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

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Abstract

We study the design of dealer compensation policy in the indirect auto lending market, where most lenders give dealers the discretion to mark up interest rates. To protect consumers from potential discrimination by the dealer discretion, several banks switched to a new compensation scheme by fixing the markup as a percentage of the loan amount. We document that the market share of these banks responded positively (negatively) in the consumer segment where the policy increased (decreased) the interest rate — a reversal of the usual demand curve — which highlights the influence of dealers on the bank choice for financing loans. Accordingly, we develop and estimate an empirical model that allows for dealer–consumer bargaining, which depends on both the dealers' and the consumers' utility. Based on the estimation results, we explore alternative compensation policies that also eliminate dealers' discretion. We show that a lump-sum compensation that pays dealers a fixed dollar amount per loan dominates the current policy for the banks in terms of gaining market share. This is because dealers' equivalent markup rates would better align with their bargaining power. Our study highlights the importance of accounting for the interests and bargaining power of middlemen in designing a compensation scheme.

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 middlemen, who typically receive compensation from the firms for each completed transaction. For example, car dealers act as the middlemen 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) sums 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.[1] This is caused by the fact that, even though the bank-receiving rate is based on consumer credit profile and loan characteristics, the discretionary dealer markup (and consequently the consumer rate) can vary by consumer characteristics such as gender and race, which are not tied to the consumer's credit worthiness.[2] Nevertheless, the CFPB and the Department of Justice held banks accountable (rather than the dealers) and fined several lenders for alleged discriminatory consumer rates.[3]

To protect consumers, a non-discretionary compensation policy was advocated by policy makers. Under such a policy, banks directly set consumer rates, and dealers are compensated by a fixed markup as a percentage of the loan amount. Due to the pressure from CFPB, several banks have switched to such a compensation policy, offering 3 percent of the loan amount as the dealer compensation. From the banks' perspective, key policy questions include not only whether the phenomenon of discriminatory consumer rates can be eliminated but also how it affects the choice of loan providers for consumers. The involvement of dealers complicates this question. For example, setting a lower consumer rate does not necessarily translate to a larger market share if it would compress the markup for dealers, who may have a significant influence on the consumer's bank choice.

In this paper, we study the problem of designing the compensation for middlemen in the auto loan market. The goal is to explore new non-discretionary compensation schemes that can eliminate

[1] See CFPB Bulletin 2013-02: "Indirect Auto Lending and Compliance with the Equal Credit Opportunity Act." The ECOA (the Equal Credit Opportunity Act) prohibits creditors from discriminating against credit applicants on the basis of race, color, religion, national origin, sex, marital status, etc.

[2] Dealers typically do not bear the risk of a consumer defaulting on the loan.

[3] See DOJ press release: "Justice Department and CFPB Reach Settlement to Resolve Allegations of Auto Lending Discrimination by Toyota," Feb. 2, 2016.

the practice of charging discriminatory consumer rates while minimizing the negative impacts on the market share of banks that adopt these schemes. To accomplish this goal, we leverage the change of dealer compensation as a policy experiment, empirically analyzing its impacts on consumers as well as banks. We investigate how the bank choice and interest rates are influenced by the incentives of both dealers and consumers. We adopt a bargaining model to capture how a dealer's compensation is determined under the discretionary markup policy. Our analysis makes use of the change induced by the policy experiment to quantify the effects of the dealer and the consumer's payoffs on the bank choice. This allows us to study the design of alternative compensation schemes for dealers.

Our modeling approach is motivated by several data observations from the policy experiment. For banks that implemented the non-discretionary markup policy (hereafter referred to jointly as "target banks"),[4] the switch reduced consumer rates for low-credit consumer segments and increased the rates for high-credit segments. This is consistent with previous studies (e.g. Lanning, 2019) showing that, when dealers have discretion over the markup, they typically charge a higher dealer rate on low-credit consumers. However, the market share of target banks *decreased* among low-credit segments and *increased* among high-credit segments — a reversal of the standard demand curve. While this result is counter-intuitive in the eyes of standard demand models where brand choices are made solely by consumers, it is consistent with our model, which takes dealers' incentives into account. Even though target banks lowered consumer rates for low-credit consumers, they would lose these consumers if dealers, for self-interest purposes, pushed consumers to other banks that allow for dealer discretion (hereafter referred to jointly as "general banks").

We specify a structural model for auto loan demand based on Nash bargaining (Nash, 1953; Zhou, 1997). We take a consumer's need for a specific auto loan (amount and length) as given, and focus on how (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 the consumer. On top of this, the choice of which bank to finance the loan is determined by the joint payoff of the dealer and the consumer weighted by their bargaining power. The party with the higher bargaining power will have a bigger influence on the bank choice.

We apply the model to a data set of 0.57 million auto loans in the U.S., within a window that covers the time before and after target banks switched their compensation policy. Estimation results show that about half of the dispersion in observed consumer rates stems from the heterogeneity in bargaining power across consumers (with the rest of the variation coming from bank-receiving rates that depend on consumer and loan characteristics). Higher bargaining power rests with consumers with (i) higher credit scores,[5] (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

[4]We combine several policy-implementing banks together as "target banks" for data privacy reasons. See Section 2 for details.

[5]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/.

report based on surveys of auto loan lenders. In addition, factors independent from the consumer credit profile and loan characteristics contribute to 13% of the variation in bargaining power, supporting the argument that dealer discretion can exacerbate the phenomenon of discriminatory consumer rates.

As our data and estimation results both reveal that target banks have lost market share after switching to the non-discretionary compensation (because of dealers' role in the bank choice), we proceed to use counterfactuals to study alternative compensation schemes that can help target banks gain market share while retaining the non-discretionary feature. We consider three types of compensation schemes: (i) paying the dealer a fixed percentage of loan amount, which is the same as the new policy adopted by target banks in our data, (ii) paying the dealer a fixed markup rate on top of the bank-receiving rate,[6] and (iii) paying the dealer a fixed lump sum amount for each transaction. Under each counterfactual scenario, we take bank-receiving rates as given, and search for the optimal markup rate or amount that maximizes the market share of target banks aggregated across consumer segments. We find that the lump-sum compensation scheme increases the market share across all consumer segments for target banks. Under lump-sum compensation, there is no longer a gap in interest rates across consumers with different bargaining power (after controlling for the observed credit profile and loan characteristics). Moreover, the interest rate is significantly lower than that under the current compensation policy adopted by target banks. These results suggest that lump-sum compensation will make both the target banks and consumers better off.

The key reason that the lump-sum scheme outperforms the other two schemes in gaining market share for target banks lies in how dealers' compensation aligns with where the bargaining power resides. In cases where the bargaining power resides with the consumer, banks should offer a relatively small dealer markup (and thus a low consumer rate) to attract loans, and *vice versa*. Since in our estimation consumers who request a larger loan amount are likely to have higher bargaining power, and the dealer's equivalent markup rate under the lump-sum scheme decreases with the loan amount, this compensation scheme is consistent with the above condition. On the other hand, the other two schemes scale the dealer compensation with the loan amount, which goes in the opposite direction of the above condition.

This paper makes several contributions. First, it has important policy implications for indirect auto lending, which is the third largest consumer loan market after mortgages and student loans. Potentially discriminatory issues have caught sizable attention in this 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 2006). 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 provide insights for this issue in a complex environment that must account for not only the consumer protection but also

[6] Although the first two schemes look similar, the compensation amount for the dealer under the second scheme varies based on the loan length while that under the first does not.

the dealer influence on bank choice. These insights also have broader relevance for other markets with middlemen.

Second, this paper bridges the literature of empirical bargaining and demand estimation. Empirical studies have applied Nash bargaining to model outcomes that bear a tension of interests between two parties, such as price negotiation (Chen et al. 2008; Jiang 2019; Zhang and Chung 2020; Jindal and Newberry 2019) and contractual terms in B2B transactions (Draganska et al. 2010; Grennan 2014; Gowrisankaran et al. 2015). This paper extends the application of Nash bargaining to the problem of demand estimation where firms' prices must pass through middlemen to reach consumers. It should be noted that a few studies have examined the impact of middlemen on consumer demand, focusing on salesperson effort (Yang et al. 2019; Roussanov et al. 2018) and quality of service (Kim 2019). However, they neither focus on nor explicitly model the tension between consumers and middlemen, which we find to be the key mechanism at play in auto loan lending. Our framework is also applicable to other settings where there is tension between two parties when choosing brands.

Third, this paper is also related to the literature on retail channel management. Channel coordination problems 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. Under the discretionary dealer compensation, the dealer markup and thus the final consumer rate vary across consumers depending on the consumer-dealer negotiation instead of being posted prices that apply to all consumers.

The rest of the paper is organized as follows. Section 2 presents the data and model-free analysis. Section 3 describes the model. Section 3.3 presents the estimation algorithm as well as the model estimates. Section 4.2 conducts counterfactual analysis on dealer compensation. Section 5 concludes.

2 Data and Reduced-Form Analysis

Our analysis leverages anonymized auto loan data from Equifax Inc., one of the three major credit bureaus in the United States. For data privacy reasons, we mix data from several banks or credit unions that switched their dealer compensation scheme in the mid 2000s. We refer them as "target banks". After the policy change, they directly set the consumer rate, and shifted the discretionary dealer markup to a non-discretionary one offering 3 percent of the loan amount. For each bank, we collect data over a 20-week horizon, 10 weeks before and 10 weeks after the change. We select counties that account for roughly a third of the total loan volume of the bank.[7] To account for competition, we also gather data from all other banks or credit unions (referred as "general banks") in these counties during the same time period. Because all auto lenders report to the credit bureau, we are able to observe loans originating from all major auto lenders in these counties during the time period, from which we can calculate the market share of each target bank. Since the target banks mainly serve the medium- to high-credit segments, we restrict the analysis to customers with credit scores of at least 600. Ultimately, our data sample include a total of 0.57 million loans.[8]

For each loan in our sample, we observe loan characteristics including the consumer's credit score, loan amount, loan length, and the interest rate in APR (i.e., the consumer rate). Table 1 shows some descriptive statistics for these loans. On average, a consumer borrows about $23K for 5.4 years with 4.2% interest rate. Table 2 reports the market share and loan characteristics for the target banks and the general banks, respectively, broken down by credit score buckets. Note that, since in each geographical market there is only one target bank and many other general banks, the overall market share of the target banks is less than 5 percent. Their market share is larger among consumers with prime credit scores, and decreases as we move to the lower-credit segments.

Table 1: Descriptive Statistics

	Mean	25 Percentile	Median	75 Percentile
	(1)	(2)	(3)	(4)
Credit score	731	680	734	787
Interest rate (i.e., consumer rate)	4.2%	2.8%	3.9%	5.2%
Loan amount ($)	22,914	14,892	21,341	29,052
Loan length (year)	5.4	5.0	5.5	6.0

2.1 Some reduced-form analyses

This sub-section presents some reduced-form analysis results that motivate our modeling approach that will be discussed in the next section. We start by showing a direct consequence of the policy change: reduction in the dispersion of consumer rates. Before the policy change, 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 personality traits. After the policy change, dealers no longer had the discretionary power. Figure 1 plots the distributions of the consumer rates at the target banks

[7]For each lender, we separate the sample geographically at the county level, and rank counties in terms of the market share. We then select counties starting from the one with the highest market share until the selected sample represent roughly a third of the lender's total loan volume.

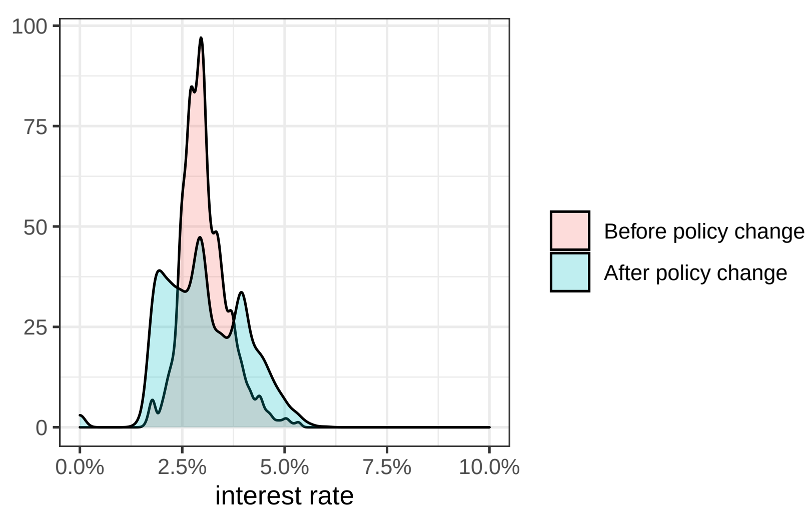
[8]The market share of target banks is very small in consumer segments with credit scores lower than 600. Furthermore, the target banks operate in different geographic markets in the U.S.; therefore, our analysis assumes that there is no competition among target banks.

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	27,657	4.8%	3.1%	23,202	5.3
By Credit Score:					
801−850	6,230	6.2%	2.6%	22,672	5.0
751−800	8,206	6.0%	2.8%	22,893	5.3
701−750	6,972	4.9%	3.2%	23,509	5.5
651−700	4,493	3.8%	3.6%	24,098	5.5
600−650	1,756	2.4%	4.0%	23,017	5.5
General Banks:					
Overall	543,186	95.2%	4.3%	22,899	5.4
By Credit Score:					
801−850	93,576	93.8%	2.7%	22,029	5.0
751−800	129,689	94.0%	3.2%	22,951	5.3
701−750	134,807	95.1%	4.0%	23,126	5.4
651−700	113,261	96.2%	5.4%	23,440	5.5
600−650	71,853	97.6%	6.9%	22,659	5.5

before and after the policy change. It shows a significant drop in the dispersion, a clear illustration of the impact from the policy. The figure also suggests there was a high level of heterogeneity in interest rates across consumers before the change.

Figure 1: Consumer Rate Distribution at Target Banks before and after Policy Change



To examine whether the drop in the dispersion of consumer rates is driven by the changes in the types of loans, we use regressions to control for observable factors. We regress the consumer rate of each loan on the loan amount, loan length, as well as credit score[9] and county-day fixed effects. Results are shown in Table 3. A larger loan amount and shorter loan length lead to a lower consumer rate for both target and general banks. More importantly, the residual standard error from the regression for target banks is 0.39% after policy change, significantly smaller than 0.67% before the change. This is consistent with the observation from Figure 1. Such pattern is not seen at general banks, however, as the residual standard errors are virtually the same before and after the policy change at target banks.[10]

Table 3: Impact of Policy Change 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)	-0.03731***	-0.01547***	-0.04801***	-0.04522***
	(0.00073)	(0.00040)	(0.00028)	(0.00026)
Loan length (years)	0.22791***	0.05561***	0.17258***	0.16764***
	(0.00856)	(0.00447)	(0.00301)	(0.00291)
Credit score FE	Yes	Yes	Yes	Yes
County Day FE	Yes	Yes	Yes	Yes
Residual Std. Error	0.00674	0.00387	0.01382	0.01374
Observations	13,782	13,875	265,927	277,259
R^2	0.54318	0.55332	0.54708	0.53967

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

Next, we look at how the loan allocation (i.e. which bank to finance a loan) was affected by the change in target banks' policy. We start by examining the relation between consumer rates and market share for target banks in data. As the consumer rate is the "price" that the consumer pays for the loan, this relation represents the demand curve in the usual sense. Figure 2 plots the average interest rate at target banks (left plot) and general banks (right plot) for each credit-score bucket. The red bars represent pre-policy rates whereas the blue bars represent the post-policy rates. It shows that at target banks the average interest rate decreased in lower-credit segments (below 750), and increased in higher-credit segments (above 750). This pattern, however, is absent at general banks. The average interest rate for each credit score bucket remained mostly unchanged before and after the policy change at target banks. Note that the policy change was implemented by only for a few sellers. The persistence of consumer rates in general banks suggests that there are no strategic response from general banks, at least during the short period after the change.

Given the changes in consumer rates, we would expect the market share of target banks to

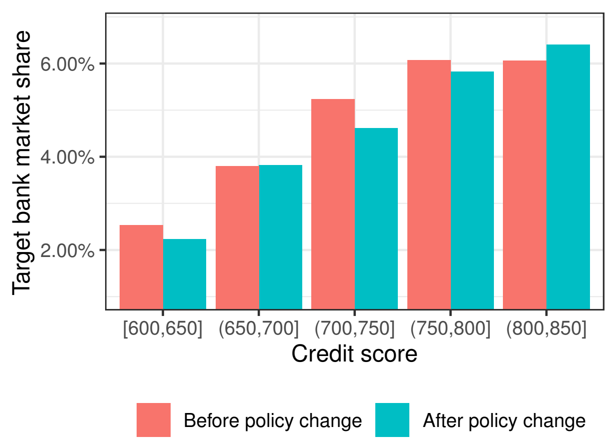
[9]We include a dummy for each credit score point.

[10]The residual standard errors at general banks are higher than those at target banks. This is because general banks are a composite of many banks. Banks generally differ in how they set interest rates.

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

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 buckets, before and after the policy change. Surprisingly, the market share actually decreased in consumer segments with credit score below 800, and increased for the segment above 800. In other words, the changes in market share mostly had *the same direction* as the changes in price, the consumer rate.

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



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

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

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 segment 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 change, and finally $\boldsymbol{X}_i$ is a vector of other controls including credit score and county fixed effects. The coefficient α_s captures the consumer rate difference between target and general banks in segment s. The coefficient η_s is the main parameter of interest that captures the rate change of target banks after the policy change in segment s. Table 4 Column 1 shows the regression results. Same pattern is shown in Figure 2: η_s is estimated to be significantly negative for lower-credit segments (below 750) and significantly positive for higher-credit segments (above 750).

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 credit score, loan amount and length, and the geographic location, that may affect the propensity of taking loan from target banks. Coefficient ϕ_s is the main parameter of interest that shows the change in the market share after policy change. Table 4 Column 2 shows the regression results. Consistent with the data pattern observed in Figure 3, ϕ_s is significantly negative for the segments with credit scores between 600 and 650, and between 701 and 750, and significantly positive for the segment with credit scores higher than 800.

How can we rationalize this seemingly counter-intuitive reversal of demand curve? In indirect auto lending, a dealer acts as the middleman that brokers loan arrangements. Therefore, its incentive plays an important role in the bank choice, in addition to the interest rate charged on the end consumer. After the policy change, 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 general banks. Therefore, despite reducing consumer rates in low-credit segments, the policy change actually led to a decrease in the market share for target banks. The opposite is true for high-credit consumers, who usually present less room for discretionary markups. For these consumers, the 3 percent compensation offered by target banks can be more profitable for dealers than the discretionary markup from general banks. The analysis results suggest that dealers' interest as well as its tension with consumers' interest should be taken into account for the

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

Dependent Variables:	Consumer Rate (%) (1)		Choose Target Banks (2)
η_s:		ϕ_s:	
Target banks after policy (600-650)	-0.45894***	After policy change: (600-650)	-0.00366***
	(0.06632)		(0.00135)
Target banks after policy (651-700)	-0.35319***	After policy change: (651-700)	0.00069
	(0.04146)		(0.00107)
Target banks after policy (701-750)	-0.08411**	After policy change: (701-750)	-0.00327***
	(0.03333)		(0.00097)
Target banks after policy (751-800)	0.09855***	After policy change: (751-800)	0.00041
	(0.03121)		(0.00099)
Target banks after policy (801-850)	0.27128***	After policy change: (801-850)	0.00527***
	(0.03589)		(0.00116)
α_s:			
Target banks (600-650)	-2.39993***		
	(0.04631)		
Target banks (651-700)	-1.47302***		
	(0.03033)		
Target banks (701-750)	-0.64930***		
	(0.02380)		
Target banks (751-800)	-0.31235***		
	(0.02280)		
Target banks (801-850)	-0.24551***		
	(0.02678)		
$\boldsymbol{\beta}$:		$\boldsymbol{\gamma}$:	
Loan amount ($1000)	-0.10136***	Loan amount ($1000)	0.00109***
	(0.00059)		(0.00008)
Loan amount^2	0.00090***	Loan amount^2	-0.00002***
	(0.00001)		(0.000001)
Loan length (years)	-0.22180***	Loan length (years)	0.04142***
	(0.01134)		(0.00155)
Loan length^2	0.04751***	Loan length^2	-0.00394***
	(0.00113)		(0.00015)
Credit score FE	Yes	Credit score FE	Yes
County FE	Yes	County FE	Yes
Observations	570,843		570,843
R^2	0.55793		0.27292

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

bank choice in the auto lending market. This calls for a modeling approach different from standard choice models.

The above data patterns also reveal a conundrum facing target banks: due to the dealer influence, their overall market share decreased after the policy change, which can hurt their profit and competitiveness in the industry. This motivates us to explore alternative compensation policies that can help increase the market share for target banks while preserving the non-discretionary feature for consumer protection. Details are in Section 4.2.

3 Model and Estimation

Our model is conditional on consumers who obtained auto loans in our data.[11] There are two parts of our model. The first part is to determine the interest rate a consumer pays given that the loan is financed by either target banks or general banks. The second part of the model determines which bank is chosen to finance the loan.

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 (as post-policy target banks do). The outcome depends on the relative bargaining power between the consumer and the dealer, and a disadvantaged consumer (with a low bargaining power) will have to pay an interest rate higher than others conditional on credit profile. This modeling approach allows us to capture the large dispersion in consumer rates after controlling for consumer and loan characteristics, a data phenomenon documented in Section 2. To simplify analysis, we group general banks as a composite of a large number of banks competing with the target banks. Such a simplification allows our model to be tractable, as such we can focus on how target banks compete with the rest of the market.

For the bank choice, the dealer and the consumer desire to choose the bank that offers oneself the highest payoff. Conflicts in interests could arise. Therefore, we model the bank choice as a joint decision based on the joint payoff (weighted by the bargaining power) determined by the interest rates bargaining as well as other non-financial factors. The choice therefore also depends on the relative bargaining power between the consumer and the dealer. This feature helps rationalize the reversed demand curve for target banks documented in Section 2.

3.1 The determination of interest rates

We first describe how consumer rates are determined for target banks and general banks *before* the policy change. For a given loan, both banks set a bank-receiving rate based on consumer credit

[11] We ignore consumers who were unable to obtain loans due to the data limitation. Given that our analysis focuses on consumers in medium- and high-credit segments (i.e. credit scores of at least 600), this restriction is quite reasonable.

profile and loan characteristics. The consumer rate is equal to the bank-receiving rate plus the dealer rate (commonly known as dealer markup or dealer participation). We use subscript t to denote target banks and g to denote general banks.

Banks set the bank-receiving rate to maximize their profit, taking account of the loan risk from the consumer and the competition from other banks. Given that the focus of our analysis is the dealer-consumer interaction, we choose to use a reduced-form approximation to specify how the rate is determined based on consumer and loan characteristics. For banks j ($j = t$ or g), the bank-receiving rate for loan i is the following

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

where $\boldsymbol{x}_i$ includes consumer credit profile and loan characteristics, and $\mathbb{L}$ is the logistic function, i.e. $\mathbb{L}(z) \equiv e^z/(1+e^z)$, which ensures a non-negative bank-receiving rate. Note that parameters $\boldsymbol{\alpha}_j$ are bank-specific, as such target banks and general banks can charge different rates on the same consumer. Moreover, R is a sufficiently high rate ceiling.[12] $\varepsilon_{i,j}$ is an idiosyncratic term that is assumed to follow a normal distribution $\varepsilon_{i,j} \sim \mathcal{N}(0, \sigma_j^2)$. It captures the dispersion in consumer rates driven by banks charging different bank-receiving rates on consumers with the same credit profile and loan characteristics, and not by the dealer-consumer bargaining.

We use $r_{i,j}$ to denote the consumer rate. The rate resides somewhere between $c_{i,j}$ and R, as an outcome of the Nash bargaining between the consumer and the dealer. We specify consumer's payoff from the bargaining as the surplus between R and the consumer rate, i.e. $u_{i,j} = R - r_{i,j}$. The dealer's payoff from the bargaining is the dealer's markup rate from the transaction, i.e. $v_{i,j} = r_{i,j} - c_{i,j}$. Note the sum of the two is $R - c_{i,j}$, which can be intuitively thought of as the size of the "pie" that the consumer and the dealer divide.

Formally, the Nash bargaining solution satisfies

$$\begin{aligned}(u_{i,j}, v_{i,j}) = \operatorname{argmax}_{(u,v)} &\left\{u^{\omega_i} v^{1-\omega_i}\right\}, \\ \text{subject to: } & u + v = R - c_{i,j},\end{aligned} \tag{2}$$

where ω_i is the bargaining power of the consumer. The above implies:

$$\begin{aligned}u_{i,j} &= \omega_i(R - c_{i,j}); \\ v_{i,j} &= (1-\omega_i)(R - c_{i,j}).\end{aligned}$$

The consumer rate as the bargaining solution is

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

[12] In the model estimation, we set $R = 12\%$, which is the maximum interest rate for all loans in our sample. Our estimation results are robust to the value of R.

This expression implies that the more bargaining power the consumer has, the closer $r_{i,j}$ is towards $c_{i,j}$, and thus the payoff for the consumer is larger while that for the dealer is smaller.

Bargaining power is an important component in our model that drives 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, as well as an unobserved component $\varepsilon_{i,\omega}$. Specifically,

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

where $\mathbb{L}$ again denotes the logistic function so that ω_i stays between 0 and 1. We assume that $\varepsilon_{i,\omega} \sim \mathcal{N}(0, \sigma_\omega^2)$. This random component represents all unobserved factors (to researchers), such as the consumer's knowledge about the financial market, her patience, and other personal traits that may help the consumer to negotiate a better loan deal. It helps explain the dispersion in consumer rates driven by the dealer charging different markups on consumers with the same credit profile and loan characteristics, a critical concern related to the consumer protection which we have discussed in the introduction. A non-discretionary dealer compensation has to make sure bargaining power does not play a role in determining the consumer rate, which is what the policy change from target banks aimed to achieve.

After the policy change, we assume that target banks and general banks continue to charge bank-receiving rates as specified in equation 1. [13] The assumption of no strategic response from general banks is consistent with the reduced-form pattern that shows persistent consumer rates at the general banks. If choosing general banks, consumers and dealers bargain interest rates in the same way as in equation 2 and 3. However, target banks now compensate the dealer with 3% of the loan amount. There is no bargaining between the consumer and the dealer. To compare this compensation with general banks, we convert the compensation amount to an equivalent dealer rate. The consumer rate then equals the bank-receiving rate plus the converted dealer rate. Let $\tilde{v}_{i,t}$ denote this equivalent 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

$$\frac{\tilde{v}_{i,t}/12}{1-(1+\tilde{v}_{i,t}/12)^{-T_i}} \cdot M_i \cdot T_i = 0.03 \times M_i. \tag{4}$$

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, i.e., the dealer rate is smaller for longer loans. However, $\tilde{v}_{i,t}$ does not change with the loan amount M_i, which cancels

[13] One may be concerned that, as target banks switch to a different dealer compensation scheme, they may also adjust the policy of setting the bank-receiving rate accordingly. Such adjustment process can be gradual and takes time, as the banks have to learn how to set the optimal rates for different consumer segments. Since we only use data 10 weeks before and after the policy change, it is reasonable to assume the policy to set bank-receiving rate has not been significantly revised within the short time window.

Another concern is that general banks may also adjust their policy in order to compete. However, target banks on average only have 4.8 percent market share; thus, we believe the competitive response should be restrictive.

out on both sides. These properties provide the basis for some important intuitions later when we compare the different counterfactual compensation schemes in Section 4.2.

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

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

As a result, the consumer's and the dealer's payoffs are

$$\begin{aligned} u_{i,t} &= R - r_{i,t} = R - (c_{i,t} + \tilde{v}_{i,t})\,; \\ v_{i,t} &= \tilde{v}_{i,t}. \end{aligned} \tag{5}$$

3.2 The bank choice

We assume that the bank choice is a joint decision made by the dealer and the consumer. The decision is first influenced by the financial incentives of both parties. Before the policy change, the feasible set of payoffs that combines the options offered by target banks and general banks is

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

The first feasible set above is provided by general banks, where the consumer and dealer divide a "pie" of size $R - c_{i,g}$. The second feasible set is provided via target banks, where the consumer and dealer divide a "pie" of size $R - c_{i,t}$.[14]

The bank choice is modeled as the outcome of a Nash bargaining game between the dealer and the consumer. The bargaining outcome maximizes $u^{\omega_i} \cdot v^{1-\omega_i}$, or $\omega_i \log(u) + (1 - \omega_i)\log(v)$, subject to this combined feasible set. Let $W_{i,j}$, $j \in \{t, g\}$, denote the joint payoffs as an outcome of the Nash bargaining process:

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

where (u_{ij}, v_{ij}) denote the maximal point within the feasible set provided via banks j. 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 in the bank choice.

It is not difficult to show that, in the pre-policy period, $W_{i,t} > W_{i,g}$ is equivalent to $c_{i,t} < c_{i,g}$. In other words, the dealer and the consumer would both prefer the bank with a lower bank-receiving rate. A result is that 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 feasible set of the joint payoffs combines the options offered by

[14] We write the constraints as inequalities rather than equalities for technical reasons in order to apply the Nash bargaining theory, but the bargaining solution will always have the constraints binding.

target banks and general banks as follows

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

The first feasible set above is provided by general banks, and the second is provided by target banks, which directly set the dealer's compensation and consumer rate.[15] For target banks in the post-policy period, we have $W_{i,t} \equiv \omega_i \log u_{i,t} + (1-\omega_i)\log \tilde{v}_{i,t}$.

In the post-policy period, the dealer and the consumer may prefer different banks. For example, as the bargaining power ω_i of the consumer decreases, the dealer will see a larger bargained markup $v_{i,g}$ from the general bank, and consequently a smaller $u_{i,g}$ is left for the consumer. However, at target banks, $\tilde{v}_{i,t}$ and $u_{i,t} = R - (c_{i,t} + \tilde{v}_{i,t})$ are not affected by ω_i. As a result, the dealer may prefer to have general banks financing the loans for consumers with low-bargaining power, even though these consumers are better off if they choose target banks.

In addition to the above financial payoffs, there is evidence in data that there exist other non-financial factors that may influence the bank choice. For example, Table 2 shows that, comparing with general banks, target banks charge significantly lower interest rates for consumers with low credit scores, while the interest rates for consumers with high credit scores are about the same as general banks. However, the market share of target banks among consumers with low credit scores is significantly lower than other segments, even before target banks switched their dealer compensation scheme. Some potential reasons are that target banks focus more on marketing to high-credit consumer segments, they may have better customer relationship with these consumers, and the general banks have more extensive dealer network accessing lower-credit consumers. These factors are hard to model in a structural way and also unobservable to researchers; therefore, we choose to model these factors in a reduced-form way by $\boldsymbol{\delta}'\boldsymbol{x}_i$, i.e. they are approximated as a function of consumer and loan characteristics.[16] These non-financial factors are assumed to stay the same before and after policy change, at least during the short period we study. With this, we specify the total value for loan i to be financed by bank j, $j \in \{g,t\}$, for the dealer and the consumer as:

$$V_{i,j} = W_{i,j} + \boldsymbol{\delta}_j'\boldsymbol{x}_i. \tag{6}$$

Target banks are chosen iff $V_{i,t} > V_{i,g}$. Since only the difference $V_{i,t} - V_{i,g}$ matters in the choice, we normalize $\boldsymbol{\delta}_g = 0$ and estimate $\boldsymbol{\delta}_t$ only.

[15] The bargaining problem here is not standard because the combined set is not 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.

[16] In particular, we let $\boldsymbol{\delta}$ be a function of the dummy variables denoting the five credit score segments. This is motivated by the market share pattern of target banks across different credit score segments in the pre-policy period.

3.3 Model estimation

We estimate our model using the method of simulated moments (McFadden 1989). The estimation algorithm matches model-predictions for each loan with empirically observed outcomes in the data. Below, we first describe two model predictions, one about which bank finances the loan, and the other the final consumer rate. We then construct the moment conditions.

Let $y_i \in \{0, 1\}$ denote whether target banks are chosen to finance loan i and $r_i = y_i r_{i,t} + (1 - y_i) r_{i,g}$ denote the consumer rate. Our model specifies $P(y_i, r_i | \boldsymbol{x}_i)$. This conditional probability can be evaluated via simulations. To simulate a pair (y_i, r_i), we draw the unobservables $\varepsilon_{i,t}$, $\varepsilon_{i,g}$, and $\varepsilon_{i,\omega}$ to simulate the associated bank-receiving rates and the consumer's bargaining power. We then solve the bargaining problem. The feasible set offered by target banks in the bargaining depends on whether the loan belongs to the pre-policy or post-policy period. Based on the simulated outcomes, we construct several prediction "errors". The first error is regarding the bank choice:

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

The second and third errors are regarding the consumer rate at target banks (for $y_i = 1$) or 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 $\boldsymbol{\zeta}_i$ be the collection of the above error terms. By construction, we have $\mathbb{E}(\boldsymbol{\zeta}_i | \boldsymbol{x}_i) = 0$, a mean independence condition from which moment conditions can be constructed. Following the identification argument which we give below, we use the following sets of moment conditions for estimation: (i) $\mathbb{E}(\boldsymbol{x}_i \zeta_{i,1}) = \mathbf{0}$, (ii) $\mathbb{E}(\boldsymbol{x}_i \zeta_{i,2}) = \mathbf{0}$, (iii) $\mathbb{E}(\boldsymbol{x}_i \zeta_{i,3}) = \mathbf{0}$, (iv) $\mathbb{E}(\zeta_{i,4}) = 0$, and (v) $\mathbb{E}(\zeta_{i,5}) = 0$. For conditions (i), (ii), and (iv) that involve target banks, we require them to hold for the pre-policy and post-policy periods respectively, to account for the policy change.[17]

[17]The objective function for the simulated method of moments is not smooth, because a small change in the parameters may flip the bank choice y_i between 0 and 1. This causes difficulty for the minimization algorithm. We smooth the simulated bank choice in the model by the kernel-smooth method (Geweke and Keane 2001; Honka 2014).

Identification We provide the intuition on how the parameters in our model are identified. A key issue in the identification is separating 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 higher consumer rate can be explained by either low consumer bargaining power or a high bank-receiving rate. Fortunately, the non-discretionary dealer compensation creates a benchmark case of which the dealer compensation, and subsequently the bank-receiving rate, are known. This helps us separate the bank-receiving rate function of target banks from the consumer's bargaining power.

Formally, we have the following parameters to be estimated: (i) $\boldsymbol{\lambda}$, which specifies the consumer's bargaining power, (ii) $\boldsymbol{\alpha}_t$, which specifies how target banks set the bank-receiving rates, (iii)$\boldsymbol{\alpha}_g$, which specifies how general banks set the bank-receiving rates, (v) $\boldsymbol{\delta}_t$, which specifies other factors that affect the bank choice, and finally (vi) σ_g, σ_t, and σ_ω, which specify the standard deviations of the unobservable terms.

The bargaining power parameters $\boldsymbol{\lambda}$ can be identified from the changes in the market share of target banks before to after policy change across consumer segments with different $\boldsymbol{x}_i$. Whether the non-discretionary compensation at target banks is chosen against general banks is informative of the bargaining power of the consumer. For example, suppose low-credit-score consumers could obtain a lower consumer rate from target banks than from general banks, but target banks ended up with a lower market share among these consumers after the policy. This change in market share suggests a relatively low bargaining power for low-credit-score consumers.

While the policy-induced changes in market shares identify $\boldsymbol{\lambda}$, the overall market shares identify the non-financial incentive parameter $\boldsymbol{\delta}_t$. For example, Table 2 shows that target banks charge an average 4.0% consumer rate on consumers in the credit score bucket 600-650, significantly lower than the 6.9% charged by general banks. In contrast, the consumer rates charged on consumers in the credit score bucket 801-850 are similar between the two sets of banks. However, target banks' market share for the former consumer segment is only 2.4%, far lower than the 6.2% for the latter consumer segment. This pattern suggests that the $\boldsymbol{\delta}_t's$ for higher credit score segments should be larger than that for lower credit score segments.

With the above parameters identified, it is not difficult to see that $\boldsymbol{\alpha}_t$ can be identified from the distribution of consumer rates across consumer segments at target banks and $\boldsymbol{\alpha}_g$ from the distribution at general banks. Of course, the observed consumer rates at either banks correspond to a selected sample of consumers who, together with dealers, choose those banks to finance their loans. This selection is accounted for by our structural model that predicts y_i and r_i jointly. Finally, after controlling for $\boldsymbol{x}_i$, the dispersion of consumer rates at general banks identifies σ_g, and the dispersions at target banks before and after policy change identify σ_ω and σ_t.

To test the model identification, 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 using the simulated method of moments. We find that our estimation algorithm does a good job recovering the true parameters. We include the details in the appendix.

4 Results

In this section, we first present the estimation results, which will inform us how bank-receiving rates are determined, and how the consumer's bargaining power is affected by the credit score and loan characteristics observed from data, as well as factors that are unobserved to researchers. We decompose how the observed and unobserved factors contribute to the dispersion. 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 find a policy that can improve the banks' market share while maintaining the non-discretionary feature in the compensation. As we showed in Section 2, target banks have lost market share to competitors after switching to the non-discretionary compensation. Finding a policy that can minimize the negative impact is important for the long-term sustainability of banks.

4.1 Estimation results

Table 5 presents the parameter estimates. All of the estimates are statistically significant. The table first shows how target and general banks set the bank-receiving rates. For both banks, the rates increase with loan amount and length, and decrease with consumers' credit scores. Typically, consumers requesting a longer loan and a large amount imply a higher default risk. Compared with general banks, target banks are less aggressive in raising the rate for low-credit consumers. One of the reasons for the difference is that the asset portfolios are different across banks and as a result, banks vary in their tolerance towards default risks.

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 the survey report by Davis and Frank (2011), 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 — which indicates a lower consumer bargaining power in our model. We also find these results conceptually reasonable. First, a consumer requiring a large loan is typically willing to spend more time (or more patient in) seeking for a lower interest rate. She may also spend more time on collecting market information about auto loan interest rates before visiting the dealer. These often translate into a higher bargaining power. Second, 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 (and unable to pay off the loan quickly). This translates into a weaker bargaining power.

In addition to financial payoffs, other factors will also affect the bank choice. The negative non-financial values indicate that target banks are less likely to be picked than general banks when the bank-receiving rate and dealer markup are the same. This result should be expected, considering that general banks are a composite of many banks, and thus almost surely have a more extensive business network compared to target banks. The relatively higher values for higher credit score segments are consistent with the fact that target banks have been primarily targeting high-credit consumer segments. Most of their existing customers (e.g., deposit account holders or mortgage borrowers) are among the high-credit segments.

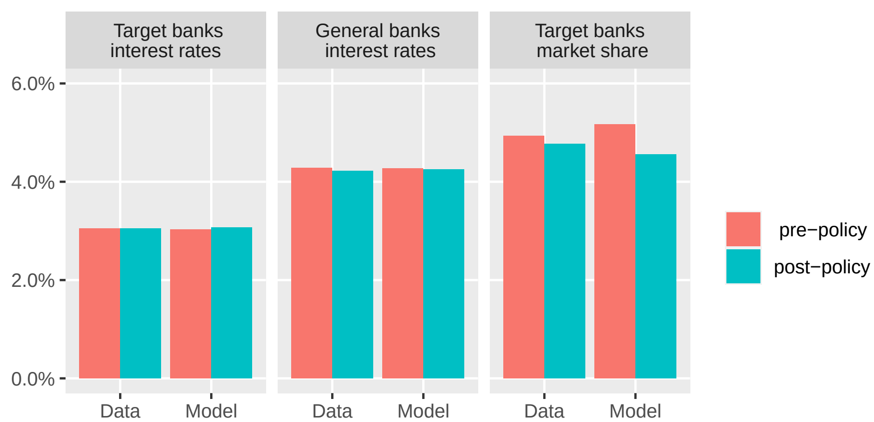
The next two rows display the estimated standard deviations for bank-receiving rates. Estimated σ_g is substantially larger than σ_t. This result is reasonable because general banks are a composite of many banks who may adopt different rules when setting bank-receiving rates. It is also consistent with the data pattern that the dispersion of consumer rates at general banks is substantially larger than that at target banks (Table 2).

Table 5: Estimation Results

	Estimates	S.E.
General banks receiving rate $\boldsymbol{\alpha}_g$:		
Constant	4.4664	(0.0980)
Loan amount	0.0021	(0.0005)
Loan length	0.0432	(0.0050)
Credit score	-0.7966	(0.0125)
Target banks receiving rate $\boldsymbol{\alpha}_t$:		
Constant	-0.1554	(0.1046)
Loan amount	0.0031	(0.0006)
Loan length	0.1096	(0.0084)
Credit score	-0.2860	(0.0108)
Bargaining power $\boldsymbol{\lambda}$:		
Constant	-2.9528	(0.0438)
Loan amount	0.0933	(0.0081)
Loan length	-0.2317	(0.0073)
Credit score	0.6059	(0.0176)
Non-financial value $\boldsymbol{\delta}_t$:		
600-650	-1.3364	(0.0140)
651-700	-0.9714	(0.0092)
701-750	-0.6759	(0.0061)
751-800	-0.4468	(0.0057)
801-850	-0.3209	(0.0062)
General banks pricing sd: $\log(\sigma_g)$	-0.1866	(0.0156)
Target banks pricing sd: $\log(\sigma_t)$	-1.1355	(0.0903)
Bargaining power sd: $\log(\sigma_\omega)$	-1.0650	(0.1054)

The estimated model allows us to separate the two sources for the dispersion in observed consumer rates: (i) differences in bank-receiving rates across loans, and (ii) the heterogeneity in bargaining power across consumers. We first compare the model-predicted dispersions of consumer rates with and without the heterogeneity in bargaining power at target banks before the policy change. For the case without the heterogeneity, we assume for every loan a constant bargaining power at the estimated average across consumers. The exercise shows that half of the dispersion in consumer rates (measured by the standard deviation) comes from the heterogeneity in bargaining power. It is consistent with the reduced-form pattern that the dispersion of consumer rate at target banks dropped significantly after they adopted the non-discretionary dealer compensation (see Figure 1). The result supports the argument that discretionary dealer markups are a major source for consumers being charged different interest rates. We further investigate the contribution of $\varepsilon_{i,\omega}$, representing the unobserved factors that are independent to consumer credit profile and loan characteristics, to the dispersion in consumer rates. This is done by simulating a case where σ_ω is set to zero so the bargaining power varies only by the observed consumer and loan characteristics. The result suggests that the variation in $\varepsilon_{i,\omega}$ contributes to about 13% of the dispersion, which is a substantial amount. What it implies is that, for two consumers under the same bank-receiving rates (as they have same $\boldsymbol{x}_i$ and ϵ_{ij} in equation 1), they can still be charged different dealer markups, which is a discriminatory practice from the dealer.

Figure 4: Compare True and Model Simulated Data



Finally, we show how the estimated model fits with the data. As shown in Figure 4, the model fits well for the overall target bank market share, the interest rates of the target banks, and the interest rates of the general banks. In particular, although our model slightly over-predicts (under-predicts) the pre-policy (post-policy) market share, it can replicate the pattern of declining market share after the policy for target banks.

4.2 Counterfactual compensation schemes

We use counterfactual analysis to investigate whether there is a policy that can improve target banks' market share while maintaining the non-discretionary feature in the compensation. We focus on three compensation schemes, under which the dispersion in consumer rates due to the dealer-consumer interaction could be eliminated. We note that these compensation schemes may still result in certain groups of consumers being charged statistically higher interest rates. For example, if minority consumers tend to have lower credit scores, an interest rate based on credit score will be systematically higher for minority consumers. Without observing the information, we cannot directly examine how the three compensation schemes impact 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 from other personal traits that are observed by dealers but are independent from the credit profile and loan characteristics.

The three compensation schemes we consider are:

1. *Fixed-percentage of loan amount*: target banks pay dealers a fixed percentage of the loan amount. This is the same as their current policy, where the percentage is set at 3%.

2. *Fixed dealer rate*: target banks compensate dealers by a fixed interest rate of the loan. The consumer rate will be equal to the bank-receiving rate plus the dealer rate.

3. *Fixed lump-sum*: target banks pays dealers a fixed lump sum payment for each loan, regardless of the loan terms.

We keep the bank-receiving rates unchanged in counterfactuals. This ensures that the profit margin stays the same for any given loan, allowing us to focus on maximizing the market share (instead of profit) for target banks. For each compensation scheme, we numerically search for the optimal percentage of the loan amount, dealer rate, or the lump-sum payment, which will maximize the market share across all consumer segments for target banks.

Table 6 compares the market outcomes under the three optimal schemes. As a benchmark, we also report the consumer rate and market share under the current dealer compensation (i.e. 3% of loan amount). For comparison, we convert the percentage of loan amount in the first scheme and the lump-sum payment in the third scheme to *equivalent dealer rates* (see Section 3.1 for the payment formula). For example, suppose for a specific loan length and amount, paying the dealer a 1% interest rate amounts to paying her \$500. Then for this loan, a lump sum \$500 compensation is equivalent to a dealer rate of 1%. If the loan amount is \$20,000, then a 2.5% of loan amount compensation is also equivalent to a dealer rate of 1%.

Column 1 of the table reports the equivalent dealer rates. The optimal dealer rate under the fixed dealer rate scheme is slightly lower than under fixed percentage of loan amount and fixed lump-sum schemes, and all of them are significantly lower than the equivalent dealer rate under the

Table 6: Market Outcomes under Different Compensation Schemes

	Equiv. Dealer Rate (1)	Consumer Rate (2)	Market Share (3)	Increase in Market Share (4)
Benchmark (3% of loan amount)	1.13%	3.06%	4.56% (0.04%)	-
Fixed percentage of loan amount	0.94% (0.04%)	2.87% (0.04%)	4.59% (0.04%)	0.7% (0.2%)
Fixed dealer rate	0.89% (0.04%)	2.82% (0.03%)	4.55% (0.04%)	-0.2% (0.7%)
Fixed lump sum	0.93% (0.03%)	2.86% (0.03%)	4.80% (0.04%)	5.3% (0.3%)

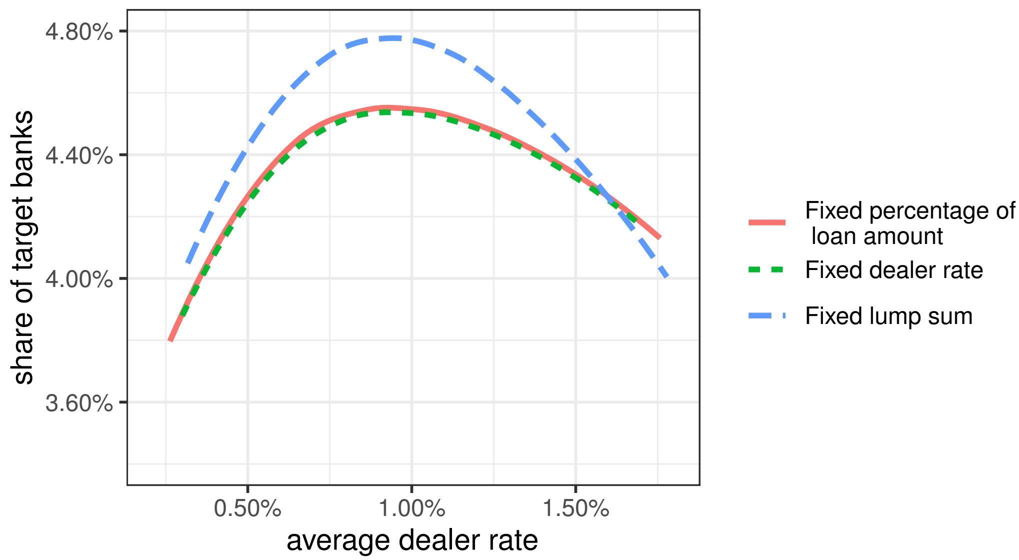
To compute target banks' market share for a compensation plan, we simulate the bank choice of every loan in the post-policy data and then aggregate these individual choices. General banks' and target banks' receiving rates follow the estimated model. The rates shown in the first two columns are averaged across the loans financed by target banks. Numbers in parentheses are standard deviations from simulations.

current 3% of loan amount. Consequently, consumers under the three counterfactual compensation schemes will pay a consumer rate significantly lower than the current 3.06%, as reported in Column 2.

The goal of this exercise to improve the market share for target banks. Column 3 of the table shows that the lump-sum compensation is the most effective, helping target banks gain a total market share of 4.80%. This represents creating a 5.3% increase from the current policy, as shown in the last column. In fact, the effectiveness of the lump-sum compensation holds over a fairly wide range of equivalent dealer rates, which we present in Figure 5. The peaks of the plotted curves correspond to the optimal equivalent dealer rates reported in Table 6. Note that we calculate market share based on the number of loans in this exercise. In the appendix, we provide a robustness check when we calculate the market share based on the total loan amount. Again, the lump-sum compensation is the most effective compensation scheme.

Table 7 further compares the consumer rate and market share of the three optimal compensation schemes, benchmarked with the current 3% of loan amount compensation, for each credit score segment. Compare with the current policy (Columns 1−2 of the table), the optimal lump-sum policy (Columns 7−8) significantly increases market share for high-credit segment, while there is no significant decline in the low-credit segment. We find this result to be a nice feature of the lump-sum scheme; it reinforces the target banks' positioning to focus on higher-credit segments, and does so not at the expense of low-credit consumers. This, together with the fact that consumer rates are lower across credit segments, indicate that the consumer welfare aggregated across segments should increase. This is a better policy from public policy makers' perspective. Since there is increase in market share across segments, target banks' profit should also increase (assuming that they don't take a loss for extending loans to any credit segment). For the other two policies (Columns 3−6), consistent with the above, we find that the market share increase happens more among higher credit score segments, and the overall interest rate descreases compared to the benchmark. This is worth noting that, among the three compensation schemes, the lump-sum policy achieves the

Figure 5: Comparing Compensation Schemes



highest market share among all credit segments.

4.2.1 Discussion on the effectiveness of dealer compensation schemes

Why does the fixed lump-sum scheme achieve a higher market share for target banks? The key reason lies in the *best aligning the dealer rate with the estimated consumer 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, and vice versa. Among the three schemes, the lump-sum scheme introduces a strong negative correlation between the dealer rate and consumer bargaining power. This is shown in the right diagram of Figure 6, which plots the average dealer rate at target banks within each quartile of consumers in terms of bargaining power. This negative correlation allows the lump-sum scheme to pass a lower rate to consumers when their bargaining power is high, and thus target banks can gain a larger market share.

So why does the lump-sum scheme result in the strong negative correlation shown in the figure? This is because of two reasons. First, under the lump sum scheme, the equivalent dealer rate decreases with the loan amount. To see this, note that under a fixed dealer rate, the dollar payment to the dealer doubles as the loan amount doubles. Thus, if the dollar payment is fixed, the equivalent 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). Indeed, among the consumer and loan characteristics, the strongest predictor for bargaining power is the loan amount. Together, these two reasons explain why the equivalent dealer rate and the consumer bargaining power are negatively correlated under the lump-sum scheme.

Table 7: Consumer Rate and Market Share Comparison by Credit Segments

	Benchmark (3% of loan amount)		Optimal percentage of loan amount (2.5%)		Optimal dealer rate (0.89%)		Optimal lump sum ($439)	
	Consumer Rate (1)	Market Share (2)	Consumer Rate (3)	Market Share (4)	Consumer Rate (5)	Market Share (6)	Consumer Rate (7)	Market Share (8)
All consumers:	3.06%	4.56%	2.87%	4.59%	2.82%	4.55%	2.86%	4.80%
	(0.004%)	(0.04%)	(0.04%)	(0.04%)	(0.04%)	(0.05%)	(0.03%)	(0.04%)
By credit segment:								
600-650	3.66%	2.24%	3.49%	2.14%	3.49%	2.09%	3.53%	2.24%
	(0.02%)	(0.08%)	(0.04%)	(0.08%)	(0.04%)	(0.10%)	(0.04%)	(0.08%)
651-700	3.41%	3.55%	3.24%	3.47%	3.23%	3.39%	3.25%	3.63%
	(0.01%)	(0.07%)	(0.04%)	(0.08%)	(0.04%)	(0.10%)	(0.03%)	(0.08%)
701-750	3.15%	4.65%	2.97%	4.62%	2.94%	4.54%	2.97%	4.84%
	(0.01%)	(0.07%)	(0.04%)	(0.07%)	(0.04%)	(0.07%)	(0.03%)	(0.07%)
751-800	2.92%	5.66%	2.73%	5.76%	2.67%	5.72%	2.71%	6.03%
	(0.01%)	(0.08%)	(0.04%)	(0.09%)	(0.04%)	(0.08%)	(0.03%)	(0.09%)
801-850	2.75%	5.73%	2.56%	5.97%	2.44%	6.04%	2.53%	6.21%
	(0.01%)	(0.09%)	(0.04%)	(0.10%)	(0.04%)	(0.12%)	(0.03%)	(0.10%)

Figure 6: Relation between Dealer Rate and Consumer Bargaining Power

Each figure plots the average (equivalent) dealer rate for the four quartiles of consumers in terms of bargaining power. Compared to the other two schemes, the lump sum scheme introduces the largest negative correlation between dealer rate and consumer bargaining power.

Under the fixed dealer rate scheme, the dealer rate is constant across loans by construction, and thus has no correlation with bargaining power (see the middle diagram of Figure 6). Interestingly, the left diagram of Figure 6 suggests that, under the scheme of fixed percentage of loan amount, the equivalent dealer rate is also negatively correlated with the consumer bargaining power (although the correlation is much weaker than under the fixed lump-sum scheme). Since this scheme implies that the equivalent dealer rate decreases with the loan length, and the loan length is negatively associated with consumer bargaining power (Table 5), one might think that the scheme will create a positive correlation between the equivalent dealer rate and consumer bargaining power. However, this is not the case.

To understand this counter-intuitive result, we note that the association between loan length and consumer bargaining power is "with everything else equal." In the data, however, there is a highly positive correlation between loan length and loan amount. With the loan amount being a stronger predictor for bargaining power than the loan length, longer loans in the data are actually associated with higher, not lower, consumer bargaining power. This result highlights the importance of conducting counterfactual exercises, rather than simply relying on parameter estimates to predict the performance of different compensation schemes.[18]

4.2.2 Eliminating discriminatory consumer rates

The current 3% of loan amount compensation as well as the proposed fixed lump-sum payment compensation intend to remove dealers' discretion to vary the dealer markup, particularly their ability to charge consumers based on factors such as gender and race that are unobserved to banks and researchers. In our model, the effect of these factors on consumer bargaining power is captured by $\varepsilon_{i,\omega}$. 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 regime allowing for the discretionary markup, which causes disadvantaged consumers with a low $\varepsilon_{i,\omega}$ to pay a higher consumer rate. Since the 3% of loan amount compensation and the fixed lump-sum implies that the equivalent dealer rate would vary by the consumer bargaining power, as shown in Figure 6, one may be concerned that the discriminatory practice may still exist among dealers under these policies. To address this concern, we simulate three different dealer compensation policies: discretionary markup (pre-policy period), 3% of loan amount (post-policy period), and the optimal \$439 lump-sum payment (our proposed policy). We examine how consumer rates at target banks vary with $\varepsilon_{i,\omega}$ under these policies.

Table 8 reports the simulated consumer rates charged on consumers with different levels of $\epsilon_{i,\omega}$. Under the discretionary markup regime (Column 1), the average consumer rate is 3.41% for the bottom quartile of $\varepsilon_{i,\omega}$, about 30 percent higher than the 2.64% for the top quartile of $\varepsilon_{i,\omega}$. Note that this gap is not caused by any systematic difference in the observed loan characteristics or consumer credit profile, because $\varepsilon_{i,\omega}$ is independent from these attributes. Instead, this gap is

[18] We note that the comparison results do not rely on the assumption in the bargaining model that dealers and consumers negotiate over interest rates. Suppose they negotiate over the dollar amount of interest payments (i.e. how much interest payment dealers should obtain and how much total interest payment consumers should give.) In this case, under the fixed lump-sum scheme a dealer's dollar payment is invariant from the consumer bargaining power. However, the dollar payment will be *positively* correlated with the consumer bargaining power under the other two schemes. The fixed lump-sum scheme thus is still the most effective compensation that helps target banks maximize their market share.

entirely driven by the unobserved factors, reflecting the important role of unobserved bargaining power in causing the dispersion in consumer rates.

Table 8: Consumer Rates by Unobserved Bargaining Power

Quartiles of unobserved bargaining power $\varepsilon_{i,\omega}$	Discretionary (pre-policy) (1)	3% of loan amount (post-policy) (2)	Lump-sum payment (proposed policy) (3)
Top 25%	2.64%	3.07%	2.89%
	(0.01%)	(0.01%)	(0.01%)
25−50%	2.87%	3.07%	2.90%
	(0.01%)	(0.01%)	(0.01%)
50−75%	3.06%	3.06%	2.90%
	(0.01%)	(0.01%)	(0.01%)
Bottom 25%	3.41%	3.06%	2.90%
	(0.02%)	(0.01%)	(0.02%)

This table breaks down the impact on consumers based on three compensation policies by unobserved bargaining power for consumers. Consumer rate reports the average consumer rate for target banks. Results are based on the average of 100 simulations.

When banks remove the dealer discretion and compensate dealers by either 3% of loan amount (Column 2) or the optimal lump-sum payment (Column 3), the gap in consumer rate largely disappears. Compared to the discretionary markup regime (Column 1), consumer rates for consumers with low bargaining power (who are more likely to be disadvantaged consumers) are much lower, and that for consumers with high bargaining power consumers are significantly higher. Therefore, discriminatory interest rates are eliminated under these two policies. Furthermore, under the optimal fixed lump-sum compensation consumer rates are significantly lower than that under the 3% of loan amount compensation scheme, suggesting that under the former policy the consumer welfare has been improved over the current policy.

5 Conclusion

This paper provides an empirical framework to investigate how final prices and consumer demand are formed when firms rely on middlemen to reach consumers. Placing emphasis on the tension of interest between middlemen and consumers, we adopt the Nash bargaining approach to model the interaction between the two parties. The model helps explain a reversal of demand curve in the auto loan market, observed after a non-discretionary dealer markup policy was introduced by several banks to replace the original discretionary policy. By focusing on a limited scale policy change, we are able to pin down the dealer–consumer interactions that determine interest rates and bank choice in our model, without being confounded by the complicated strategic responses from other competitors. The estimated model enables us to investigate counterfactual compensation policies that help maximize the banks' market share.

Our exercise is particularly useful for banks to navigate the complex landscape of designing dealer compensation while fulfilling the requirement of consumer protection. 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 has led to various legal actions, as disadvantaged consumers (e.g., minority consumers) are claimed to have been systematically discriminated by paying a higher markup. Our study shows how a fixed lump sum compensation scheme can eliminate such practice while helping banks to protect their market share. As of now, we are not aware of such a compensation scheme used in the auto loan market. Most current practices peg compensation to the loan amount, possibly due to the intuitive thinking to reward dealers for bringing in higher value loans. However, our model estimates show that larger loans typically indicate more bargaining power on the consumer side, which provides a reason to suppress the dealer compensation on larger loans so that a lower interest rate can be passed to the consumer. This reason renders the lump-sum a better solution than the fixed-rate or fixed-percentage scheme.

There are several limitations of this research that should be addressed in future studies. Since only a few sellers adopted the policy change, we assume there are no strategic responses from general banks, especially during the short period after the policy change. We do not attempt to describe how a new market equilibrium may arise when general banks shift their pricing policy in response. Along a similar line, we also do not consider what would happen if all banks are required to adopt a non-discretionary dealer compensation scheme. A data set that combines additional information on the cost from banks as well as outside options from consumers can enable future research along this direction. Finally, we call for more research in the future to directly quantify the impact on minority consumers from different dealer compensation schemes, which requires data on the ethnicity of individual consumers.

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A Appendix

A.1 Monte Carlo

We generate a data set of 0.57 million loans by drawing loan amount, loan length and credit score with means and standard deviations close to those in the actual data. With a set of assumed "true" model parameters, we simulate the loan outcomes using our model. Specifically, we first draw the error terms in the bank pricing functions (i.e., $\varepsilon_{i,g}$ and $\varepsilon_{i,t}$) and in the bargaining power function (i.e., $\varepsilon_{i,\omega}$), then compute the bargaining outcomes, which determine both the bank choice y_i and consumer rate r_i.

Table 9: Monte Carlo Estimation Results

	True values	Estimates	S.E.
General banks: receiving rate $\boldsymbol{\alpha}_g$:			
Constant	1.00	0.9349	(0.0692)
Loan amount	0.10	0.1021	(0.0006)
Loan length	0.05	0.0521	(0.0031)
Credit score	-0.50	-0.4996	(0.0093)
Target banks: receiving rate $\boldsymbol{\alpha}_t$:			
Constant	0.30	0.2471	(0.0347)
Loan amount	0.05	0.0514	(0.0004)
Loan length	0.02	0.0185	(0.0033)
Credit score	-0.25	-0.2494	(0.0042)
Bargaining power $\boldsymbol{\lambda}$:			
Constant	-2.00	-2.0597	(0.0568)
Loan amount	0.10	0.1001	(0.0003)
Loan length	-0.30	-0.2976	(0.0029)
Credit score	0.20	0.2055	(0.0073)
Non-financial value $\boldsymbol{\delta}_t$:			
600-650	-0.55	-0.5644	(0.0103)
651-700	-0.50	-0.5160	(0.0087)
701-750	-0.45	-0.4679	(0.0082)
751-800	-0.40	-0.4132	(0.0083)
801-850	-0.35	-0.3766	(0.0091)
General banks pricing sd: $\log(\sigma_g)$	-0.3	-0.2721	(0.0114)
Target banks pricing sd: $\log(\sigma_t)$	-0.6	-0.6027	(0.0034)
Bargaining power sd: $\log(\sigma_\omega)$	-1.0	-1.0411	(0.0180)

The estimation results for the Monte Carlo study are reported in Table 9. Column 1 shows the true parameters we use in the simulation. Columns 2 and 3 show the parameter estimates and the standard errors. We see the parameter estimates are close to the true values. This Monte Carlo exercise suggests that our proposed model can be identified. In particular, the bargaining power and bank pricing functions can be separately identified.

A.2 Market share by total loan amount

Table 10 repeats the comparison exercise across the three compensation schemes, but apply an alternative definition of market share. Market share is computed in terms of the total loan amount, instead of the number of loans. Not all loans are of the same size; this alternative definition gives larger loans a higher weight in calculating market shares. Again, the lump-sum compensation is the most effective.

Table 10: Comparing Optimized Compensation Schemes (Market Share in Dollars)

	Equiv. Dealer Rate (1)	Consumer Rate (2)	Market Share (3)	Increase in Market Share (4)
Benchmark (3% of loan amount)	1.13%	3.06%	4.57% (0.04%)	-
Fixed percent of loan amount	0.72% (0.04%)	2.64% (0.04%)	4.74% (0.04%)	3.6% (0.3%)
Fixed dealer rate	0.69% (0.03%)	2.62% (0.03%)	4.73% (0.04%)	3.5% (0.3%)
Fixed lump sum	0.94% (0.04%)	2.86% (0.04%)	4.99% (0.04%)	9.1% (0.4%)

This table repeats the exercise in Table 6 but under the definition of market share by total loan amount instead of number of loans.