2	0.1192***	(0.0022)	Loan length^2	-0.0146***	(0.0007)
Credit score FE	Yes		Credit score FE	Yes	
County FE	Yes		County FE	Yes	
Observations	181,103			181,103	
R^2	0.2383			0.0821	

Note: *p<0.1; **p<0.05; ***p<0.01

We then run a regression to quantify the impact of the policy on the market share of target banks in each credit score segment. Let $Target_i$ be a dummy variable indicating whether loan i is financed by target banks. The regression is specified as follows:

$$Target_i = \sum_s \phi_s \cdot C_{i,s} \cdot Policy_i + \boldsymbol{\gamma}' \boldsymbol{X}_i + \epsilon_i,$$

where $Policy_i$, and $C_{i,s}$ are defined in the same way as before, and $\boldsymbol{X}_i$ includes a list of control variables including the credit bracket dummies. The main coefficient of interest is ϕ_s, which shows the change in the market share in credit segment s after policy. The right side of Table 4 displays the results. We see that ϕ_s is significantly negative for the lower-credit segments (below 750) and significantly positive for high-credit segments (above 800). This is consistent with Figure 3.

How can we rationalize the reversal of demand curve? In indirect auto lending, a dealer acts as the middleperson that brokers loan arrangements. Therefore, dealers can play an important role in the bank choice by recommending different options to different consumers. After the policy, the target banks fixed the compensation for dealers (3 percent of loan amount), but competing general banks were still offering dealers the discretion to vary their markups. When serving consumers that usually present more room for discretionary markups, such as consumers with low credit scores (Davis and Frank 2011), dealers would prefer financing loans through the general banks. Therefore, despite reducing consumer rates in low-credit segments, the policy actually led to a decrease in the market share for the target banks in these segments. The opposite is true for high-credit consumers, who usually present less room for discretionary markups.

In Appendix A.1, we replicate the above pattern but with respect to minority presence (using zip-code level demographics). We find that after the policy, the consumer rates decreased among minority consumers at the target banks. However, the target banks' market share also decreased among these consumers. This result indicates that, though the policy change by the target banks was intended to help minority consumers, the impact was weakened by the role of dealers in loan allocation.

Overall, our reduced-form results show that dealers' influence has a considerable impact on consumers' bank choices in the auto lending market. Thus, it is crucial for auto lenders as well as policy makers to take the incentives of both consumers and dealers into account when designing policies in this market. This calls for a modeling approach different from standard demand models where choices are made solely by consumers. We do so in Section 3.

The dealers' influence creates a conundrum for the target banks: their overall market share decreased after the policy, which not only weakened the impact of the policy but also hurt their profits and competitiveness in the industry. This motivates us to explore alternative compensation schemes that can help increase the target banks' market share while preserving the non-discretionary feature for consumer protection. We do so in Section 5.

3 Model and Estimation

We take a consumer's need for a specific auto loan, in terms of loan amount and length, as given. Conditional on these loan characteristics and consumer characteristics, our model describes the determination of consumer rate as well as bank choice (i.e., whether the target banks or general banks are chosen to finance the loan). We think this assumption is reasonable because the need for loan largely depends on the car price, which is usually determined prior to the negotiation on financing (see Section 2.1).

We first describe how the consumer rate is determined given a bank choice. The consumer prefers as low a rate as possible. In contrast, the dealer prefers a higher markup. Given this tension, we model the consumer rate as a bargaining outcome between the two parties, unless the bank directly dictates the rate (i.e., post-policy target banks). The outcome depends on the relative bargaining power between the consumer and dealer. A disadvantaged consumer (with a low bargaining power) will have to pay an interest rate higher than others conditional on credit profile and loan characteristics. The dispersion in consumer rates, which we have documented in Section 2, can be partly attributed to the heterogeneity in the bargaining power.

Next, we consider the choice between the general banks and target banks (see Section 2.2 for details on why and how we construct these two groups of banks). The dealer and consumer may prefer different banks. Thus, we model the bank choice as a bargained outcome between the two parties. The choice therefore depends on the respective preferences as well as the relative bargaining power of the two parties. The bargaining model helps us rationalize the reversed demand curve for the target banks documented in Section 2.3.

3.1 Interest rates

We first describe how consumer rates are determined *before* the policy. We use subscript t to denote the target banks and g to denote the general banks. In reality, banks set the bank-receiving rate to maximize their profit, taking account of the default risk and competition. Given that the focus of our analysis is the dealer-consumer interaction, we use a reduced-form approximation to specify how the bank-receiving rate is determined based on consumer and loan characteristics. For banks j ($j = t$ or g), the bank-receiving rate for loan i is given as

$$c_{i,j} = \exp\left(\boldsymbol{x}_i'\boldsymbol{\alpha}_j + \varepsilon_{i,j}\right), \tag{1}$$

where $\boldsymbol{x}_i$ includes consumer credit profile and loan characteristics. The exponential function is to ensure a non-negative bank-receiving rate. Note that parameters $\boldsymbol{\alpha}_j$ are bank-specific, as such the target bank and general banks may price loans differently. The idiosyncratic term $\varepsilon_{i,j}$ is assumed to follow a normal distribution $\varepsilon_{i,j} \sim \mathcal{N}(0, \sigma_j^2)$.

We use $r_{i,j}$ to denote the consumer rate if banks j is chosen for the loan. Before the policy,

$r_{i,j}$ is an outcome of the Nash bargaining between the consumer and the dealer. Let R_i denote an interest rate ceiling for consumer i, and we specify the bargaining process as splitting the surplus of $R_i - c_{i,j}$. We specify R_i as the lowest bank-receiving rate that consumer i can obtain in the market plus a margin $\bar{R}$ that is fixed across consumers. That is, $R_i = \min_j\{c_{i,j}\} + \bar{R}$.[12] The dealer's payoff from the bargaining is how much he or she marks up the interest rate: $v_{i,j} = r_{i,j} - c_{i,j}$. This $v_{i,j}$ is also the dealer rate. The consumer's payoff from the bargaining is $u_{i,j} = R_i - r_{i,j}$. Note the sum of the consumer and dealer payoffs is always $R_i - c_{i,j}$, the surplus.

Formally, the Nash bargaining solution satisfies

$$(u_{i,j}, v_{i,j}) = \text{argmax}_{(u,v)} \left\{ u^{\omega_i} v^{1-\omega_i} \right\}, \quad \text{subject to: } u + v = R_i - c_{i,j}, \tag{2}$$

where ω_i is the bargaining power of the consumer. Note that we assume the disagreement point to be $(0, 0)$. Our data does not allow us to separately identify the disagreement point and the bargaining power. For example, if a consumer has a higher disagreement payoff, the consumer will be able to obtain a lower interest rate. This will be captured by a higher bargaining power when we estimate the model.

The maximization problem in (2) implies:

$$u_{i,j} = \omega_i(R_i - c_{i,j});$$
$$v_{i,j} = (1 - \omega_i)(R_i - c_{i,j}).$$

The consumer rate implied by this bargaining solution is

$$r_{i,j} = c_{i,j} + v_{i,j} = (1 - \omega_i)R_i + \omega_i c_{i,j}. \tag{3}$$

This expression is intuitive. It says that when the consumer bargaining power ω_i increases, the consumer rate $r_{i,j}$ moves closer to $c_{i,j}$, and consequently the consumer's payoff becomes larger while the dealer's payoff becomes smaller.

Bargaining power ω_i is a key component in our model that contributes to the dispersion of consumer rates. We allow ω_i to be heterogeneous across consumers, as a function of $\boldsymbol{x}_i$ that includes the credit score and loan characteristics, plus an unobserved component $\varepsilon_{i,\omega}$. Specifically, let $\mathbb{L}$ denote the logistic function, we specify

$$\omega_i = \mathbb{L}(\boldsymbol{\lambda}'\boldsymbol{x}_i + \varepsilon_{i,\omega}),$$

[12] $\bar{R}$ needs to be set at a value high enough that the observed consumer rate is always below the upper bound R_i. In the model estimation, we set $\bar{R} = 12\%$ because almost all loans have consumer rates below 12%. With this choice of $\bar{R}$, the probability for $c_{i,j}$ to be larger than R_i is virtually zero at our parameter estimates. The main results of the paper are not sensitive to the choice of $\bar{R}$.

The logistic function ensures that ω_i stays between 0 and 1. We assume $\varepsilon_{i,\omega} \sim \mathcal{N}(0, \sigma_\omega^2)$. This residual component captures factors unobserved to researchers, such as the consumer's patience, negotiation skill, and knowledge about the loan market, that can help the consumer to negotiate a better deal. If $\varepsilon_{i,\omega}$ is associated with race, gender, and other socio-economic variables, it may lead to discriminatory rates for consumers. These discriminatory rates constituted the CFPB's concern (see Section 1 and 2).

We now describe how consumer rates are determined *after* the policy. We assume that the target and general banks continue to charge the same bank-receiving rates as specified in equation (1) after the policy. One may be concerned that, as the target banks switch to a different dealer compensation scheme, they may also adjust how they set the bank-receiving rate. We discuss this concern and provide supporting evidence for our assumption in Section 3.3. Another concern is that the general banks may adjust their rates in response to the target banks' policy. However, such adjustment, if any, likely would take time, and we examine only a short post-policy period (10 weeks). In the data, the consumer rates at general banks stayed virtually the same after the policy (see Section 2.3), suggesting little response from the general banks.

If choosing the general banks, consumers and dealers bargain on the interest rate in the same way as before (the policy was implemented only by the target banks). This is described by the bargaining problem in equation (2). If choosing the target banks, consumers and dealers no longer bargain on the interest rate. Instead, the policy compensates dealers with a fixed 3% of the loan amount. The consumer rate then equals the bank-receiving rate plus the dealer rate equivalent to this compensation. Let $\tilde{v}_{i,t}$ denote this equivalent dealer rate, T_i the loan length in months, and M_i the loan amount. Using the standard monthly payment formula for loans, we can approximate $\tilde{v}_{i,t}$ as the solution of

$$\frac{\tilde{v}_{i,t}/12}{1-(1+\tilde{v}_{i,t}/12)^{-T_i}} \cdot M_i \cdot T_i = 1.03 \times M_i. \tag{4}$$

In the above, the left hand side equals the sum of the monthly payments for the loan that is to be paid off at an annual rate of $\tilde{v}_{i,t}$. It can be shown that $\tilde{v}_{i,t}$ is decreasing in T_i. That is, the equivalent dealer rate is smaller for longer loans. However, $\tilde{v}_{i,t}$ is invariant to the loan amount M_i.

Given the equivalent dealer rate, the consumer rate if borrowing from the target banks in the post-policy period is

$$r_{i,t} = c_{i,t} + \tilde{v}_{i,t}. \tag{5}$$

As a result, the payoffs for the consumer and the dealer are

$$u_{i,t} = R_i - r_{i,t} = R_i - (c_{i,t} + \tilde{v}_{i,t}), \tag{6}$$

$$v_{i,t} = \tilde{v}_{i,t}. \tag{7}$$

Note that the bargaining power ω_i no longer enters the consumer rate or payoffs.

3.2 The bank choice

So far, we have described the determination of interest rate given the bank choice (i.e., target vs. general banks). Next, we describe the bank choice. We first consider only financial incentives (i.e., interest rates), then we add the potential influence of non-financial factors (e.g., existing relations with consumers, bank-dealer networks).

Before the policy, the feasible set of payoffs that combines the options offered by the target banks and general banks is

$$\{(u,v) : u+v \leq R_i - c_{i,g}\} \cup \{(u,v) : u+v \leq R_i - c_{i,t}\}.$$

This a union of two feasible sets. The first set is provided by the general banks, where the consumer and dealer divide a "pie" of size $R_i - c_{i,g}$. The second set is provided by the target banks, where the consumer and dealer divide a "pie" of size $R_i - c_{i,t}$. Note that we write the constraints as inequalities (rather than equalities) as in a typical formulation of Nash bargaining problems, but the bargaining solution will always have the constraints binding.

The bank choice is modeled as the outcome of a Nash bargaining game between the dealer and consumer. The bargaining outcome maximizes $u^{\omega_i} \cdot v^{1-\omega_i}$, or equivalently, $\omega_i \log(u) + (1-\omega_i)\log(v)$, subject to the combined feasible set. To more easily characterize this outcome, let us define $W_{i,j}$, $j \in \{t, g\}$, as follows.

$$W_{i,j} \equiv \omega_i \log u_{i,j} + (1-\omega_i) \log v_{i,j},$$

where (u_{ij}, v_{ij}) denotes the point that maximizes $u^{\omega_i} \cdot v^{1-\omega_i}$ within banks j's feasible set. Note that (u_{ij}, v_{ij}) has been described in Section 3.1. Intuitively, $W_{i,j}$ is a bargaining-power weighted average of the consumer and dealer's payoffs. The party with a higher bargaining power has her payoff weighted more. The bargaining solution, which maximizes $u^{\omega_i} \cdot v^{1-\omega_i}$ over the combined feasible set, resides in the target banks' feasible set if $W_{i,t} > W_{i,g}$ and resides in the general banks' feasible set if $W_{i,t} < W_{i,g}$. In other words, the bank choice can be characterized by a simple comparison between $W_{i,t}$ and $W_{i,g}$ (without considering non-financial factors).

After the policy, the combined feasible set becomes

$$\{(u,v) : u+v \leq R_i - c_{i,g}\} \cup \{(u,v) : u \leq R_i - (c_{i,t} + \tilde{v}_{i,t}) \text{ and } v \leq \tilde{v}_{i,t}\}.$$

The first set above is provided by the general banks, and the second set is provided by the target banks, which directly set the dealer's compensation and consumer rate.[13] We can define $W_{i,j}$ in the same way as above for $j \in \{t, g\}$, and the target banks is chosen if $W_{i,t} > W_{i,g}$.

Some discussion can be made on the tension between dealer and consumer implied by the above

[13]The bargaining problem here is not standard because the combined set may not be convex. However, one can apply the result in Zhou (1997) on bargaining over non-convex set; if a solution for a non-convex feasible set satisfies IIA, INV, and a variation of PO, then it must be in the form of a Cobb-Douglas function.

model on the bank choice, and particularly how this tension differs before and after the policy. For the pre-policy period, from Section 3.1 we know $v_{i,j} = (1-\omega_i)(R_i - c_{i,j})$ and $u_{i,j} = \omega_i(R_i - c_{i,j})$ for $j \in \{t, g\}$. It is not difficult to see that, in this case $c_{i,t} < c_{i,g}$ implies $W_{i,t} > W_{i,g}$. In other words, the dealer and the consumer would both prefer the banks with a lower bank-receiving rate. The bargaining power ω_i effectively plays no role in the bank choice in the pre-policy period. However, this is not the case for the post-policy period.

In the post-policy period, the dealer and the consumer may prefer different banks. For example, as the consumer bargaining power ω_i decreases, the dealer obtains a larger bargained payoff $v_{i,g} = (1-\omega_i)(R_i - c_{i,g})$ from the general banks, and consequently a smaller payoff $u_{i,g} = \omega_i(R_i - c_{i,g})$ is left for the consumer. However, at the target banks, $v_{i,t} = \tilde{v}_{i,t}$ and $u_{i,t} = R_i - (c_{i,t} + \tilde{v}_{i,t})$ do not change with ω_i. As a result, dealers tend to prefer to have general banks financing the loans for consumers with low-bargaining power, even though these consumers are better off with loans from the target banks.

In addition to the above financial payoffs, there is evidence in data that there exist other non-financial factors that influence the bank choice. For example, Table 2 shows that, compared to the general banks, the target banks charge significantly lower interest rates in low-credit segments, while the interest rates in high-credit segments are about the same as general banks. However, the target banks' market share in low-credit segments is significantly lower than in other segments. Potential reasons include that the target banks focus more on marketing to high-credit segments, they have better existing customer relationship with high-credit consumers, and the general banks have more extensive dealer networks accessing lower-credit consumers.

These non-financial factors are hard to model in a structural way and also unobservable to us; therefore, we choose to model these factors in a reduced-form fashion as follows. Let $\boldsymbol{z}_i$ collect the dummies for credit brackets. For $j \in \{g, t\}$, let

$$V_{i,j} = W_{i,j} + \boldsymbol{\delta}_j' \boldsymbol{z}_i. \tag{8}$$

The target banks is chosen iff $V_{i,t} > V_{i,g}$. Because only the difference $V_{i,t} - V_{i,g}$ matters, we normalize $\boldsymbol{\delta}_g = 0$ and estimate $\boldsymbol{\delta}_t$ only. Thus, the effects of the non-financial factors are captured as a function of consumer credit segments. For example, suppose the general banks have stronger relationships with the low-credit segments, then this will be reflected by a negative coefficient in $\boldsymbol{\delta}_t$ in front of the low credit bracket. The non-financial factors are assumed to stay the same before and after the policy. This is a reasonable assumption because we focus on a relatively short time period before and after the policy change.

3.3 Model estimation

We estimate our model using the method of simulated moments (MSM, McFadden 1989). The estimation algorithm matches model-predicted loan outcomes (consumer rate and bank choice) with the observed outcomes in the data. We do not use maximum likelihood estimation (MLE) because although one can use simulations to evaluate the likelihood for bank choices (which are discrete), it is difficult to do so for interest rates (which are continuous). With any finite number of simulations, the probability of simulating the exact interest rate observed for any individual loan is always zero.

We now describe how we construct the moment conditions. Let $y_i \in \{0,1\}$ denote whether the target banks is chosen to finance loan i and r_i denote the consumer rate for loan i. Both y_i and r_i are observed in the data. Our model specifies the conditional distribution $P(y_i, r_i|\boldsymbol{x}_i)$. We can evaluate various moments of this distribution through simulations. To draw a pair (y_i, r_i), we first draw the unobservables $\varepsilon_{i,t}$, $\varepsilon_{i,g}$, and $\varepsilon_{i,\omega}$. These unobservables, together with $\boldsymbol{x}_i$, determine the bank-receiving rates $c_{i,g}, c_{i,t}$, and the consumer's bargaining power ω_i. Then, we compute $r_{i,g}$, $r_{i,t}$, and y_i according to the model. The final consumer rate is given by $r_i = y_i r_{i,t} + (1-y_i) r_{i,g}$. We construct several "prediction errors." The first error considers the bank choice:

$$\zeta_{i,1} = y_i - \mathbb{E}\left(y_i|\boldsymbol{x}_i\right).$$

The second and third errors consider the consumer rate at the target banks (for $y_i = 1$) and general banks (for $y_i = 0$), respectively:

$$\begin{aligned}
\zeta_{i,2} &= y_i r_i - \mathbb{E}(y_i r_i|\boldsymbol{x}_i), \\
\zeta_{i,3} &= (1-y_i) r_i - \mathbb{E}\left[(1-y_i) r_i|\boldsymbol{x}_i\right].
\end{aligned}$$

To estimate the variance parameters σ_g, σ_t, and σ_ω, we need to use the second moments of consumer rates. Accordingly, we compute the fourth and fifth error terms:

$$\begin{aligned}
\zeta_{i,4} &= y_i r_i^2 - \mathbb{E}(y_i r_i^2|\boldsymbol{x}_i), \\
\zeta_{i,5} &= (1-y_i) r_i^2 - \mathbb{E}\left[(1-y_i) r_i^2|\boldsymbol{x}_i\right].
\end{aligned}$$

Let vector $\boldsymbol{\zeta}_i$ collect these five error terms. By construction, we have $\mathbb{E}(\boldsymbol{\zeta}_i|\boldsymbol{x}_i) = 0$, a mean independence condition from which one may use to construct moment conditions. Following the identification argument which we give below, we use the following sets of moment conditions for estimation:

$$\text{(i)}\ \mathbb{E}(\boldsymbol{x}_i\zeta_{i,1}) = \mathbf{0},\ \text{(ii)}\ \mathbb{E}(\boldsymbol{x}_i\zeta_{i,2}) = \mathbf{0},\ \text{(iii)}\ \mathbb{E}(\boldsymbol{x}_i\zeta_{i,3}) = \mathbf{0},\ \text{(iv)}\ \mathbb{E}(\zeta_{i,4}) = 0,\ \text{(v)}\ \mathbb{E}(\zeta_{i,5}) = 0.$$

For conditions (i), (ii), and (iv) that involve the target banks, we require them to hold for both the pre-policy and post-policy periods, respectively.

A detail in estimation is that a small change in the parameters may flip the bank choice y_i between 0 and 1. As a result, the MSM objective function is not smooth, which makes optimization difficult. To this end, we smooth the simulated bank choice in the model by the kernel-smooth method (Geweke and Keane 2001; Honka 2014).

We conduct a Monte Carlo exercise by fixing the "true" model parameters and simulate loan outcomes. We then use the simulated data to estimate the model. We find that our estimation algorithm does a good job recovering the true parameters. We include the details in Appendix A.3.

3.4 Identification

We discuss the identification of model parameters. A key issue in the identification is to separate the bank-receiving rate and bargaining power. Without observing bank-receiving rates (which is typical in studies of auto loans), identifying the bargaining power is challenging because a high consumer rate can be explained by either low consumer bargaining power or a high bank-receiving rate. We leverage the policy change to address this challenge. Below, we first describe the identification argument, and then discuss the assumptions used in the argument.

We first discuss the identification of the target banks' pricing parameter $\boldsymbol{\alpha}_t$. The dealer rates at the target banks post policy are known because they can be directly calculated from the 3-percent compensation rule. Then, the bank-receiving rates at the target banks post policy can be obtained by subtracting the dealer rates from the observed consumer rates. This allows us to identify the target banks' pricing parameter. We have assumed that target banks did not change how they price their receiving rates after implementing the policy (at least during the short 10 weeks period), therefore the bank-receiving rates at the target banks before the policy are known too (up to a residual term). The dealer rates at the target banks before the policy can then be obtained by subtracting the bank-receiving rates from the observed consumer rates.

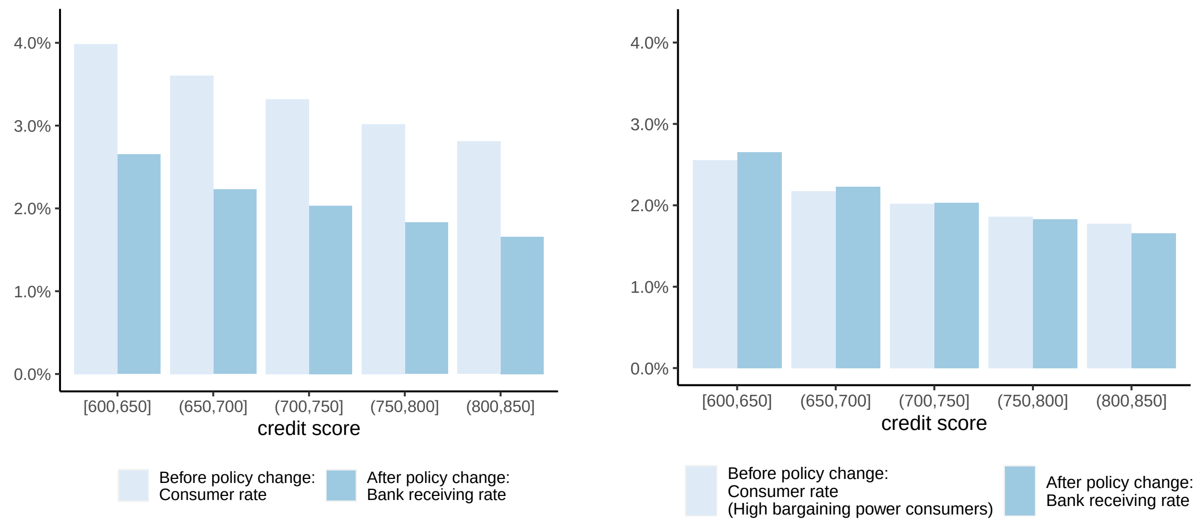
Next, we discuss the identification of the bargaining power parameter $\boldsymbol{\lambda}$. By the above argument, we know the dealer rates at the target banks before and after the policy. In addition, the consumer rates are directly observed from data. Therefore, we know how the consumers' and dealers' preferences towards the target banks changed from before to after the policy. The bargaining power is then identified from the change in the target banks' market share after the policy. For example, if the policy granted some consumers a better rate but dealers a worse rate, but the market share from these consumers decreased, then we know these consumers have a low bargaining power. This identification argument is closely related to the "reversed demand curve" shown before (Figure 3). The target banks' policy led to the largest reduction in consumer rate in low-credit segments, yet the target banks' market share in these segments decreased the most. This data pattern tells us that low-credit consumers tend to have a lower bargaining power.

Lastly, we discuss the identification of the general banks pricing parameter $\boldsymbol{\alpha}_g$ as well as the non-financial factors $\boldsymbol{\delta}_t$. With the bargaining power identified, we know the split of surplus between the dealer and consumer. So we know the dealer rates and subsequently the bank-receiving rates at the general banks. This allows us to identify the general banks pricing parameter $\boldsymbol{\alpha}_g$. With pricing from both the general and target banks identified, the level of market share before the policy allow us to identify the effects of non-financial factors $\boldsymbol{\delta}_t$, which explain the market share of the target banks before the policy beyond what could be explained by bank-receiving rates. For example, in the low-credit segments, the market shares for the target banks are low despite having lower bank-receiving rates than the general banks. This data pattern before the policy tells us that the general banks have a better reach to low-credit segments.

The above identification strategy relies on two key assumptions. The first assumption is that the target banks made no changes to how they set their bank-receiving rates after the policy. We believe this assumption is reasonable as we study a fairly short time window after the policy (10 weeks). Although this assumption is not directly testable due to the bank-receiving rates being unobserved in the data, we find some empirical support for the assumption. Specifically, note that the target banks' receiving rates can be calculated from the data and the policy in the post-policy period, but not so in the pre-policy period. However, one way to approximate the pre-policy bank receiving rates is using the pre-policy consumer rates for the consumers with *high-bargaining power*. This is because a high bargaining power implies a small gap between the consumer rate and bank-receiving rate. We carry out this idea in Figure 4. The left graph displays the average pre-policy consumer rate (lighter-colored bars) and post-policy bank-receiving rate (darker-colored bars) for every credit bracket at the target banks. We see significant differences between the lighter and darker bars, which is expected. However, the differences become very small as we move to the right graph, where the lighter bars restrict attention to loans with the lowest decile of the consumer rates after controlling for loan terms and credit score (Specifically, we regress consumer rates on loan terms and credit score, then use the loans in the lowest decile of the residual value). These loans were likely taken by very high-bargaining-power consumers who had consumer rates close to the bank-receiving rates. This comparison in Figure 4 supports the assumption that the target banks did not change how they set the bank-receiving rates after implementing the policy.

The second assumption is that the choice set of each loan includes both the target banks and the general banks selected in our sample. This assumption would fail if the general and target banks cater to very different consumer segments. This concern is partly addressed by parameter $\boldsymbol{\delta}_t$ in equation (8). If, for example, the target banks focus less on low-credit segments, then the coefficients in $\boldsymbol{\delta}_t$ for low-credit segments will be more negative than those for high-credit segments. To further alleviate this concern, when constructing data we include a bank in the "general banks" group only if it operates in the same county and have a similar pricing strategy as the target banks (see Section 2.2 for more details). Therefore, these general banks are likely close competitors to the target banks and thus appear in the choice set together with the target banks.

Figure 4: Did Target Banks Change How They Set Bank-receiving Rates?



4 Results

In this section, we first present the estimates of the model. These estimates tells us how both the bank-receiving rates and the consumer's bargaining power vary with consumer credit profile and loan characteristics. We then investigate the "residual" part of bargaining power that is unexplained by credit profile or loan characteristics, particularly how it relates to demographics such as race and socio-economic status.

4.1 Parameter Estimates

Table 5 presents the parameter estimates. The table first shows how the target and general banks set the bank-receiving rates by consumer credit profile and loan characteristics. For both banks, the rates increase with loan amount and length, and decrease with consumers' credit scores. Typically, a longer loan and a larger loan amount are associated with a higher default risk. Compared with the general banks, the target banks are less aggressive in raising the rate for lower credit scores.

Next, the table shows the estimates for consumers' bargaining power. The bargaining power is positively associated with the credit score and loan amount, and is negatively associated with the loan length. These results are consistent with Davis and Frank (2011), an auto-dealer survey which finds that the consumers who: (i) have a lower credit score, (ii) borrow a smaller loan, or (iii) carry a longer loan, typically pay a higher dealer markup. We also find our estimates intuitive. First, a consumer getting a large loan is typically willing to spend more time (or more patient in) seeking for a lower interest rate. Given the large loan, she may also spend more time researching the loan market before visiting the dealer. These all translate into a higher bargaining power. Second,

Table 5: Parameter Estimates

	Estimates	S.E.
General banks receiving rate $\boldsymbol{\alpha}_g$:		
Constant	-2.3722	(0.1373)
Loan amount	0.0084	(0.0006)
Loan length	0.0183	(0.0137)
Credit score	-0.2217	(0.0159)
Target banks receiving rate $\boldsymbol{\alpha}_t$:		
Constant	-3.6035	(0.2573)
Loan amount	0.0292	(0.0012)
Loan length	0.0174	(0.0270)
Credit score	-0.1305	(0.0168)
Bargaining power $\boldsymbol{\lambda}$:		
Constant	0.5457	(0.3806)
Loan amount	0.0965	(0.0099)
Loan length	-0.4482	(0.0604)
Credit score	0.2926	(0.0411)
Non-financial factors $\boldsymbol{\delta}_t$:		
600-650	-0.2122	(0.0148)
651-700	-0.1625	(0.0109)
701-750	-0.1228	(0.0085)
751-800	-0.0962	(0.0076)
801-850	-0.0823	(0.0074)
General banks pricing sd: $\log(\sigma_g)$	-0.8462	(0.0301)
Target banks pricing sd: $\log(\sigma_t)$	-1.1201	(0.0958)
Bargaining power sd: $\log(\sigma_\omega)$	-0.6350	(0.0891)

Note: Loan amount in \$1000. Loan length in years. Credit score in 100.

consumers with a higher credit score typically have better access to alternative financial resources, which will also translate to a higher bargaining power. Lastly, with everything else equal, a longer loan duration typically indicates a consumer with weaker financial resources (thus unable to pay off the loan quickly). This translates into a weaker bargaining power.

Next, the table shows the effects of non-financial factors. The negative estimates across all credit-score brackets indicate that the target banks are less likely to be chosen than the general banks overall. This result is expected, because the general banks are a composite of more and relatively larger banks, and thus likely have a more extensive dealer network than the target banks. The coefficient estimates for the higher credit score brackets are less negative. Indeed, the target banks primarily marketed to the higher-credit consumer segments.

The last rows display the estimated standard deviations for the residual terms. The estimate for σ_g is substantially larger than that for σ_t. This result is expected because the general banks are a composite of more banks each of which may adopt a somewhat different rule when setting bank-receiving rates. It is also consistent with the data pattern that the dispersion of consumer rates at the general banks is larger than that at the target banks (see Table 2).

With the model estimates, we can back out the dealer compensation before the policy at target banks. We find that the average dealer compensation per loan before and after the policy are fairly close. Specifically, the average estimated dealer rate per loan is 1.01% before the policy and 1.11% after the policy. If expressed as a percentage of loan amount, the estimated dealer compensation is 2.87% of loan amount before the policy, which is close to the 3% of loan amount dealer compensation after the policy. This suggests that the target banks tried to keep the average dealer compensation unchanged when they implemented the policy. However, the policy inevitably led to a change in the distribution of dealer compensation across different consumer segments. Under our model, this distributional change will have an impact on the target banks' overall market share (as we see in the data) because of the differential bargaining power across consumer segments.

4.2 Bargaining power and interest rate dispersion

The estimated model allows us to separate the two sources of consumer rate dispersion: (i) differences in bank-receiving rates across loans, and (ii) the heterogeneity in bargaining power across consumers. We compare the model-predicted dispersions of consumer rates with and without the heterogeneity in bargaining power at the target banks before the policy. For the scenario without heterogeneity, we set the bargaining power equal to its average value across all consumers. The comparison indicates that about 50% of the dispersion (in terms of variance) in consumer rates comes from the bargaining power.

Further, we investigate the contribution of $\varepsilon_{i,\omega}$ to the dispersion in consumer rates. Note that $\varepsilon_{i,\omega}$ represents the "residual" bargaining power unexplained by consumer credit profile and loan characteristics. For example, if minority consumers are likely to receive a higher consumer rate conditional on credit profile and loan characteristics under the discretionary compensation scheme, it is explained by these consumers having a lower $\varepsilon_{i,\omega}$ in the model. We compare the model-predicted dispersions in consumer rates under two scenarios − with and without the residual bargaining power. For the latter scenario, we set σ_ω to zero so that $\varepsilon_{i,\omega}$ is zero for all consumers. The comparison indicates that 37% of the dispersion in consumer rates comes from the residual bargaining power, which is rather substantial.

Overall, the above results are consistent with the reduced-form pattern that the dispersion of consumer rate at the target banks dropped significantly after they adopted the non-discretionary dealer compensation (see Figure 1). The results support the argument that discretionary dealer markups are a major source for consumers being charged different interest rates and resulted in disadvantaged consumers (with lower bargaining power) paying higher interest rates.

4.3 Bargaining power and discrimination

We investigate to what extent the heterogeneity in the residual bargaining power is associated with demographics. If the heterogeneity significantly relates to demographics, one should be concerned that certain consumer groups are disadvantaged in the negotiation with dealers, and non-discretionary dealer compensations should be favored.

For each consumer i in the data, we compute the best estimate for $\varepsilon_{i,\omega}$ given the data and model: $\widetilde{\varepsilon}_{i,\omega} \equiv \mathbb{E}(\varepsilon_{i,\omega}|y_i, r_i, \boldsymbol{x}_i)$.[14] We do not have the demographic information at the individual consumer level. Thus, we regress $\widetilde{\varepsilon}_{i,w}$ on the demographics at the zip code of consumer i. Table 6 shows the results. We see that consumers tend to have a lower residual bargaining power if they live in a zip code with a larger proportion of African American or Hispanic population, a lower median household income, or a lower rate of college education. The results on the African American and Hispanic populations indicate that minority groups were indeed disadvantaged in the bargaining process. This is consistent with the alleged disparate impact on African American and Hispanic borrowers in the CFPB lawsuits.

Table 6: How Residual Bargaining Power Relates to Demographics

	Dependent Variable $\widetilde{\varepsilon}_{i,\omega}$
African American population percentage	-0.0540***
	(0.0055)
Hispanic population percentage	-0.0687***
	(0.0048)
Median household income	0.0110***
	(0.0041)
College education percentage	0.0749***
	(0.0156)
Constant	0.0130***
	(0.0029)
Observations	177,593
R^2	0.00321

There is, however, a caveat in interpreting our results. The residual bargaining power may reflect systematic differences in the number of dealers in a region. If some areas have very few dealers that consumers can get to, then dealers are more likely to have an upper hand in bargaining, all else equal. For example, we find that consumers living in a zip code with a large proportion of minorities tend to have a lower residual bargaining power. This can happen either because minority

[14] This best estimate is evaluated via simulations. We draw 1000 points of the residual terms in the model $(\varepsilon_{i,t}, \varepsilon_{i,g}, \varepsilon_{i,\omega})$ and for each point compute the bank choice and consumer rate given the observed characteristics $\boldsymbol{x}_i$. We select the points with same bank choice and similar consumer rates as those observed in data. We use the average of $\varepsilon_{i,\omega}$ across these selected points as an estimate for $\widetilde{\varepsilon}_{i,\omega}$.

consumers are less skilled in bargaining, or because minority consumers live in regions with fewer dealers. Without data on the number of dealers across regions, we cannot separate the two cases. However, either case implies a lower bargaining power, which our model estimates capture.

5 Counterfactual compensation schemes

Based on the estimation results, we use counterfactuals to explore the impacts of alternative dealer compensation schemes on consumer rates and target banks' market share. The goal is to improve the target banks' market share while maintaining the non-discretionary feature in the compensation scheme.

One might wonder what will happen if there is an industry-wide regulation of eliminating discretionary dealer compensation. However, such a regulatory change would be hard to pass given auto dealers' high lobbying power. In addition, the counterfactual analysis of such an industry-wide change is unlikely complete without analyzing a new equilibrium where banks compete on both the dealer compensation and bank-receiving rates. Our model does not go so far to specify such an equilibrium. Thus, we focus our counterfactual on the design of non-discretionary compensation schemes for the target banks.

We focus on non-discretionary compensation schemes, which removes the dispersion in consumer rates due to dealer-consumer bargaining. We note that these compensation schemes may still result in certain groups of consumers being charged higher interest rates. For example, if minority consumers statistically have lower credit scores, an interest rate based on credit score will be systematically higher for minority consumers. Our focus in this exercise is to ensure consumer protection in the sense that the consumer rates are based solely on the credit profile and loan characteristics, and not on personal traits (e.g., race, gender, age) that dealers may observe and use under the discretionary compensation scheme.

Specifically, we consider three relatively simple non-discretionary compensation schemes, described below. It is possible that more complex schemes can perform better than these schemes. For example, the banks can specify a formula of compensation that combines the elements of these three schemes. However, such schemes may be less well understood by dealers. More importantly, focusing on simpler schemes allows us to more clearly isolate the key intuition for our counterfactual results. We also note that though these schemes differ in how each calculates the dealer compensation, the compensation can always be distributed as a one-time payment to the dealer right after the sale of the car.

1. *Fixed percentage of loan amount*: the target banks pay dealers a fixed percentage of the loan amount. This compensation scheme follows the policy implemented by the target banks. In the counterfactual, we allow the level of compensation (in percentage of loan amount) to be different from the implemented 3%.

2. *Fixed dealer rate*: the target banks compensate dealers by a fixed dealer rate. The consumer rate will be equal to the bank-receiving rate plus the dealer rate. This scheme follows from the pre-policy context, where dealers are compensated by an interest rate markup. So the only required change with this scheme is to fix the markup cross loans instead of letting it be at the discretion of dealers for each loan.

3. *Fixed lump-sum*: the target banks pay dealers a fixed lump sum payment (e.g., $400) for each loan, regardless of the loan terms. This compensation scheme is in the CFPB's initial recommendation for lenders.[15] This compensation scheme is also straightforward to implement.

Neither the data or estimates tell us the profit margin for each loan. Thus we do not attempt to optimize the bank-receiving rates. Instead, we keep the pricing of bank-receiving rates unchanged at its estimates (equation 1). Given this, we focus on maximizing the market share for the target banks. Specifically, we simulate the consumer rate and bank choice of every loan in the post-policy data and then aggregate the choices to obtain the target banks' market share. For each compensation scheme, we numerically search for the optimal percentage of the loan amount, dealer rate, or the lump-sum payment that maximizes the market share for the target banks. We average results across 100 simulations, each under a set of parameters drawn from the estimated parameter distribution.

Table 7 compares the market outcomes under the optimized schemes. As a benchmark, we also report the market outcomes under the adopted scheme (i.e. 3% of loan amount) as given by the model simulation. For comparison across schemes, we convert both the lump-sum compensation and the compensation in percentage of loan amount to equivalent dealer rates (see Section 3.1 for the conversion formula). For example, suppose a loan is $20,000 and is to be paid off in 5 years. Then, paying the dealer a 1% interest rate amounts to paying her $512. Thus, for this loan, both a lump-sum of $512 and 2.56% of the loan amount have an equivalent dealer rate of 1%.

Column 1 of the table reports the optimal compensation under each of the three compensation schemes. Under the fixed percentage of loan amount scheme, we find the optimal compensation to be 2.79% of the loan amount. This is slightly lower than the implemented 3% of loan amount but the difference is not statistically significant. Under the fixed dealer rate scheme, the optimal compensation is a dealer rate of 1.07%. Under fixed lump-sum scheme, the optimal compensation is $543.3 per loan. Column 2 reports the equivalent dealer rates (averaged across all loans) at the target banks. The equivalent dealer rates under the three optimized schemes are very close, and all of them are slightly lower than the equivalent dealer rate under the adopted 3%-of-loan-amount scheme. Consequently, consumers under all these three counterfactual compensation schemes will

[15] The recommendation reads: "[lenders should] eliminate dealer discretion to mark up buy rates and fairly compensating dealers using another mechanism, such as a flat fee per transaction, that does not result in discrimination." See https://files.consumerfinance.gov/f/201303_cfpb_march_-Auto-Finance-Bulletin.pdf

Table 7: Market Outcomes at Target Banks by Compensation Scheme

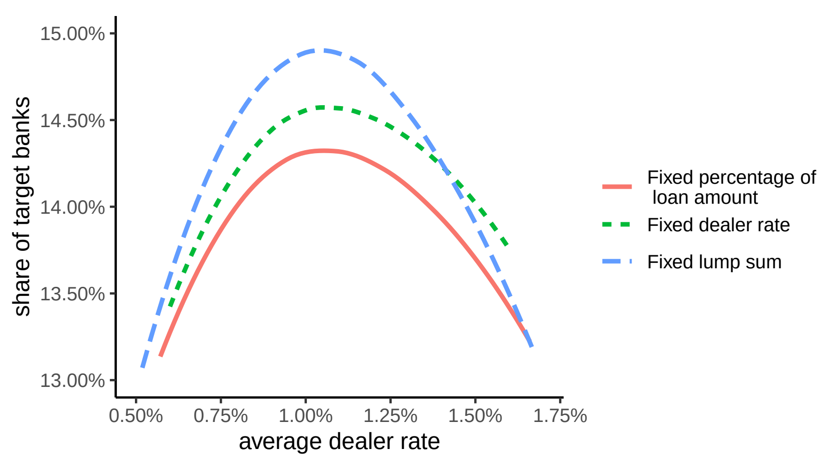
	Optimal Compensation (1)	Equiv. Dealer Rate (2)	Consumer Rate (3)	Market Share (4)	Increase in Market Share (5)
3% of loan amount		1.12%	3.08%	14.34%	-
		(0.005%)	(0.09%)	(2.43%)	
Fixed % of loan amount	2.79%	1.05%	3.01%	14.42%	0.54%
	(0.33%)	(0.12%)	(0.16%)	(2.46%)	(0.62%)
Fixed dealer rate	1.07%	1.07%	3.03%	14.64%	2.14%
	(0.12%)	(0.12%)	(0.16%)	(2.48%)	(0.62%)
Fixed lump-sum	\$543.3	1.05%	3.05%	14.98%	4.44%
	(\$61.5)	(0.11%)	(0.16%)	(2.57%)	(0.72%)

Note: Numbers in parentheses are standard errors.

pay slightly lower consumer rates than under the adopted scheme, as reported in Column 3.

Column 4 shows the market shares. We see that the lump-sum scheme gives the target banks the highest market share, at 14.98%. This represents a 4.44% ($= 14.98/14.34 - 1$) increase from the adopted scheme, as shown in the last column. The increase is statistically significant. To visually compare the three non-discretionary schemes, in Figure 5 we plot their market share curves under the parameter point estimates. We see that the optimality of the lump-sum scheme holds over a fairly wide range of equivalent dealer rates. Finally, we note that so far we have calculated market shares based on the number of loans. In Appendix A.4, we provide a robustness check where we calculate market shares based on the total loan amount. Again, the lump-sum scheme leads to the highest market share.

Figure 5: Market Share by Compensation Schemes



5.1 Why lump-sum scheme achieves a higher market share?

Why does the lump-sum scheme achieve a higher market share for the target banks? The key reason lies in *how to best align the dealer rate with the bargaining power.* To attract loans, banks should offer a lower dealer rate (and thus a lower consumer rate) to consumers with a higher bargaining power. Among the three schemes, the lump-sum scheme introduces a significant negative correlation between the equivalent dealer rate and consumer bargaining power. This is shown in the right plot of Figure 6, which displays the average dealer rate at the target banks within each quartile of consumer bargaining power. With this negative correlation, the lump-sum scheme passes a lower rate to consumers when their bargaining power is high, and thus the target banks gain a larger market share.

Figure 6: Relation between Dealer Rate and Consumer Bargaining Power

Why does the lump-sum scheme result in the negative correlation in the right plot of Figure 6? It comes from two facts. First, under the lump sum scheme, the equivalent dealer rate decreases with the loan amount. (To see this, note that for any given dealer rate, the dollar payment to the dealer doubles as the loan amount doubles. Thus, if we fix the dollar payment, the dealer rate must decrease as the loan amount increases.) Second, our estimation results show that the loan amount is positively associated with consumer bargaining power (see Table 5). Actually, loan amount is a stronger predictor for bargaining power than credit score and loan length. Together, these two facts imply that the lump-sum scheme uses a lower dealer rate in cases of higher consumer bargaining power, thus the negative correlation.

The fixed-dealer-rate scheme uses a constant dealer rate across loans. As a result, there is no correlation between the dealer rate and bargaining power, as shown in the middle plot of Figure 6. The percentage-of-loan-amount scheme varies the dealer rate across loans, which suggests a correlation between the dealer rate and bargaining power. However, the correlation turns out to be close to zero, as shown in the left plot of Figure 6. This result is due to two countering factors. Under the percentage-of-loan-amount scheme, the equivalent dealer rate decreases with loan length, which in itself is negatively associated with consumer bargaining power (see Table 5). However, there is a positive correlation between loan length and loan amount in the data, and as mentioned above, loan amount is strongly positively associated with consumer bargaining power. The close-to-zero correlation is a result of these two factors offsetting each other.

5.2 Is there still discrimination?

The adopted compensation scheme (3%-of-loan-amount) as well as the proposed lump-sum compensation both remove dealers' discretion to mark up the interest rate. The discretion allows dealers to charge consumers beyond credit profile and loan characteristics, which is captured by the residual bargaining power $\varepsilon_{i,\omega}$ in our model. As a result, consumer rates may systematically differ by $\varepsilon_{i,\omega}$. (Also see Section 4.3 which shows how $\varepsilon_{i,\omega}$ relates to zip-code level presence of minority population.) Below, we check whether such systematic differences are eliminated under the lump-sum scheme.

Consumers with a low $\varepsilon_{i,\omega}$ have a low bargaining power beyond what can be explained by loan characteristics and consumer credit profile. Dealers can observe it and use it under the discretionary compensation regime, which causes disadvantaged consumers with a low $\varepsilon_{i,\omega}$ to pay a higher consumer rate. Because the fixed lump-sum scheme implies that the equivalent dealer rate varies by the consumer bargaining power, as shown in Figure 6, one may be concerned that the discriminatory practice may still exist among dealers under this compensation scheme. To address this concern, we simulate three different dealer compensation schemes: the discretionary compensation scheme, the 3%-of-loan-amount scheme, and the optimal lump-sum scheme. We examine how consumer rates at target banks vary with $\varepsilon_{i,\omega}$ under these schemes.

Table 8 reports the consumer rates in different quartiles of $\varepsilon_{i,\omega}$ in our simulations. Under discretionary compensation (Column 1), the average consumer rate is 3.97% for the bottom quartile, about 50 percent higher than the 2.60% for the top quartile. This difference is due to the dealers charging a higher markup on consumers with lower residual bargaining power. The difference disappears under either the 3%-of-loan-amount scheme (Column 2) or the lump-sum scheme (Column 3). In particular, compared to the discretionary scheme, rates are reduced for consumers with low residual bargaining power (who are more likely to be minority consumers). Consumer rates no longer differ systematically by the residual bargaining power. In this sense, discriminatory interest rates are eliminated.

With regard to the lump-sum scheme, one may wonder how to reconcile the result here (i.e., consumer rate is flat with respect to *residual* bargaining power) with the result in Figure 6 (i.e., dealer rate correlates with bargaining power). The two results do not conflict each other, as the *residual* bargaining power is only a part of the bargaining power unexplained by credit profile and loan characteristics. The lump-sum scheme removes the correlation between dealer rate and *residual* bargaining power that exists in discretionary scheme. But unlike the other non-discretionary

Table 8: Consumer Rates at Target Banks by Residual Bargaining Power

Quartiles of residual bargaining power $\varepsilon_{i,\omega}$	Discretionary (pre-policy) (1)	3% of loan amount (post-policy) (2)	Lump-sum payment (proposed policy) (3)
Top 25%	2.60%	3.09%	2.91%
	(0.13%)	(0.10%)	(0.11%)
25−50%	2.93%	3.09%	2.91%
	(0.15%)	(0.10%)	(0.11%)
50−75%	3.29%	3.10%	2.91%
	(0.18%)	(0.11%)	(0.11%)
Bottom 25%	3.97%	3.10%	2.91%
	(0.22%)	(0.10%)	(0.11%)

schemes, it still gives a correlation between dealer rate and bargaining power that benefits the target banks' market share. In this sense, one may view the lump-sum scheme essentially as a compromise between the discretionary compensation and the adopted policy.

5.3 Impact by credit score segments

In Table 7 we have compared, in aggregate, the proposed lump-sum scheme and the adopted compensation scheme (3% of loan amount). How does this comparison vary across different credit segments? Table 9 breaks down the consumer rates and market share of the target banks for each credit score segment under the adopted scheme (Columns 1-2) and the proposed scheme (Columns 3-4). The last column displays the relative changes between the two schemes. As to the consumer rates, we see very little changes in the high-credit segments and slight decreases in the low-credit segments. All the changes, however, are statistically insignificant. As to the market shares, we see increases across all credit segments, with larger and significant increases in the higher-credit segments. To see the implication on consumer welfare, we also note that under the proposed scheme, the consumer rates at the target banks are no higher than the general banks in all credit segments, and lower in the low-credit segments (not reported in the table). Together, these results suggest that compared to the adopted scheme, the proposed scheme does not reduce the consumer welfare in the high-credit segments and improves the consumer welfare in low-credit segments.

What are the intuitions behind the results in Table 9? The larger market share increases in the higher-credit segments come not from the switch of compensation scheme but from the optimization of the degree of compensation.[16] Our estimates indicate a relatively high level of consumer bargaining power overall, which implies that optimally banks should offer less dealer compensation regardless of the compensation scheme (also see Table 7). A lower level of dealer

[16]In fact, the result that the market share increases more in the higher-credit segments also holds if we compare the adopted scheme with the optimal percentage-of-loan-amount scheme.

Table 9: Consumer Rate and Market Share at Target Banks by Credit Segments

	3% of loan amount		Optimal lump-sum			
	Consumer Rate	Market Share	Consumer Rate	Market Share	Consumer Rate Change	Market Share Change
	(1)	(2)	(3)	(4)	(5)	(6)
All consumers:	3.08%	14.34%	3.05%	14.98%	-1.06%	4.44%
	(0.09%)	(2.43%)	(0.16%)	(2.57%)	(3.40%)	(0.72%)
By credit segment:						
600-650	3.50%	11.23%	3.42%	11.45%	-2.37%	2.05%
	(0.12%)	(2.21%)	(0.17%)	(2.19%)	(2.75%)	(2.29%)
651-700	3.35%	12.70%	3.28%	13.15%	-2.14%	3.62%
	(0.11%)	(2.23%)	(0.16%)	(2.26%)	(2.85%)	(1.59%)
701-750	3.14%	14.56%	3.10%	15.17%	-1.40%	4.20%
	(0.10%)	(2.46%)	(0.16%)	(2.54%)	(3.18%)	(1.59%)
751-800	2.98%	15.30%	2.96%	16.09%	-0.48%	5.07%
	(0.09%)	(2.61%)	(0.16%)	(2.81%)	(3.18%)	(0.95%)
801-850	2.85%	15.29%	2.86%	16.09%	0.12%	5.15%
	(0.08%)	(2.52%)	(0.16%)	(2.78%)	(3.89%)	(2.48%)

compensation dis-incentivizes dealers, but with a smaller effect in the higher-credit segments where consumers have higher bargaining power. This leads to more market share increases in the higher-credit segments. As to the consumer rates, the slightly larger decreases in the lower-credit segments are due to the difference between the two compensation schemes. The adopted scheme pegs the dealer compensation to loan amount, while the lump-sum scheme does not. In the data, lower-credit consumers tend to have a larger loan amount. Thus, the dealer rates in the lower-credit segments decrease more as we switch from the percentage-of-loan-amount to lump-sum scheme.

5.4 Long-term implication

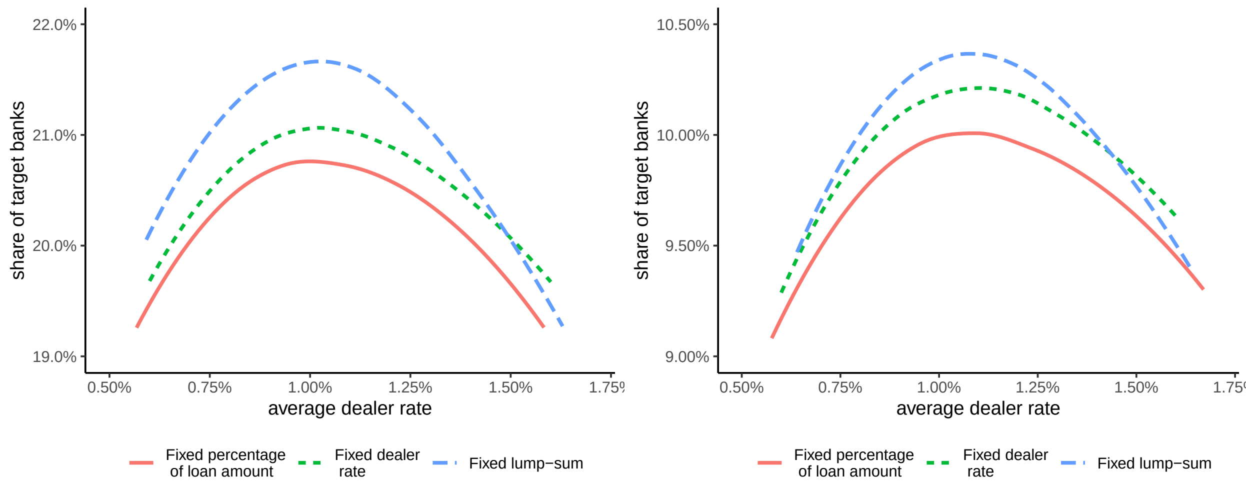
Our analysis focuses on data in a relatively short window (20 weeks total) before and after the policy. This allows us to assume that the bank-receiving rates stay unchanged. However, one may wonder whether our counterfactual finding stays robust in the longer term when bank-receiving rates change. We address this question by re-conducting our counterfactual analysis under scenarios where the target banks change their receiving rates.

We re-conduct the analysis in Figure 5. Specifically, we take the estimated bank-receiving rates at the target banks and increase (or decrease) them by 20% for each loan. Then, we simulate the market share of the target banks under the three non-discretionary compensation schemes: fixed percentage of loan amount, fixed dealer rate, and fixed lump-sum. Results are shown in Figure 7. We see that the fixed lump-sum compensation scheme still achieves a higher market share than the other two schemes. The patterns are consistent with that in Figure 5.

Figure 7: Market Share by Compensation Schemes under Different Bank-Receiving Rates

Target Banks' Receiving Rates - 20%

Target Banks' Receiving Rates + 20%



To summarize, though our model does not prescribe how the bank-receiving rates will change in the long term, the main counterfactual result of the paper is robust to changes in bank-receiving rates and thus likely to hold in the long run. Intuitively, this is because the key mechanism that makes the lump-sum compensation better – the dealer rate better aligns with the bargaining power – continues to hold even when the bank-receiving rates change.

6 Conclusion

This paper provides an empirical framework to investigate how final prices and consumer demand are formed when firms rely on middlepersons to reach consumers. Placing emphasis on the tension of interest between middlepersons and consumers, we adopt Nash bargaining to model the interaction between the two parties. The model explains a reversal of demand curve in the auto loan market, observed after a non-discretionary dealer compensation scheme was introduced by several banks to replace the original discretionary compensation scheme. By focusing on this limited-scale policy change, we are able to pin down the relative bargaining power in the dealer–consumer interactions that determine the interest rate and bank choice. The estimated model enables us to evaluate alternative non-discretionary compensation schemes.

This paper has important managerial implication for indirect auto lending. Under the commonly adopted practice of dealer compensation, dealers are given the discretion to mark up consumer rates on a loan-by-loan basis. Such practice allows room for discriminatory consumer rates. The CFPB, together with DOJ, took several legal actions against auto lenders, alleging that certain consumers (e.g., minority consumers) were systematically paying higher interest rates even under the same credit profile and loan characteristics. Consistent with these claims, we show that the residual bargaining power in our model differs systematically across consumers, and in particular is lower for consumers living in neighborhoods with higher minority presence.

While the adopted policy removed the dealer's discretion and subsequently discriminatory consumer rates, it also affected dealer incentives, resulting in a lower market share for the banks that adopted the policy. Our study on the alternative compensation schemes proposes a fixed lump-sum compensation scheme. It eliminates discriminatory rates while helping banks retain their market share as much as possible. As of now, we are not aware of such a compensation scheme used in the auto loan market. The adopted policy pegs compensation to the loan amount, possibly due to the intuitive thinking to reward dealers for bringing in larger loans. However, our model estimates show that larger loans typically indicate more bargaining power on the consumer side, which suggests banks limit the dealer compensation and pass lower interest rates to consumers on larger loans. This reasoning renders a fixed lump-sum payment a better option among non-discretionary compensation schemes in terms of capturing market share.

There are limitations of this research that can be addressed in future studies. First, we do not observe dealer information on the loans. It will be very interesting to see how dealer characteristics relate to the relative bargaining power in addition to consumer characteristics. Second, by focusing on a short period after the policy, we assume there were no adjustments in bank-receiving rates. Optimal pricing of bank-receiving rates under different compensation schemes is out of the scope of this paper. However, data with additional information on the lending costs of banks can enable future research to explore this topic. Third and related, we do not attempt to prescribe equilibria where banks compete strategically. Thus, we refrain from evaluating wider policies, e.g., all banks are required to adopt non-discretionary compensation. An understanding of the pricing behavior with respect to bank-receiving rates may enable future research in this direction.

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A Appendix

A.1 Reduced-form results in respect of minority presence

In Section 2.3, we focus on credit score segments to demonstrate the role of dealers in the indirect auto lending market. In this appendix, we replicate results in Section 2.3 but in respect of minority consumers. Unlike credit score, we do not observe the demographics of consumers at the individual loan level. Thus, we approximate them with zip-code level demographics. We focus on the percentage of African American plus Hispanic population (as provided by the Census).

We separate loans into four quartiles of minority presence at the zip code level. The presences in the four quartiles are below 8.0%, 8.0-16.9%, 16.9%-33.4%, and 33.4% or above, respectively. The left plot of Figure 8 compares, within each quartile, the average consumer rates at the target banks before and after the policy. It shows that the average consumer rate decreased more in areas with higher minority presence. The right plot makes the same comparison but at the general banks, where the average consumer rates remained mostly unchanged in all quartiles.

Figure 8: Average Consumer Rate before and after Policy by Minority Presence

Target banks: General banks:

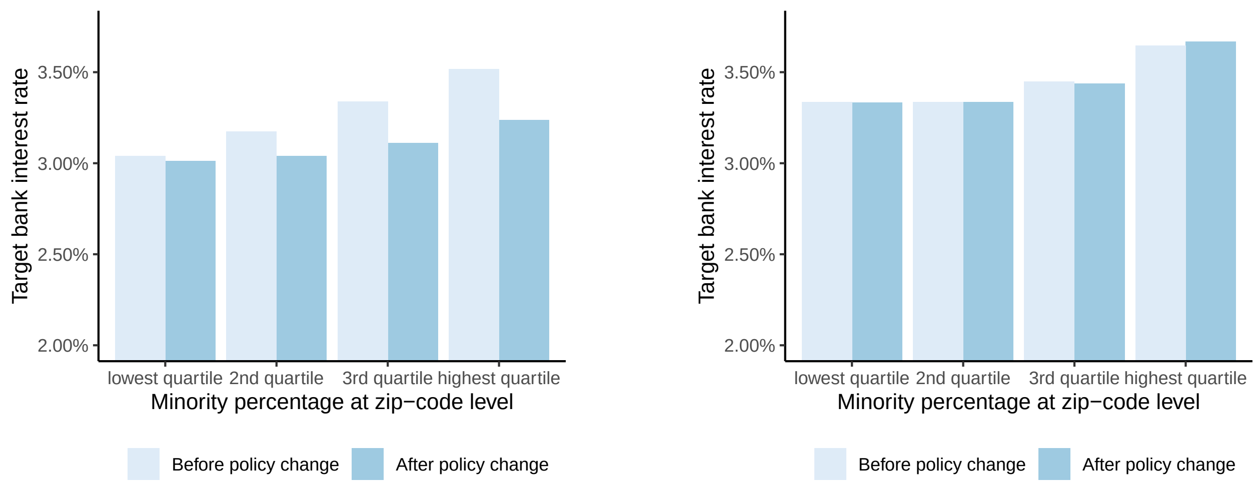
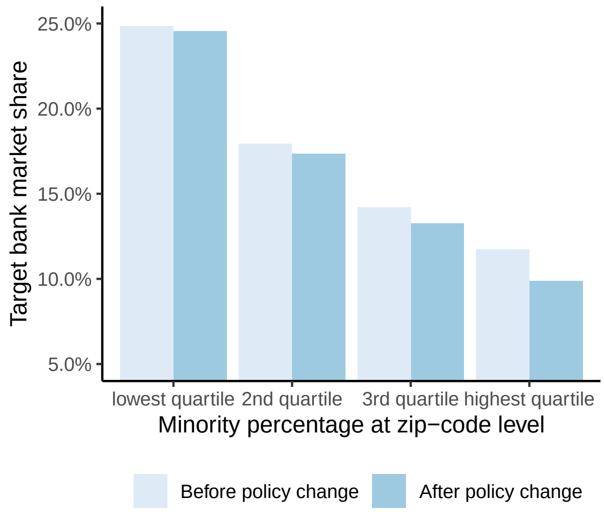


Figure 9 plots the target banks' market share before and after the policy. Consistent with Section 2.3, we see a reversed demand curve. The market share decreased more in areas with higher minority presence, where also saw larger drops in consumer rate. The intuition is similar to that given in Section 2.3. After the policy, dealers have an incentive to push low-bargaining-power consumers to the general banks where they can get a high discretionary markup, which leads to a lower market share for the target banks among these consumers despite the lower consumer rates.

We further show that the patterns presented in Figures 8 and 9 continue to hold after controlling for covariates that may affect the consumer rates and market share. We use the same specifications in Section 2.3 with the exception that subscript s now denotes the quartiles of minority presence (instead of the credit segments). Table 10 shows the regression results. The sample size is slightly smaller than that in Table 4 because 0.7% of the observations miss zip code level demographic information. We see that η_s is significantly

Figure 9: Target Banks' Market Share before and after Policy by Minority Percentage



negative for areas with high minority presence. We also see that ϕ_s is significantly negative for areas with high minority presence. These results are consistent with what we have learned from Figure 8 and 9.

To summarize, we find that after the policy, the consumer rates indeed decreased among minority consumers at the target banks. However, despite the lower consumer rates, the market share of the target banks decreased among these consumers. This result indicates that, though the policy by the target banks was intended to help minority consumers, the impact was weakened by the influence of dealers in loan allocation.

A.2 Robustness check on sample construction

A.2.1 County selection

For the analysis in the main body of the paper (i.e., the main analysis), we construct the data sample to focus on the main markets that the target banks operate in. This is done by selecting the top counties in terms of the target banks' loan origination. In this appendix, we no longer select the top counties, and instead use all the counties where there was any loan from the target banks during our sample period. We end up with 324 counties (instead of 13 counties used in the main analysis).

We re-plot Figure 2 and 3 using this larger sample. Results are shown in Figure 10. (We omit the plot for the consumer rates at the general banks, which again shows no differences before and after the policy). At the target banks after the policy, the consumer rates decreased in low-credit segments, but the market share decreased in these segments. This shows a reversal of demand curve. For the top credit score consumers (>800), the consumer rate increased and the market share decreased. However, the drop in market share is the smallest compared to the other segments despite the largest increase in consumer rate.

Thus, the pattern still points to a substantial role of dealers in loan allocation. Note that the larger sample includes counties where the target banks had almost no presence. Because the paper leverages the policy change by the target banks, it seems sensible for us to focus on areas where the target banks have a

Table 10: Impact of Policy on Consumer Rates and Target Banks' Market Share by Minority Presence

	Consumer Rate (%)			Choose Target Bank	
	(1)			(2)	
η_s: Target banks post policy			ϕ_s: Post policy		
1st quartile	0.0280	(0.0212)	1st quartile	0.0528***	(0.0026)
2nd quartile	-0.0414*	(0.0249)	2nd quartile	0.0042	(0.0026)
3rd quartile	-0.1431***	(0.0279)	3rd quartile	-0.0243***	(0.0026)
4th quartile	-0.2112***	(0.0315)	4th quartile	-0.0545***	(0.0026)
ρ_s: Target banks					
1st quartile	-0.3358***	(0.0154)			
2nd quartile	-0.2812***	(0.0178)			
3rd quartile	-0.2070***	(0.0200)			
4th quartile	-0.0889***	(0.0217)			
$\boldsymbol{\beta}$:			$\boldsymbol{\gamma}$:		
Loan amount ($1000)	-0.0465***	(0.0006)	Loan amount ($1000)	-0.0041***	(0.0002)
Loan amount^2	4.5e-4***	(1e-5)	Loan amount^2	2e-5***	(3e-6)
Loan length (years)	-0.9065***	(0.0220)	Loan length (years)	0.1504***	(0.0072)
Loan length^2	0.1203***	(0.0021)	Loan length^2	-0.0139***	(0.0007)
Credit score FE	Yes		Credit score FE	Yes	
County FE	Yes		County FE	Yes	
Observations	179,778			179,778	
R^2	0.2343			0.0875	

Note: *p<0.1; **p<0.05; ***p<0.01

non-trivial presence (as we did in the main analysis).

A.2.2 Matched general banks

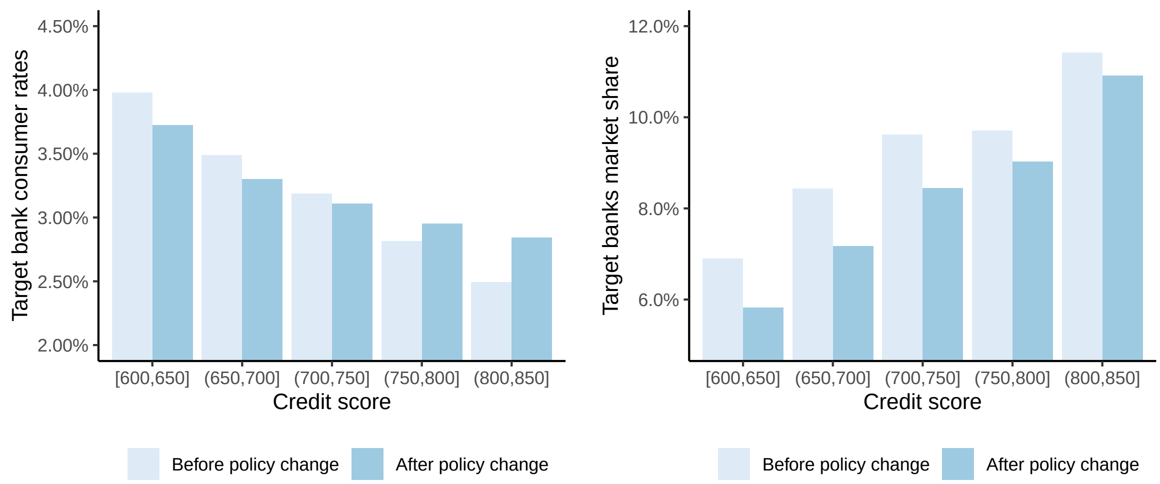
In the main analysis, we identify the general banks who are likely competitors to the target banks using their pricing strategy and size. We use a margin of +/-20% for the matching (see Section 2.2). In this appendix, we construct two alternative samples by varying the margin of matching. We show that our the main results continue to hold under these alternative samples.

Relaxed margin of matching (+/-30%) We relax the margin for matching from +/-20% to +/-30%. This leads to eight matched general banks in the sample (instead of the five general banks in the main analysis).

We re-plot Figure 2 and 3 using this larger sample. Results are shown in Figure 11. (We omit the plot for the consumer rates at the general banks, which again shows no differences before and after the policy). At the target banks after the policy, the consumer rates decreased in low-credit segments, but the market share decreased in these segments. The consumer rate increased for the top credit segment (>800), but the

Figure 10: Consumer Rate and Market Share at Target Banks by Credit Score before and after Policy, with All Counties

Consumer Rates: Market Share:



market share increased in this segment. The pattern here is consistent with that in our main analysis.

We re-estimate the model using the alternative sample. The estimates are shown in Table 11. They are qualitatively consistent with the main analysis. For both banks, the bank-receiving rates increase with loan amount and length and decrease with credit score. The consumer bargaining power is positively associated with the credit score and loan amount, and is negatively associated with the loan length.

Figure 11: Consumer Rate and Market Share at Target Banks by Credit Score before and after Policy, with More General Banks

Consumer Rates: Market Share:

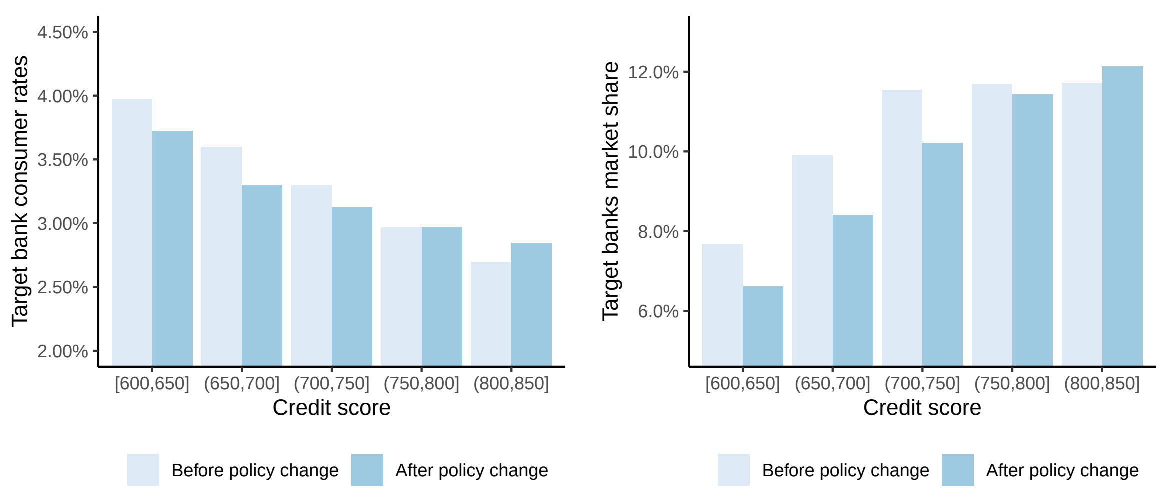


Table 11: Parameter Estimates, with More General Banks

	Estimates	S.E.
General banks receiving rate $\boldsymbol{\alpha}_g$:		
Constant	-2.0054	(0.1588)
Loan amount	0.0066	(0.0007)
Loan length	0.0437	(0.0160)
Credit score	-0.2816	(0.0199)
Target banks receiving rate $\boldsymbol{\alpha}_t$:		
Constant	-4.2921	(0.3986)
Loan amount	0.0301	(0.0016)
Loan length	0.1628	(0.0400)
Credit score	-0.1185	(0.0231)
Bargaining power $\boldsymbol{\lambda}$:		
Constant	0.4137	(0.5175)
Loan amount	0.0847	(0.0108)
Loan length	-0.3297	(0.0667)
Credit score	0.2623	(0.0580)
Non-financial factors $\boldsymbol{\delta}_t$:		
600-650	-0.3553	(0.0148)
651-700	-0.2459	(0.0109)
701-750	-0.1714	(0.0085)
751-800	-0.1291	(0.0076)
801-850	-0.1069	(0.0074)
General banks pricing sd: $\log(\sigma_g)$	-0.7588	(0.0298)
Target banks pricing sd: $\log(\sigma_t)$	-0.6567	(0.0620)
Bargaining power sd: $\log(\sigma_\omega)$	-0.9290	(0.1950)

We re-conduct the counterfactuals using the estimates in Table 11 and the alternative sample. Table 12 shows the results. Consistent with the main analysis, we show that the lump-sum compensation scheme leads to the largest improvement in the market share for the target banks.

Tighter margin of matching (+/-15%) We tighten the margin for matching from +/-20% to +/-15%. This tighter margin leads to three matched general banks in the sample (instead of the five general banks in the main analysis).

We re-plot Figure 2 and Figure 3 using this smaller sample. Results are shown in Figure 12. (We omit the plot for the consumer rates at the general banks, which again shows no differences before and after the policy). At the target banks after the policy, the consumer rates decreased in low-credit segments, but the market share decreased in these segments. The consumer rate increased for the top credit segment (>800), but the market share increased in this segment. The pattern here is again consistent with that in our main analysis.

We re-estimate the model using the alternative sample. The estimates are shown in Table 13. They are qualitatively consistent with the main analysis. For both banks, the bank-receiving rates increase with loan amount and length and decrease with credit score. The consumer bargaining power is positively associated

Table 12: Market Outcomes at Target Banks by Compensation Scheme, with More General Banks

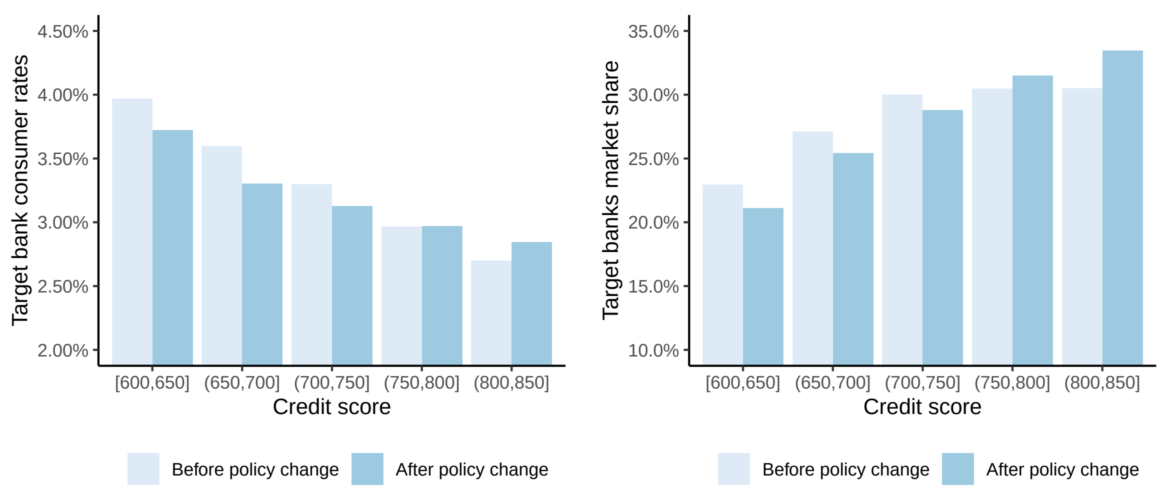
	Optimal Compensation (1)	Equiv. Dealer Rate (2)	Consumer Rate (3)	Market Share (4)	Increase in Market Share (5)
3% of loan amount		1.14%	3.13%	9.39%	-
		(0.01%)	(0.12%)	(1.99%)	
Fixed % of loan amount	2.81%	1.07%	3.06%	9.48%	0.93%
	(0.46%)	(0.17%)	(0.20%)	(2.02%)	(1.13%)
Fixed dealer rate	1.10%	1.10%	3.08%	9.62%	2.44%
	(0.18%)	(0.18%)	(0.20%)	(2.03%)	(1.15%)
Fixed lump-sum	\$512.2	1.04%	3.07%	9.74%	3.67%
	(\$8.9)	(0.17%)	(0.20%)	(2.09%)	(1.22%)

with the credit score and loan amount, and is negatively associated with the loan length.

Figure 12: Consumer Rate and Market Share at Target Banks by Credit Score before and after Policy, with Fewer General Banks

Consumer Rates:

Market Share:



We re-conduct the counterfactuals using the estimates in Table 13 and the alternative sample. Table 14 shows the results. Consistent with the main analysis, we show that the lump-sum compensation scheme leads to the largest improvement in the market share for the target banks.

A.3 Monte Carlo

We generate a data set of 10,000 loans by drawing loan amount, loan length, and credit score for each loan. Specifically, loan amount (in \$1000) is draw from a normal distribution with a mean of 23 and a standard deviation of 11. Loan length (in years) is drawn as 4, 5, or 6 with equal probabilities. Credit score (in 100) is drawn from a uniform distribution over [6, 8.5]. Then, under a set of "true" parameter values, we use our

Table 13: Parameter Estimates, with Fewer General Banks

	Estimates	S.E.
General banks receiving rate $\boldsymbol{\alpha}_g$:		
Constant	-3.0576	(0.1438)
Loan amount	0.0035	(0.0008)
Loan length	0.0558	(0.0114)
Credit score	-0.1189	(0.0163)
Target banks receiving rate $\boldsymbol{\alpha}_t$:		
Constant	-3.9635	(0.2378)
Loan amount	0.0231	(0.0010)
Loan length	0.1198	(0.0207)
Credit score	-0.1262	(0.0186)
Bargaining power $\boldsymbol{\lambda}$:		
Constant	-0.5410	(0.4308)
Loan amount	0.1051	(0.0121)
Loan length	-0.3356	(0.0567)
Credit score	0.3458	(0.0533)
Non-financial factors $\boldsymbol{\delta}_t$:		
600-650	-0.1378	(0.0230)
651-700	-0.1039	(0.0185)
701-750	-0.0892	(0.0156)
751-800	-0.0797	(0.0140)
801-850	-0.0758	(0.0131)
General banks pricing sd: $\log(\sigma_g)$	-0.8555	(0.0362)
Target banks pricing sd: $\log(\sigma_t)$	-0.8840	(0.0954)
Bargaining power sd: $\log(\sigma_\omega)$	-0.8314	(0.2102)

model to simulate the consumer rate and bank choice for each loan. We recover our model parameters from the simulated dataset, using the MSM estimator described in Section 3.3. We repeat this exercise 50 times and obtain 50 parameter estimates.

The results are reported in Table 15. Column 1 displays the true parameter values we use in the simulation. Columns 2 and 3 reports the average and standard deviation of the parameter estimates, respectively. We see that the average parameter estimates are close to the true values. The result suggests that the parameters are identified, and the estimator works reasonably well to recover parameter values.

A.4 Market share by total loan amount

We re-conduct the counterfactual exercise that compares the three compensation schemes, but with an alternative definition of market share. In the main analysis, we calculate the market share in terms of the number of loans. However, loans vary in size. As a robustness check, here we compute the market share in terms of the total loan amount. That is, a $20k loan contributes to the market share twice as much as a $10k loan. Table 16 reports the results. Again, we see that the lump-sum compensation scheme achieves a higher market share than the other compensation schemes.

Table 14: Market Outcomes at Target Banks by Compensation Scheme, with Fewer General Banks

	Optimal Compensation (1)	Equiv. Dealer Rate (2)	Consumer Rate (3)	Market Share (4)	Increase in Market Share (5)
3% of loan amount		1.13%	3.15%	26.18%	-
		(0.004%)	(0.09%)	(3.15%)	
Fixed % of loan amount	2.76%	0.91%	2.94%	26.62%	1.64%
	(0.30%)	(0.12%)	(0.15%)	(3.28%)	(1.36%)
Fixed dealer rate	1.07%	0.92%	2.94%	26.65%	1.77%
	(0.12%)	(0.11%)	(0.15%)	(3.27%)	(1.34%)
Fixed lump-sum	$545.8	0.90%	2.96%	27.87%	6.44%
	($62.4)	(0.11%)	(0.15%)	(3.40%)	(1.25%)

Table 15: Monte Carlo Results

	True values	Estimates	SDs
General banks receiving rate $\boldsymbol{\alpha}_g$:			
Constant	1.00	0.9896	0.0542
Loan amount	0.10	0.1019	0.0040
Loan length	0.05	0.0491	0.0221
Credit score	-0.50	-0.5063	0.0205
Target banks receiving rate $\boldsymbol{\alpha}_t$:			
Constant	0.30	0.2787	0.0644
Loan amount	0.05	0.0515	0.0027
Loan length	0.02	0.0149	0.0165
Credit score	-0.25	-0.2516	0.0158
Bargaining power $\boldsymbol{\lambda}$:			
Constant	-2.00	-2.0066	0.0759
Loan amount	0.10	0.0999	0.0018
Loan length	-0.30	-0.3006	0.0163
Credit score	0.20	0.2002	0.0156
Non-financial factors $\boldsymbol{\delta}_t$:			
600-650	-0.55	-0.5581	0.0476
651-700	-0.50	-0.5132	0.0418
701-750	-0.45	-0.4597	0.0418
751-800	-0.40	-0.4053	0.0397
801-850	-0.35	-0.3559	0.0410
General banks pricing sd: $\log(\sigma_g)$	-0.3	-0.2860	0.0569
Target banks pricing sd: $\log(\sigma_t)$	-0.6	-0.6018	0.0294
Bargaining power sd: $\log(\sigma_\omega)$	-1.0	-1.0328	0.1004

Table 16: Market Outcomes at Target Banks by Compensation Scheme, with Market Share by Total Loan Amount

	Optimal Compensation (1)	Equiv. Dealer Rate (2)	Consumer Rate (3)	Market Share (4)	Increase in Market Share (5)
3% of loan amount		1.12%	3.09%	12.15%	-
		(0.005%)	(0.10%)	(2.21%)	
Fixed % of loan amount	2.76%	1.04%	3.01%	12.33%	1.40%
	(0.30%)	(0.11%)	(0.16%)	(2.26%)	(1.51%)
Fixed dealer rate	1.07%	1.07%	3.02%	12.40%	2.05%
	(0.12%)	(0.12%)	(0.16%)	(2.26%)	(1.49%)
Fixed lump-sum	$545.8	1.05%	3.06%	13.14%	8.09%
	($62.4)	(0.11%)	(0.16%)	(2.41%)	(1.31%)