

The impact of discriminatory pricing based on customer risk: an empirical investigation using indirect lending through retail networks

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Abstract

Purpose – The purpose of this study is to understand the profit implications of analytics-driven centralized discriminatory pricing at the headquarter level compared with sales force price delegation in the purchase of an aftermarket good through an indirect retail channel with symmetric information.

Design/methodology/approach – Using individual-level loan application and approval data from a North American financial institution and segment-level customer risk as the price discrimination criterion for the firm, the authors develop a three-stage model that accounts for the salesperson's price decision within the limits of the latitude provided by the firm; the firm's decision to approve or not approve a sales application; and the customer's decision to accept or reject a sales offer conditional on the firm's approval. Next, the authors compare the profitability of this sales force price delegation model to that of a segment-level centralized pricing model where agent incentives and consumer prices are simultaneously optimized using a quasi-Newton nonlinear optimization algorithm (i.e. Broyden–Fletcher–Goldfarb–Shanno algorithm).

Findings – The results suggest that implementation of analytics-driven centralized discriminatory pricing and optimal sales force incentives leads to double-digit lifts in firm profits. Moreover, the authors find that the high-risk customer segment is less price-sensitive and firms, upon leveraging this segment's willingness to pay, not only improve their bottom-line but also allow these marginalized customers with traditionally low approval rates access to loans. This points out the important customer welfare implications of the findings.

Originality/value – Substantively, to the best of the authors' knowledge, this paper is the first to empirically investigate the profitability of analytics-driven segment-level (i.e. discriminatory) centralized pricing compared with sales force price delegation in indirect retail channels (i.e. where agents are external to the firm and have access to competitor products), taking into account the decisions of the three key stakeholders of the process, namely, the consumer, the salesperson and the firm and simultaneously optimizing sales commission and centralized consumer price.

Keywords Price discrimination, Price optimization, Consumer credit, Risk-based pricing, Financial services, Sales incentives

Paper type Research paper



1. Introduction

Advances in artificial intelligence (AI) and analytics and falling costs for data storage have led firms to increasingly take advantage of data-driven models and automation to improve marketing decisions and, subsequently, increase top- and bottom-line performance. Banking is one such industry that benefits from AI and analytics, delivering around \$1tn in additional value per year globally (Biswas *et al.*, 2020), the majority of which (i.e. 60%) is expected to come from marketing and sales applications. Undeniably, personal selling is one of the most critical activities for firms, receiving a substantial portion of the marketing budget. In the USA, the total amount allocated to personal selling is greater than \$800bn (Zoltners *et al.*, 2013), which is four times that of advertising. Salespeople's proximity to customers allows them to directly gauge their purchase drivers and willingness to pay (WTP; Frenzen *et al.*, 2010), while also managing any negotiations that might arise in the process (Jindal and Newberry, 2022). These unique characteristics of sales forces make them highly empowered within organizations, so much so that they are commonly delegated partial pricing authority (Hansen *et al.*, 2008). While the customized nature of sales force discretionary pricing allows firms' flexibility, speed and responsiveness, it potentially leads to prices that are far from optimized levels, which can more easily be accomplished using advanced analytics and AI at the headquarters. This work aims to understand the profit implications of analytics-driven centralized discriminatory pricing at the headquarter level compared with sales force price delegation, using the context of an indirect retail channel for an aftermarket good with symmetric information across channel members.

Indeed, this is an outstanding question for firms in many markets. The problem becomes further convoluted for indirect retail channels where sales agents are external to the firm and, thus, have access to competitor offerings. Consequently, this puts more emphasis on sales force compensation and incentives as mechanisms firms rely on to influence the sales force's decision-making processes (Caldieraro and Coughlan, 2007). In summary, price delegation in an indirect retail channel is a complex process because firms must simultaneously account for the extent of delegatory power, competition and sales force incentive structures.

Academic literature on price discrimination and sales force price delegation collectively provide initial support for using optimized AI and analytics-based pricing over the more traditional approach of sales force price delegation (Phillips *et al.*, 2015). However, there remain numerous empirical and substantive challenges that deserve further attention before one can reach empirical generalizations. Specifically, research on sales force price delegation has been scant and mostly analytical because of the lack of high-quality data (Misra and Nair, 2011). While the analytical results provide important insights, many of the nuances that exist in real life are not accounted for, especially when considering the context of an *indirect retail channels*, thus, limiting generalizations. For instance, focusing on internal salesperson behavior, extant literature largely overlooks competition (Bhardwaj, 2001; Joseph, 2001; Mishra and Prasad, 2004). In an *indirect retail channel*, salespeople have access to competitors' products in addition to those of the focal firm. This complicates the pricing problem because firms risk salespeople switching to the competitor option when they take away pricing authority through purely centralized pricing. Thus, one cannot compare centralized discriminatory pricing with salesperson price authority without explicitly accounting for competitor prices and commissions. Moreover, research to date examines pricing independent of incentive rates and structures (Phillips *et al.*, 2015), which does not allow for insights regarding the effect of commissions on sales force pricing decisions. Accounting for this interaction is critical for any reliable estimate of the profit lift associated with AI-based pricing over price delegation within an indirect retail channel. Lastly, and importantly, extant literature does not account for the interdependencies between the *three key stakeholders* in the indirect retail network – the firm,

salesperson and customer – which is critical for a realistic representation of the context and the reliability of the insights generated. Thus, without addressing these empirical challenges, the question of how much (if any) incremental bottom-line benefit AI-driven discriminatory pricing offers over and above the more traditional partial price discrimination is still outstanding.

We address the aforementioned points by developing a model framework that explicitly accounts for the nuances of the *indirect retail channel*, using the context of auto loans and consumer risk as a price discrimination mechanism. Specifically, our framework incorporates the effect of competition by accounting for a competitor option when optimizing the price and commission of the focal firm's product. This prevents overestimation of the optimized price and corresponding profits associated with centralized AI-based pricing, which occurs if one ignores competitive pressures. The framework also encapsulates the effect of commission on the salesperson's pricing decision through simultaneous optimization of these two variables. This is critical because commissions influence the salesperson's pricing decision. Lastly, and importantly, our framework comprehensively considers the decisions and interdependencies between the *three key stakeholders* in the indirect retail network – the firm, salesperson and customer. Specifically, we account for the sequential decisions within the conceptual framework by factoring in the salesperson's expectation regarding the firm and customer's responses to their pricing decisions.

Our intended contributions are fourfold. First, we conceptualize the indirect retail channel while accounting for the complex realities of the context, which allows us to empirically investigate the profit implications of analytics-driven segment-level centralized pricing (i.e. no pricing authority) compared with sales force price delegation (i.e. partial pricing authority) in an *indirect retail channel*. Second, we offer insights into the optimal pricing and commission structure design within an indirect retail channel through which salespeople have access to competitors' and focal firm's products (i.e. external sales force). Third, theorizing from the sales force literature, we identify *expected* commissions as a key driver of external sales force pricing decisions; thus, we demonstrate the importance of the sales force's forward-looking behavior. Fourth, we introduce consumer risk to the marketing literature as an important variable for segmentation and price discrimination purposes by examining potential differences in price sensitivity across risk segments.

The paper proceeds as follows. In Section 2, we highlight the relevant academic literature related to price discrimination and price delegation to guide the model development, which is described in Section 3. Then, in Section 4, we discuss the empirical analysis, including data description, model-free evidence and estimation/optimization results. We validate these results in Section 5, using predictive performance measures, both in sample and out of sample. In our discussion in Section 6, we identify the importance of our results, from a theoretical, managerial and consumer welfare perspective, while also guiding academics with concrete suggestions for future research.

2. Conceptual development

This article draws from and contributes to two main streams of literature: price discrimination and sales force price delegation. Below we discuss both streams and highlight our contributions in relation to the extant work.

2.1 Price discrimination

Price discrimination refers to pricing similar goods or services at different ratios to marginal cost (Stigler, 1987) and is one of the most prevalent forms of marketing practices. While the most common objective of price discrimination is to extract larger surplus from different groups of customers through accounting for variation in their WTP, firms also resort to

discriminatory prices for reasons such as demand management (i.e. controlling the timing of purchase), inventory management (i.e. use up spare capacity and clear inventory) and improved cash flow (i.e. increase volume of purchase).

In theory, discriminatory pricing is categorized into three types: first-, second- and third-degree price discrimination (Pigou, 1920). However, first-degree or perfect price discrimination, which refers to charging a price for each good that is equal to the maximum WTP for that unit (Varian, 1989), is difficult to implement and rarely seen in practice. Second-degree price discrimination, or nonlinear pricing, occurs when prices differ based on the quantity sold, but not across customers. This happens either through cash or cash equivalent discounts such as gift cards (Khouja *et al.*, 2011). Alternatively, under third-degree price discrimination, sellers segment the market based on some consumer characteristic and price the segments according to their different price sensitivities (Moorthy, 1984). Under this type, firms can either use firm-initiated price discrimination by directly segmenting the market and tailoring pricing to each segment, leaving consumers with the choice of accepting or rejecting the firm's offer, or resort to price discrimination through self-selection by developing marketing programs with different benefits, thereby allowing consumers to self-select into the category that best suits their needs (Moorthy, 1984). Some examples of the former include store-level pricing (Chintagunta *et al.*, 2003; Khan and Jain, 2005; Montgomery, 1997), demographic-based pricing (Frank *et al.*, 2014; Gary-Bobo and Larribeau, 2004), motivation-based pricing (Lee *et al.*, 2013), lifestyle-based pricing (Bruwer and Li, 2017), knowledge-based pricing (Barrutia and Espinosa, 2014), targeted advertising/promotion (Esteves and Resende, 2016; Sayman and Hoch, 2014), behavior-based price discrimination (Caillaud and De Nijs, 2014; Conitzer *et al.*, 2012; Shin and Sudhir, 2010) and situational/contextual price discrimination (Wakefield and Inman, 2003). Examples for the latter include the use of warranties (Soberman, 2003; Chu and Chintagunta, 2011), quantity discounts (Khan and Jain, 2005; Cohen, 2008; Subramaniam and Gal-Or, 2009), multi-period pricing (Geng *et al.*, 2007), coupons (Anderson and Song, 2004; Dhar and Hoch, 1996; Narasimhan, 1984; Shaffer and Zhang, 1995), price promotions (Empen *et al.*, 2015), price matching/price difference refund policies (Jain and Srivastava, 2000; Nalca *et al.*, 2010; Nalca *et al.*, 2013), bonus buys (Dhar and Hoch, 1996; Cui *et al.*, 2008), rebates (Chen *et al.*, 2005; Lu and Moorthy, 2007), probabilistic product offerings (Fay *et al.*, 2015), metering (Gil and Hartmann, 2009) and multiple shipping options (Li and Dimlersoz, 2012).

Recent research advocates for the use of analytics and AI in price setting (Huang and Rust, 2021) and use of consumers' private information for price personalization (Montes *et al.*, 2019). While the latter is largely applicable to e-commerce platforms where firms have access to individual-level search information through cookies, other examples also exist in offline contexts. For example, in consumer lending, financial institutions gain access to consumer credit scores that they use to assess customer's risk profiles, which can be used as a criterion for personalized prices (Magri, 2015).

It is important to note that the common industry practice of risk-based price discrimination ignores differences in WTP (Chun and Lejeune, 2016) and solely applies a fixed mark-up to the marginal cost of each loan. This is problematic because prices much higher than consumers' WTP decrease the sales probability, and the opposite decrease firms' margins. In either case, prices are not being optimized, highlighting the low adoption rate of pricing optimization systems in the financial sector compared with other industries such as the airline industry (Phillips, 2013). AI and analytics help fully capture the benefits of discriminatory pricing based on risk because they enable firms to not only capture the differences in cost but also differences in WTP across segments.

Our research contributes to the price discrimination literature in two ways. First, we investigate the impact of analytics-driven discriminatory prices based on risk on firm

profitability, which has not been studied in the marketing literature. To investigate this form of price discrimination, we use the consumer credit market for automobile loans context. One of the unique traits of the consumer credit market is that prices are often dispersed, with different lenders offering the same loan to the same consumer at different rates (Phillips, 2013), likely because consumers have imperfect information regarding pricing (Stigler, 1961). This feature of the market makes it well suited for discriminatory pricing. In addition, firms can reduce equity concerns and inferences of disrespect by using category-relevant characteristics to differentiate prices (Ashworth and McShane, 2012), risk being one such criterion in the context of consumer lending. Moreover, adoption of risk-based price discrimination would have significant consumer welfare implications because it would allow consumers with higher than average risk scores, who traditionally have low credit approval rates, to have access to loans. This is not possible at a fixed price (i.e. house rate) as it would not be profitable for lenders (Bostic, 2002; Collins *et al.*, 2005). Finally, the finance and economics literature have investigated risk-based pricing, mostly focusing on mortgages (see, for example, Barrutia and Espinosa, 2014; Al-Bahrani and Su, 2015; Phillips, 2013; Allen *et al.*, 2014), because the auto loan market has refrained from adopting discriminatory pricing based on risk. The auto loan sector has instead heavily relied on indirect channels and sales force price delegation, which we discuss in detail in the next section.

Second, most of the price discrimination literature in marketing focuses on contexts that involve core goods. In contrast, we focus on discriminatory pricing of an *aftermarket good*, which augments the core product. More specifically, in our context, the price decision relates to the loan (i.e. aftermarket good) for an automobile purchase (i.e. core product). This nuance makes the salesperson–customer interaction unique because customers usually exert their negotiation efforts and cognitive capacity for the core product and approach the sales of the aftermarket good in a different mindset. Insurance, warranty and concession sales at the movie theaters are other examples of such products for which consumers' price sensitivities and negotiation desires might be lower (Soberman, 2003; Ancarani and Shankar, 2004; Gil and Hartmann, 2009).

2.2 Sales force price delegation

Firms often delegate pricing authority to the sales force because of their proximity to consumers and potential ability to better gauge their WTP. While price delegation is an established practice, how much authority is granted to the sales force varies significantly. A recent survey by Hansen *et al.* (2008) reports that firms that grant full, partial and no price authority to the sales force account for 11%, 61% and 28% of the sample, respectively. A similar variation was reported by Stephenson *et al.* (1979).

Given the disparity of pricing delegation across organizations in practice, researchers have investigated how and under which conditions sales force price discretion is profitable. Findings across several studies suggest that both the likelihood and benefits of pricing delegation are highest when sales commission is based on gross margin rather than sales revenue (Homburg *et al.*, 2012; Bhardwaj, 2001; Weinberg, 1975). In addition, information asymmetry between the firm and sales force is one of the key drivers of profitability of price delegation, and in the absence of such asymmetry, centralized pricing is shown to be a better choice (Lal, 1986; Mishra and Prasad, 2004). Similarly, the optimal level of pricing authority should vary as a function of costs of prospecting to maximize profits (Joseph, 2001). More specifically, when costs of prospecting are moderate (low or high), the extent of pricing authority should be limited (full).

While these findings provide important insights into the price delegation decision, most of the studies in this literature are theoretical or focus on strategic questions using firm-level survey data. However, what happens in practice is an empirical question. To further enhance

our understanding on this topic, we supplement these studies through an empirical approach using field data. In addition, competition has largely been ignored and attention has been given to direct channels where salespeople are internal to the firm. The current study fills this gap by examining an indirect retail channel, where the sales force is external and has access to competitor offerings. Moreover, the decisions of the key stakeholders in the retail channel – consumer, sales force and firm – have not been collectively accounted for, and researchers have mostly focused on one or two of these players (see for example Phillips *et al.*, 2015). In contrast, we explicitly account for each of the three players in the indirect retail setting, thus providing more robust pricing recommendations for indirect retail channels. Finally, the key decision variables in this setting include price and sales force commission, which have not been simultaneously accounted for within the academic literature (see for example Phillips *et al.*, 2015). Alleviating this concern, we jointly optimize price and sales force commission. Collectively, these contributions to the academic literature allow us to better understand the profit implications of AI/analytics-driven centralized pricing versus more traditional pricing delegation approaches. We summarize the aforementioned contributions to the extant pricing delegation marketing literature in Table 1.

Given the literature review and intended contributions, we hypothesize that centralized analytics-driven discriminatory pricing will provide superior profitability compared with pricing delegation. This hypothesis hinges upon three points. First, our context involves very little information asymmetry (i.e. the firm and sales representatives have access to similar information, including salary and customer risk tier). Because information asymmetry is minimal, because of the extensive data that is available to the firm, analytics-driven approaches should be more capable of quantifying differences in WTP across consumer segments, thereby resulting in optimized pricing. Second, the use of centralized analytics-driven discriminatory pricing based on category-relevant characteristics (such as risk), compared with discretionary pricing made by a sales representative, should minimize feelings of consumer unfairness. Third, our context involves consumers who are purchasing an aftermarket good through an indirect retail channel (i.e. as opposed to a core product). Because the dynamics of negotiation is likely to be minimized for aftermarket vs core goods, we expect sales force pricing authority to be less critical, thereby reducing the potential benefit of using sales force price delegation.

3. Model development

Our goal is to understand the potential bottom-line benefits of centralized discriminatory pricing compared with delegating pricing decisions to the sales force. We use consumer credit pricing for the empirical setting and present this in Figure 1, where we outline the sequence of the decisions within the retail network as well as a detailed example of what the pricing structure available to the salesperson looks like.

Our methodological approach follows two steps. First, we develop a three-stage econometric model that mathematically represents the decisions of the three key stakeholders in the retail network. Specifically, we account for:

- (1) the *salesperson's* price decision within the limits of the latitude provided by the firm;
- (2) the *firm's* decision to approve or not approve a customer application; and
- (3) the *customer's* decision to accept or reject a sales offer conditional on the firm's approval.

This three-stage representation not only comprehensively captures the flow of decisions in the retail channel but also allows us to account for the interdependencies between them. For example, a salesperson's pricing decision is influenced by their expectation about firm's

Table 1.
Contribution to the
extant literature

Criteria	Mishra and Prasad (2004)				Wainberg (1975)	This study
	Phillips <i>et al.</i> (2015)	Bhardwaj (2001)	Joseph (2001)	Lal (1986)		
Sales force price delegation	Yes	Yes	Yes	Yes	Yes	Yes
Segment-level discriminatory pricing	-	-	-	-	-	Yes
Optimization of customer price	Yes	-	-	-	-	Yes
Optimization of agent incentive	-	Accounted for but not optimized	Accounted for but not optimized	Accounted for but not optimized	Accounted for but not optimized	Yes
Type of sales force	External	Internal	Internal	Internal	Internal	External
Competition	-	Yes	-	-	-	Yes
Firm's utility/decision	-	-	Yes	Yes	Yes	Yes
Sales force's utility/decision	-	-	Yes	Yes	Yes	Yes
Customer's utility/decision	Yes	Yes	-	-	-	Yes
Endogeneity of price	Yes	-	-	-	-	Yes
Modeling approach	Empirical (field data)	Analytical	Analytical	Analytical	Analytical	Empirical (field data)
Model type	Probit model	Game theoretic model between two competing firms	Optimization of firm profit and salesperson utility	Optimization of firm profit and salesperson utility	Optimization of firm profit and salesperson utility	Three-stage logit model
Research question	How much (if any) price discretion should headquarters grant salespeople?	What is the impact of competition on the delegation decision and how does delegation impact prices and incentives?	When is it optimal to delegate pricing authority to sales force?	What are the conditions under which the sales manager may allow the salesperson to set product prices?	Under what compensation system is it appropriate for a salesman to have control over price?	What are the profit implications of analytics-driven segment-level pricing compared with sales force price delegation?

Source: Authors' own work

approval of the loan application and the customer's acceptance of the loan offer, and hence, their expected compensation [see equation (1)]. Next, given the estimation results, we compare the profitability of this sales force price delegation model to that of a segment-level centralized pricing model where agent incentives and customer prices are simultaneously optimized for each customer risk segment. The comprehensive framework with interdependencies and the simultaneous optimization of salesperson incentives and prices are key contributions to the literature, as we discussed in Section 1.

In the following sections, we detail and model the decisions made by these three key stakeholders, describe the estimation method including how we handle price endogeneity and finally outline the optimization approach.

3.1 Salesperson decision

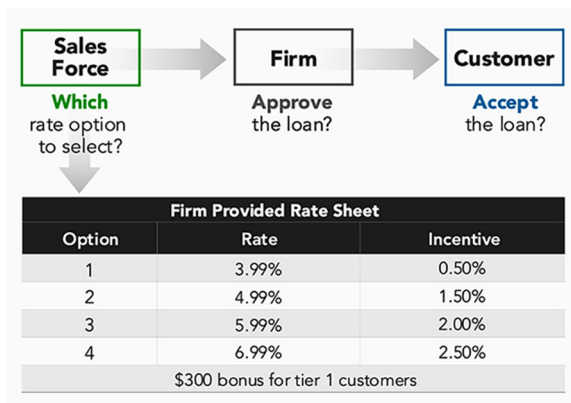
We begin by modeling the behavior of the salesperson, who is the first decision-maker in the indirect lending framework and is responsible for selecting a price (i.e. interest rate for the loan) from the rate sheet provided by the firm. We identify the salesperson-related equations with the superscript A and assume that the salesperson's decision to select one of the firm's J price options for loan applicant n is represented by:

$$y_n^A = \begin{cases} 1, & \text{If the salesperson selects rate sheet option 1 for loan applicant } n \\ \vdots \\ J, & \text{If the salesperson selects rate sheet option } J \text{ for loan applicant } n \end{cases}$$

where y_n^A is the realization of a multinomially distributed random variable Y_n^A that takes the value of j with a probability of $\pi_{nj}^A, j = 1, \dots, J$ and $\pi_{n1}^A + \pi_{n2}^A + \dots + \pi_{nJ}^A = 1$.

When the sales force is deciding between the firm's pricing options, they chose the one that maximizes their utility, U^A , which we model using the linear specification in equation (1):

$$U_{nj}^A = \sum_{q=1}^Q \beta_q^A X_{qnj}^A + \varepsilon_{nj}^A \tag{1}$$



Source: Author's own work

Figure 1.
Visual representation
of empirical setting

The utility in [equation \(1\)](#) comprises a deterministic component, $\sum_{q=1}^Q \beta_q^A X_{qnj}^A$, where X_{qnj}^A are the $Q = 2$ independent variables that include the sales force incentive and the expected incentive (which is calculated by multiplying the incentive by the predicted probability of firm approval – described in Section 3.2 – and the predicted probability of customer acceptance – described in Section 3.3) for price j and loan applicant n , and β_q^A represents the impact of variable X_{qnj}^A on the salesperson utility. In other words, the specification includes Q alternative-specific regressors, X_{qnj}^A , which vary across the N customers and J rate sheet options, as well as Q parameters, β_q^A , that are the same across customers and alternatives. The error term, ε_{nj}^A , accounts for other factors that may have an impact on the salesperson decision but are not explicitly included in the model. Under the assumption that the error term is independently and identically distributed (iid) following a Weibull distribution, the probability of the salesperson choosing price j out of all J options for offer to customer n is provided in [equation \(2\)](#) ([McFadden, 1974](#)):

$$P_n^A(y_n^A = j) = \frac{\exp\left(\sum_{q=1}^Q \beta_q^A X_{qnj}^A\right)}{\sum_{j=1}^J \exp\left(\sum_{q=1}^Q \beta_q^A X_{qnj}^A\right)} \quad (2)$$

Given the model framework, we then write the likelihood for customer n as in [equation \(3\)](#) and log-likelihood over the whole sample of customers as in [equation \(4\)](#):

$$L_n = \prod_{j=1}^J P_n^A(y_n^A = j)^{I[y_n^A=j]} \quad (3)$$

$$LL(\beta^A) = \sum_{n=1}^N \sum_{j=1}^J I[y_n^A = j] \ln \left[P_n^A(y_n^A = j) \right] \quad (4)$$

where $I[\cdot]$ is a binary indicator variable that is equal to 1 if the argument in the squared brackets is true and equal to 0 otherwise. To determine the parameter estimates for the salesperson decision, we maximize [equation \(4\)](#) with respect to β^A .

3.2 Firm decision

Once a loan application is submitted, it enters the firm’s adjudication process to determine whether it is approved. We model the firm’s decision to approve a loan application using a binomial logit model under the assumption that there are N customers that the firm considers for approval. We use the L superscript to identify the firm-related equations and define the approval decision as follows:

$$y_n^L = \begin{cases} 1, & \text{if customer } n \text{ is approved by the lender} \\ 0, & \text{Otherwise} \end{cases}$$

where y_n^L is the realization of a binomially distributed random variable Y_n^L that takes the value of 1 with a probability of π_n^L and 0 with a probability $1 - \pi_n^L$ as in [equation \(5\)](#):

$$P(Y_n^L = y_n^L) = \pi_n^{L y_n^L} (1 - \pi_n^L)^{1 - y_n^L} \tag{5}$$

In the approval decision, the firm acts to maximize its utility as specified in equation (6).

$$U_n^L = \sum_{k=1}^K \beta_k^L X_{kn}^L + \sum_{p=1}^P \phi_p^L Z_{pn}^L + \varepsilon_n^L \tag{6}$$

where $\sum_{k=1}^K \beta_k^L X_{kn}^L$ represents part of the deterministic component of the utility function, where X_{kn}^L are the $K = 9$ individual-level variables for customer n that includes the requested loan amount, cash down payment, loan-to-value (LTV) ratio, total debt service ratio (TDSR), vehicle age, income, amortization, customer risk class and a dummy variable for whether or not the applicant has a deposit relationship with the bank. These context-specific variables are defined in Tables 2 and 3. The impact of variable X_{kn}^L on the utility of the firm is measured by β_k^L . In addition to this, we include a second part to the deterministic component of the utility function, $\sum_{p=1}^P \phi_p^L Z_{pn}^L$, where Z_{pn}^L are the $P = 2$ control variables that include customer region and vehicle manufacturer, which are categorical variables that account for region- and manufacturer-specific factors. Parameter ϕ_p^L measures the effect of control variable Z_{pn}^L on the firm approval decision. ε_n^L represents the stochastic component, which accounts for other factors that may influence approval process but are not included in the model. By assuming that the error term is *iid* following a Weibull (i.e. extreme value)

Variable	Description	Mean	Std. dev.	Min	Max
Requested amount	Loan amount requested by the customer (\$)	27,552	14,089	7,500	357,046
Cash down payment	Amount paid up front by the customer (\$)	1,971	3,909	0	120,000
Loan-to-value ratio (LTV ratio)	<i>Loan amount (\$)/vehicle value (\$)</i>	1.43	0.44	0.16	6.08
Total debt service ratio (TDSR)	<i>Annual debt payments/gross income</i>	0.32	0.18	0.01	8.61
Vehicle age	Age of vehicle (years)	3.72	1.85	0.00	10.00
Income	Customer monthly income (monthly \$)	5,132	3,813	0	99,000
Amortization	Amortization of loan (months)	65.77	16.90	12.00	240.00
Customer rate	Customer interest rate (%)	6.09	0.87	3.98	7.97
Difference	<i>Requested amount (\$)</i> – <i>Approved amount (\$)</i>	–877	3,581	–257,046	28,138
Agent incentive	Commission paid to dealer (\$)	926	589	19	7,957
Cost of funds (COF)	Interest paid by financial institutions for funds (%)	1.75	0.13	0.94	2.20
Probability of default (PD)	Probability that debtor is unable to repay debt (%)	4.41	4.99	0.03	12.00
Loss given default (LGD)	Percentage of loan that is lost when default occurs (%)	35.54	17.36	20.00	60.00

Table 2. Summary statistics for continuous variables

Source: Authors' own work

Variable*	Description	Category	Frequency	%
Lender approval indicator	Whether customer was approved by the lender	Yes/No	45,782	67.17
		Yes/No	22,381	32.83
Customer acceptance indicator	Whether loan offer was accepted by the customer	Yes/No	26,509	38.89
		Yes/No	41,654	61.11
Deposit relationship	Whether customer has a deposit relationship with lender	Yes/No	6,491	9.52
		Yes/No	61,672	90.48
Risk class**	Risk tier that customer belongs to	Tier 1/Tier2/Tier3	37,212	54.59
		Tier 1/Tier2/Tier3	17,907	26.27
		Tier 1/Tier2/Tier3	13,044	19.14

Table 3. Summary statistics for categorical variables

Notes: *Region and manufacturer are also categorical variables we control for, both with many levels. Therefore, they are not represented in Table 3 for simplicity; **customer risk increases from Tier 1 to Tier 3
Source: Authors' own work

distribution, we can then specify the probability of the firm's approval decision as in equation (7) (McFadden, 1974):

$$P_n^L(y_n^L = 1) = \frac{\exp\left(\sum_{k=1}^K \beta_k^L X_{kn}^L + \sum_{p=1}^P \varphi_p^L Z_{pn}^L\right)}{1 + \exp\left(\sum_{k=1}^K \beta_k^L X_{kn}^L + \sum_{p=1}^P \varphi_p^L Z_{pn}^L\right)} \quad (7)$$

Given the above model framework, we then write the likelihood for customer n as in equation (8) and log-likelihood over the whole sample of loan applicants as in equation (9).

$$L_n = P_n^{L y_n^L} (1 - P_n^L)^{1 - y_n^L} \quad (8)$$

$$LL(\beta^L, \varphi^L) = \sum_{n=1}^N \ln \left[P_n^{L y_n^L} (1 - P_n^L)^{1 - y_n^L} \right] \quad (9)$$

To determine the impact of customer, product/brand and loan characteristic variables on the lender approval decision, we then maximize equation (9) with respect to β^L and φ^L .

3.3 Customer decision

After the firm approves the loan application, the salesperson presents the loan offer to the customer, who then decides whether to accept it. We use superscript C to identify customer-related equations and model customer choice using a binomial logit model, under the assumption that there are I approved customers (i.e. $I \leq N$), as in:

$$y_i^C = \begin{cases} 1, & \text{If approved customer } i \text{ accepts the loan offer} \\ 0, & \text{Otherwise} \end{cases}$$

where y_i^C is the realization of a binomially distributed random variable Y_i^C that takes the value of 1 with a probability of π_i^C and 0 with a probability $1 - \pi_i^C$, as in equation (10).

$$P\left(Y_i^C = y_i^C\right) = \pi_i^{C y_i^C} \left(1 - \pi_i^C\right)^{1-y_i^C} \quad (10)$$

The customer accepts the loan offer when his/her latent utility from this decision is greater than that of rejecting the loan offer. We model the utility of the customer using the linear specification in [equation \(11\)](#),

$$U_i^C = \sum_{v=1}^V \beta_v^C X_{vi}^C + \sum_{w=1}^W \varphi_w^C Z_{wi}^C + \varepsilon_i^C \quad (11)$$

which comprises three components. The first term in [equation \(11\)](#), $\sum_{v=1}^V \beta_v^C X_{vi}^C$, represents part of the deterministic component of the utility function, where X_{vi}^C are the $V = 9$ individual-level variables for approved customer i that includes customer risk class, customer income, customer rate, the difference between the requested and approved loan amount, a dummy variable for whether or not the applicant has a banking relationship with the bank, vehicle age, loan amortization as well as an interaction term between customer rate and risk class and between customer rate and region to allow customers' price sensitivity to vary as a function of risk class and region. [Tables 2](#) and [3](#) provide definitions of these variables. The impact of variable X_{vi}^C on the utility is measured by β_v^C . We also include a second part of the deterministic component of the utility function in [equation \(11\)](#), $\sum_{w=1}^W \varphi_w^C Z_{wi}^C$, where Z_{wi}^C are the $W = 2$ categorical variables that control for region- and manufacturer-specific effects and φ_w^C measures the impact of control variable Z_{wi}^C on the customer utility. ε_i^C represents the stochastic component, which accounts for other factors that are not included in the model. We assume that this error term is *iid* following a Weibull (i.e. extreme value) distribution, which then allows us to specify the probability of the approved customer i accepting loan offer using a logistic formulation as in [equation \(12\)](#) ([McFadden, 1974](#)):

$$P_i^C\left(y_i^C = 1\right) = \frac{\exp\left(\sum_{v=1}^V \beta_v^C X_{vi}^C + \sum_{w=1}^W \varphi_w^C Z_{wi}^C\right)}{1 + \exp\left(\sum_{v=1}^V \beta_v^C X_{vi}^C + \sum_{w=1}^W \varphi_w^C Z_{wi}^C\right)} \quad (12)$$

Given this model specification for the customer choice, we can then write the likelihood for approved customer i as in [equation \(13\)](#) and log-likelihood over the whole sample of loan applicants as in [equation \(14\)](#).

$$L_i = P_i^{C y_i^C} \left(1 - P_i^C\right)^{1-y_i^C} \quad (13)$$

$$LL(\beta^C, \varphi^C) = \sum_{i=1}^I \ln \left[P_i^{C y_i^C} \left(1 - P_i^C\right)^{1-y_i^C} \right] \quad (14)$$

We then maximize [equation \(14\)](#) with respect to β^C and φ^C to determine the impact of customer, product/brand and loan characteristic variables on the customer accept decision.

3.4 Endogeneity of price

Before proceeding with the estimation, it is important to discuss the potential endogeneity of price (i.e. interest rate for the loan). If any existing unobserved factors not included in [equation \(12\)](#) are correlated with price, this would imply that price is endogenous. The effect of such unobserved factors would be captured by the price coefficient, thus biasing the results. For example, if males are more likely to accept loans, salespeople might be more prone to select higher interest rates for them, implying a high correlation between price and gender. Given that we do not control for gender in our model, the price coefficient would be confounded with the gender influence on acceptance.

Another reason that might cause endogeneity issues in the model is simultaneity. Specifically, if price impacts the probability of customer acceptance and the same probability influences the salesperson's choice among the available price options, then price would be jointly determined with customer acceptance.

For endogeneity correction, we use a control function approach ([Petrin and Train, 2010](#)), which involves two steps. First, we regress the endogenous price on all exogenous variables and a suitable instrument using OLS. In instrument selection, we follow [Phillips et al. \(2015\)](#) and use the average customer rate that was offered on similar loans (i.e. loans from the same term class, loan amount cluster and month) as the instrumental variable. This instrument is highly correlated with price, and it is uncorrelated with the error term because unobserved customer characteristics and demand factors such as local advertising and promotions are averaged out. Second, we use the residuals from the first step regression as a variable in the customer response model in addition to the exogenous variables and endogenous customer rate. By taking this approach, the parameter estimate for price becomes an unbiased measure of its true impact on the customer's loan acceptance decision, which is critical for the optimization discussed next.

3.5 Price and sales force incentive optimization

After we obtain the parameter estimates for the salesperson, firm and customer decisions, we determine price, r , and salesperson incentive, AI , that maximize the focal lender's total expected profit, Π , for each of the s risk classes as in [equation \(15\)](#).

$$\Pi = \left\{ \sum_{n=1}^N \sum_{s=1}^S \left\{ \left[\left(\frac{r_s}{12} - \frac{CF_n}{12} \right) \times \frac{AT_n}{2} \times AR_n \right] - (AT_n \times PD_n \times LGD_n) - (AI_s \times AT_n) \right\} \times p(y_n^A = 1) \times p(y_n^C = 1) \times p(y_n^S = 1) \times I[RC_n = s] \right\} \quad (15)$$

where CF is the cost of funds, AT is the loan amount, AR is the amortization, PD is the probability of default, LGD is the loss given default and $I[RC_n = s]$ is an indicator variable that is equal to 1 if customer n belongs to risk class (RC) s and 0 otherwise. Because we are seeking a single price and sales incentive for each risk class at the end of the optimization, we consider two potential options for the salesperson. The focal firm, $y_n^A = 1$, or the outside option that is available from the competition, $y_n^A = 2$. The outside option implies zero profits for the focal firm; therefore, it does not factor into profit [equation \(15\)](#).

We run the optimization using R 3.6.0 and the `optim` command in the stats package ([R Core Team, 2019](#)), while specifying the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm as the method. The BFGS algorithm is a quasi-Newton method that was developed in 1970 ([Broyden, 1970a](#); [Broyden, 1970b](#); [Fletcher, 1970](#); [Goldfarb, 1970](#); [Shanno, 1970](#)) and solves unconstrained nonlinear optimization problems, such as the one in [equation \(15\)](#), by taking an iterative approach and building up a visual of the surface that is to be optimized, using both gradients and function values.

4. Empirical analysis

4.1 Data

We use a data set from a large North American financial institution that provides indirect auto loans through dealerships. The data set includes 68,163 loan applications that were received by the lender from June 2015 to December 2015. Of these loans, 45,782 (67%) were approved and 26,509 (39%) were booked by the lender. For the analysis, we used loan information, which we describe in [Table 2](#), such as the LTV ratio, TDSR, amortization, customer rate, cash down payment, cost of funds, probability of default, loss given default, agent incentive as well as the dollar amount that was requested, approved and booked. Taking the difference between the approved and the requested dollar amounts, we also constructed an additional variable that we label as “approval differential,” which captures the extent to which the loan request was covered by the lender. We would like to note that the “approval differential” variable takes both positive and negative values, where the former (latter) reflects applications for which the bank approves a larger (smaller) amount than requested. In addition to loan specific information, we also include customer- and vehicle-specific information, including monthly income, region, an indicator for whether the customer currently has a deposit relationship with the financial institution, risk class, vehicle age and vehicle manufacturer. We provide summary statistics and a description for our continuous and categorical variables in [Tables 2](#) and [3](#), respectively.

4.2 Model-free evidence

Before discussing the estimation results, we begin by examining model free evidence to glean initial insight into the key factors that potentially impact the decisions within the three-stage indirect retail channel. The first step within this framework involves the salesperson who selects a price option from the rate sheet provided by the firm (see [Table 4](#)). We predict that the commission influences the selection of the sales force such that the options with higher commission rates would have a higher selection probability. The last column in [Table 4](#) confirms this prediction because Options 1 and 2 are selected 70% of the time, thus demonstrating the importance of the incentive mechanism in influencing the sales force decision.

Once the salesperson submits the loan application to the firm (i.e. lender) with the selected price-incentive option, the lender decides whether to approve it. We expect the risk profile of the customer to play a role in the firm’s approval decision such that the approval rates are higher for the low-risk customers (Tier 1) and lower for the higher risk groups (Tiers 2 and 3). [Figure 2](#) plots approval rates (# of applicants approved/total # of applicants) for each of the three risk classes and shows that the firm, indeed, approves Tier 1 customers

Rate sheet option	Avg. price (interest rate %)	Avg. incentive (\$)*	Selection rate (%)
Option 1	6.65	1,137	54.61
Option 2	5.77	949	15.31
Option 3	5.17	733	12.53
Option 4	4.73	542	13.19
Option 5	4.16	165	3.30
Option 6	3.98	109	1.05

Notes: *In addition to agent incentive, agents also received a credit quality bonus for Tier 1 customers. This value ranged from \$150–\$300 by month

Source: Authors’ own work

Table 4.
Rate sheet
descriptive statistics

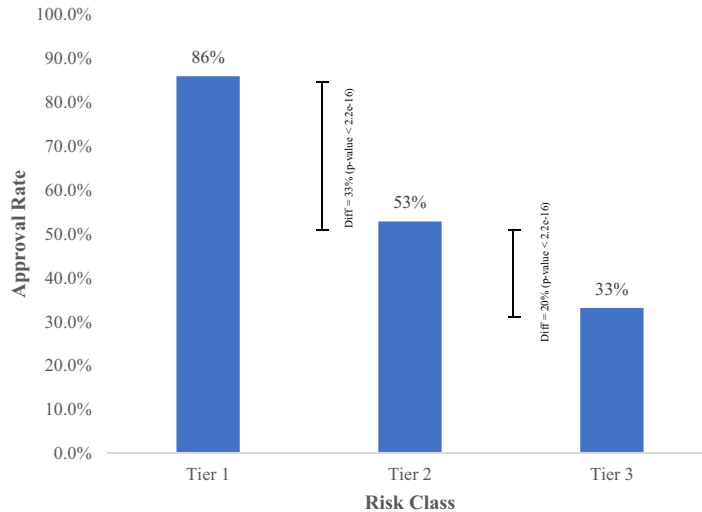


Figure 2.
Lender approval rates
by segment

Source: Author's own work

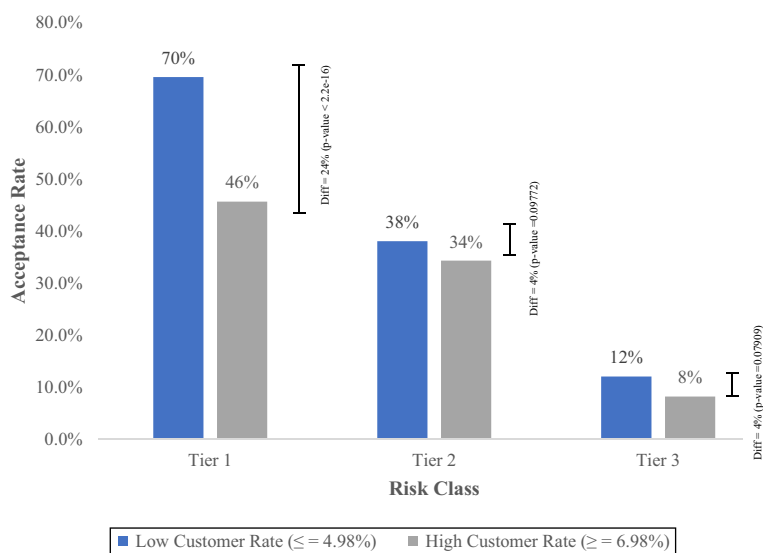
more often than Tier 2 customers (difference = 33%, p -value < $2.2e-16$) and approves Tier 2 customers more often than Tier 3 customers (difference = 20%, p -value < $2.2e-16$). Therefore, the data suggests that less risky segments have significantly higher approval rates than riskier segments.

Next, customers that are approved enter the third stage, where the salesperson presents the firm's loan offer to the customer who decides whether to accept it. We predict that price is one of the important drivers of customer acceptance. Figure 3 plots the acceptance rates by price (low $\leq 4.98\%$ vs high $\geq 6.98\%$) and risk class. The results indicate that, overall, customers are more likely to accept a loan offer when the customer rates are lower. More importantly, there is evidence that the price sensitivities of customers vary by risk class. Specifically, the acceptance rate drops drastically when prices increase for Tier 1 customers (difference = 24%, p -value < $2.2e-16$) but not for Tier 2 (difference = 4%, p -value = 0.09772) or Tier 3 (difference = 4%, p -value = 0.07909) customers. Thus, model-free evidence suggests that price is, indeed, an important factor that impacts customers' propensity to accept an offer, with price being more important for Tier 1 (i.e. lowest risk) customers compared with Tier 2 and Tier 3 (i.e. the higher risk) customers.

4.3 Estimation results: drivers of salesperson, firm and customer decisions

To test the model-free evidence and quantify the impact of drivers of the decisions made by the different stakeholders of the indirect retail chain, we estimate the three-stage choice model introduced earlier.

Staying consistent with the model development, we start with the salesperson decision to select among the rate sheet options provided by the firm. As seen in Table 5, the parameter estimates for both the incentive and the expected incentive (i.e. calculated by multiplying the incentive by the predicted probability of firm approval and the predicted probability of customer acceptance) are positive and significant. Hence, the sales force is more likely to select rate sheet options that pay larger incentives from both an absolute ($\beta = 0.002$,



Source: Author's own work

Figure 3. Customer acceptance by segment and customer rate

Predictor variable	Estimate	Std. error
Agent incentive	0.002***	0.00002
Expected agent incentive	0.002***	0.00004
LnLik	-91,986	
AIC	183,975	

Notes: ***significant at 0.1%, **significant at 1%, *significant at 5%, †significant at 10%
Source: Authors' own work

Table 5. Salesperson choice model estimates

SE = 0.000) and expected value ($\beta = 0.002$, SE = 0.000) perspective. Specifically, the odds of the salesperson selecting a rate sheet option increases by 19.55% (24.42%) for every \$100 increase in incentives (expected incentives). This finding is important because it demonstrates the balancing act that salespeople engage in. While they care about the absolute incentives that they will receive from brokering the loan deal, they do not always select the rate sheet option with the highest agent incentive and price combination because higher customer rates also decrease the propensity of customer acceptance, thus decreasing the expected incentive. Instead, we show that salespeople are forward-looking and select the rate sheet options that balance the trade-off between receiving a high commission and closing the sale.

Next, we examine the firm's decision to approve or not approve a loan application submitted by the salesperson on behalf of the customer. The parameter estimates and standard errors for this decision, which can be seen in Table 6, demonstrate the importance of risk in four ways. First, the odds of the firm approving Tier 2 ($\beta = -1.919$, SE = 0.024) and Tier 3 ($\beta = -2.893$, SE = 0.029) customers are 85.33% and 94.46% lower compared with

Predictor variable	Estimate	Standard error
Intercept	5.651***	0.10669
Requested amount	-0.000	0.00000
<i>Deposit relationship (base level = no)</i>		
Yes	0.062†	0.03454
Cash down payment	-0.000**	0.00000
LTV ratio	-2.403***	0.03011
TDSR	-0.680***	0.06095
Vehicle age	0.008	0.00845
Income	0.000***	0.00000
Amortization	-0.002*	0.00100
<i>Risk class (base level = 1)</i>		
2	-1.919***	0.02424
3	-2.893***	0.02914
Region	Too many	
Manufacturer	Too many	
LnLik	-30,352	
AIC	60,791	

Table 6.Firm approval choice
model estimates

Notes: ***significant at 0.1%, **significant at 1%, *significant at 5%, †significant at 10%
Source: Authors' own work

Tier 1 customers, respectively. This confirms the model-free evidence, which suggests that customers from more risky tiers are less likely to be approved. In addition to risk class, the odds of the firm approving a loan application decrease by 90.96% for every unit increase in the LTV ratio (i.e. loan to vehicle value) ($\beta = -2.403$, $SE = 0.030$) and by 49.33% for every unit increase in TDSR (i.e. total debt to gross income) ($\beta = -0.680$, $SE = 0.061$). Second, the odds of approval are 6.39% higher for customers that have a deposit relationship with the bank ($\beta = 0.062$, $SE = 0.035$), likely because firms have additional information about their current customers, which reduces the uncertainty. Third, the odds of approval increase by 2.51% for every \$1,000 increase in income ($\beta = 0.000$, $SE = 0.000$), likely because the firm perceives income as a signal of the customer's ability to make future loan payments. Fourth, every one-year increase in amortization ($\beta = -0.002$, $SE = 0.001$), the odds of approval decreases by 2.62%, as the longer a loan is outstanding, the more likely the borrower is to default. In addition to risk, every \$1,000 increase in the down payment of a loan decreases odds of firm approval by 0.86% ($\beta = -0.000$, $SE = 0.000$), which is likely because of the negative impact that down payments have on the profitability of each loan because a larger down payment equates to a smaller principal and, consequently, less interest revenue.

Finally, we examine the customer's decision to accept or reject a loan offer from the firm. To test for potential price endogeneity and quantify its impact on the parameter estimates of the customer model, we estimate the model with and without endogeneity correction as we discussed previously. [Table 7](#) presents the results from the first stage of the control function estimation and [Table 8](#) provides the parameter estimates for the models with and without endogeneity correction. As shown in [Table 7](#), the parameter estimate for the average customer rate on similar loans is positive and significant, suggesting that the instrument is positively correlated with the price variable in the data. Moreover, in [Table 8](#), we can see that the residuals from the first stage of the control function estimation approach are significant in the second-stage regression, suggesting that the loan price is indeed endogenous. The magnitude of the

Predictor variable	Estimate	Std. error	Impact of discriminatory pricing
Intercept	0.005***	0.00082	
<i>Deposit relationship (base level = no)</i>			
Yes	-0.000***	0.00011	
<i>Risk class (base level = 1)</i>			
2	0.003***	0.00007	
3	0.004***	0.00009	
Vehicle age	0.001***	0.00002	
Income	-0.000***	0.00000	
Amortization	0.000***	0.00000	
Difference	0.000***	0.00000	
Region		Too many	
Manufacturer		Too many	
Average customer rate (instrument)	0.813***	0.01326	
R ²		15.7	
F-value		317.2	

Notes: ***significant at 0.1%, **significant at 1%, *significant at 5%, †significant at 10%
Source: Authors' own work

Table 7.
 First-stage linear regression coefficients

Predictor variable	Base model		Endogeneity-corrected model	
	Estimate	Std. error	Estimate	Std. error
Intercept	5.0344***	0.16610	9.050***	0.33181
<i>Deposit relationship (base level = no)</i>				
Yes	0.1946***	0.03723	0.164***	0.03740
<i>Risk class (base level = 1)</i>				
2	-1.3320***	0.18349	-1.146***	0.18438
3	-2.4482***	0.30858	-2.115***	0.31276
Vehicle age	-0.0939***	0.00799	-0.053***	0.00848
Income	-0.0000**	0.00000	-0.000***	0.00000
Amortization	-0.0226***	0.00099	-0.018***	0.00103
Customer rate	-38.5598***	2.36572	-114.153***	5.88714
Difference	-0.0000	0.00000	0.000	0.00000
Region		Too many		Too many
Manufacturer		Too many		Too many
<i>Risk class × customer rate (base level = 1)</i>				
2	12.3916***	2.97647	12.523***	2.98559
3	1.7127	4.99895	1.797	5.05616
Region × customer rate		Too many		Too many
Residuals (stage 1)	NA	NA	79.981***	5.69119
LnLik		-26,704		-26,605
AIC		53,516		53,320

Notes: ***significant at 0.1%, **significant at 1%, *significant at 5%, †significant at 10%
Source: Authors' own work

Table 8.
 Customer acceptance choice model estimates

bias induced by endogeneity can be understood by comparing the parameter estimates for price under the two models. Specifically, in absolute value, the estimate for the price coefficient is $2.96\times$ larger (-114.15 vs -38.56) for the endogeneity-corrected model compared with the base model, which indicates that the negative impact of customer rate on customers' propensity to accept a loan offer is significantly underestimated in the base model. Given that price is endogenous, we discuss the estimation results from the endogeneity-corrected model in Table 8 next.

First, the odds of a customer accepting a loan offer from the firm increases by 17.79% if he/she has a pre-existing deposit relationship with the lender ($\beta = 0.164$, $SE = 0.037$), highlighting the synergy that is obtained by firms when offering complimentary services and demonstrating the importance of fostering customer relationships and brand loyalty. Moreover, combined with the firm approval results, we show that a pre-existing relationship has a dual impact on the closing of the deal, positively influencing both the firm and customer decisions. Second, the odds of a Tier 1 (i.e. less risky) customer accepting a loan offer decrease by 68.07% for every 1% increase in customer rate ($\beta = -114.153$, $SE = 5.887$), which confirms our expectations and is consistent with economic theory. However, and more interestingly, not all customers react to price the same way. Specifically, riskier customers are less price sensitive than lower-risk customers, as indicated by the positive coefficients for the interaction between customer rate and risk class. While every 1% increase in price decreases the odds of acceptance for all customers, the magnitude is 4.26 percentage points smaller for Tier 2 customers ($\beta = 12.523$, $SE = 2.986$) and 0.58 percentage points smaller for Tier 3 customers ($\beta = 1.797$, $SE = 5.056$) compared with Tier 1 customers. Figure 4 demonstrates these segment-level differences in customer price sensitivity through price response curves, which we constructed by varying the customer rate between 0% and 20% for all observations and plotting the average predicted probability of customer acceptance at each of these customer rates. Third, individuals' propensity to accept a loan offer also differs as a function of vehicle age ($\beta = -0.053$, $SE =$

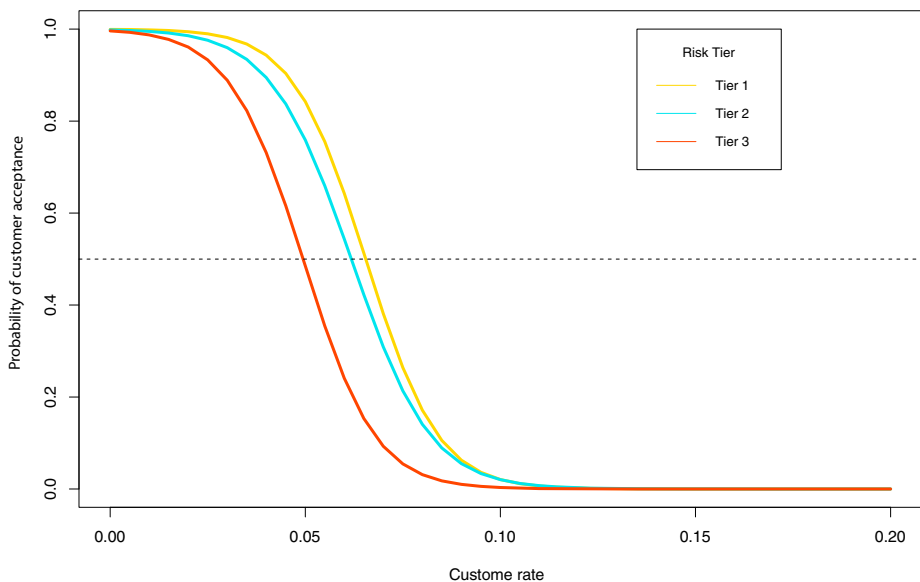


Figure 4.
Price response
functions by segment

Source: Author's own work

0.008), loan amortization ($\beta = -0.018$, $SE = 0.001$) and income ($\beta = -0.000$, $SE = 0.000$) with the odds of customer acceptance decreasing by 5.12% for every one year increase in vehicle age, decreasing by 19.74% for every one year increase in amortization and decreasing by 1.70% for every \$1,000 increase in income.

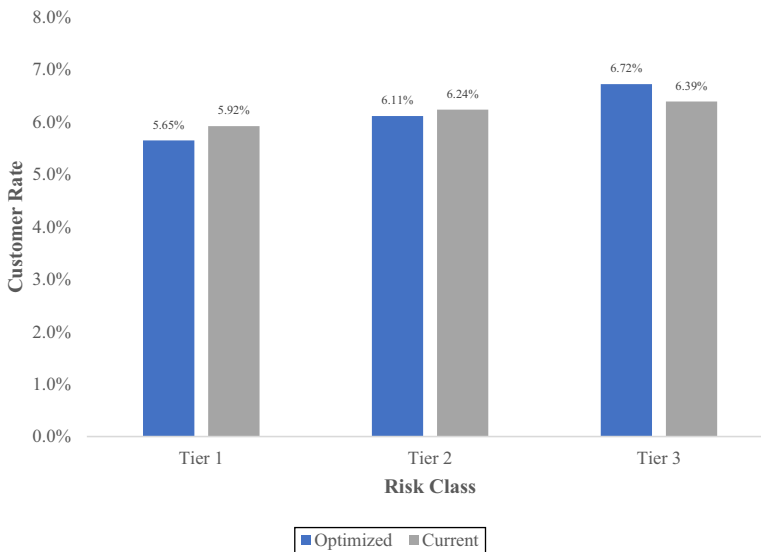
4.4 Centralized pricing based on risk versus price delegation

Next, we set out to investigate the profit implications of a centralized pricing approach (i.e. discriminatory pricing based on risk) compared with the firm's current approach of price delegation. The analytics-driven segment-level optimal price-incentive combination can be achieved by maximizing equation (15) with respect to price, r_s , and agent incentive, AI_s , for each of the s risk segments. As discussed previously, the optimization assumes that the agent has two options to select from:

- (1) the inside option that is offered by the focal firm, which is the price and agent incentive that is being optimized; and
- (2) an outside option from the competition.

Although the data set does not include applicant-level information for loans that were sent to the competitors, we do know the average price and incentive that were offered by the competitor firms at the time of the data set. Thus, for the outside option within the optimization, we use the average loan price, 5.45%, and average salesperson incentive, 2.92%, that was offered by the competitor over the period that is covered by the data set.

We plot the optimized/actual values for price and salesperson incentive, by risk segment in Figures 5 and 6, respectively. The optimal price increases proportional to the riskiness of the segment, and is 5.6%, 6.1% and 6.7% for Tier 1, Tier 2 and Tier 3 customers, respectively. While the current prices follow a similar trend, the differences across segments



Source: Author's own work

Figure 5.
Optimized vs current
customer rate by
segment

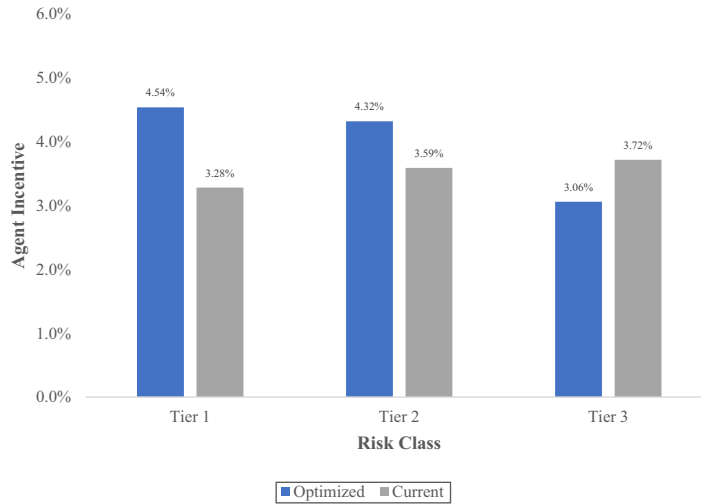


Figure 6.
Optimized vs current
agent incentive by
risk class

Source: Author's own work

are much smaller, particularly for the higher risk segments. In other words, we see a substantial difference in prices because of AI-driven discriminatory centralized strategy compared with the current strategy of salesperson pricing authority.

An even larger variation is evident when observing the optimal and actual values for the salesperson incentive. The former recommends setting commission rates at 4.5%, 4.3% and 3.1% for Tier 1 (least risky), Tier 2 and Tier 3 (most risky) customers, respectively, while the actual commission rates are set at 3.3%, 3.6% and 3.7% for the same segments. Hence, in the case of salesperson commission, unlike the scenario with the pricing strategies, the optimal and the current approaches differ not only at the values for each segment but also the trend as a function of risk. Specifically, while the optimal policy recommends decreasing incentive rates as the risk level increases, with the largest drop for the riskiest segment, the current commission structure increases commission rates as the risk level goes up.

The results suggest that implementing these AI-driven centralized discriminatory prices and optimal sales incentives together lead to a 34% increase in profits for the firm. By better tailoring pricing to each risk segment and implementing incentives that target Tier 1 and Tier 2 customers more than Tier 3 customers, the firm not only leverages higher WTP of high-risk segments but also balances its own risk through salesperson incentives.

5. Model validation

Next, we validate the three-stage model framework by examining its predictive performance for the customer, firm and salesperson decisions both in and out of sample. We use an 80–20 split ratio for the training and test samples. Tables 9 and 10 and Figure 7 demonstrate the classification and hold-out performance for the customer, firm and salesperson decisions. The overall prediction accuracy for the customer (firm) decision is 70% (81%). Moreover, the prediction rates for customer (firm) acceptance (i.e. true positive rate/sensitivity) and

Panel A: firm approval decision

Actual	Predicted	
	Rejected	Approved
Rejected	14,148	8,233
Approved	4,700	41,082
Overall accuracy	Performance metrics	
81%	Specificity	Sensitivity
	63%	90%

Panel B: customer acceptance decision

Actual	Predicted	
	Rejected	Accepted
Rejected	10,197	9,076
Accepted	4,644	21,865
Overall accuracy	Performance metrics	
70%	Specificity	Sensitivity
	53%	82%

Table 9.
Classification
performance

Note: Threshold = 0.50
Source: Authors' own work

Panel A: firm approval decision

Actual	Predicted	
	Rejected	Approved
Rejected	2,789	1,674
Approved	975	8,194
Overall accuracy	Performance metrics	
81%	Specificity	Sensitivity
	62%	89%

Panel B: customer accept decision

Actual	Predicted	
	Rejected	Accepted
Rejected	2,107	1,799
Accepted	1,007	4,243
Overall accuracy	Performance metrics	
69%	Specificity	Sensitivity
	54%	81%

Table 10.
Holdout performance

Note: Threshold = 0.50
Source: Authors' own work

rejection (i.e. true negative rate/specificity) of the loan offer (application) are 82% (90%) and 53% (63%), respectively, lending further validity to the model's ability to predict both decision outcomes. While these results are based on a classification threshold of 0.50, it can be adjusted to align with corporate goals because a higher (lower) threshold would decrease (increase) sensitivity but would increase (decrease) specificity. Therefore, if predicting accepted/approved (not accepted/not approved) applicants is more important, then the threshold can be decreased (increased) to align with corporate goals.

Salesperson rate sheet (i.e. price) option selection predictions are similarly successful, with the most frequently selected options, 1 and 2, having the highest prediction accuracy

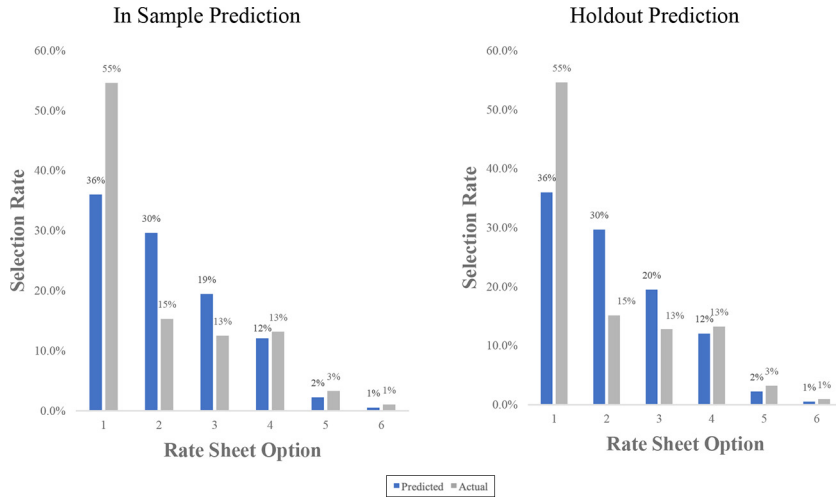


Figure 7.
Salesperson price
selection prediction

Source: Author's own work

(see Figure 7). Not surprisingly, the model attains the lowest prediction scores for rate sheet options 5 and 6, which are the least selected options by the sales force. Overall, the results indicate reasonably strong prediction accuracy for the salesperson decision because the predictions mirror the actual choice patterns quite well.

These results remain relatively consistent for the holdout sample, demonstrating strong external validity of the model and ensuring generalizability of the findings.

6. Discussion

In this paper, we investigate how much (if any) bottom-line improvements firms within an indirect retail network achieve by switching from a more traditional and widely accepted structure of partial sales force price authority to a centralized AI/analytics-driven pricing model. Below we explain the contributions to theory and practice, followed by a discussion about future research.

6.1 Theoretical contributions

This study has important implications for marketing theory. Specifically, we contribute to the price delegation and price discrimination literature in several ways.

Starting with the former, extant research on sales force pricing authority has been scant and primarily analytical because of the lack of high-quality data at the level of granularity required (Misra and Nair, 2011). While analytical work has provided valuable high-level insights (Bhardwaj, 2001; Joseph, 2001; Mishra and Prasad, 2004), it has done so using restrictive assumptions, which do not reflect the nuances of real-life settings. We complement extant work by empirically investigating the profitability of partial price delegation and comparing with that of optimized centralized analytics-driven pricing, using a rich individual-level data set from a North American financial institution. Our model framework allows for several intricacies of the indirect retail channel setting, which are critical for generating reliable insights. First, we account for the interdependencies between the decisions of the three key stakeholders (i.e. customer, sales force, firm). Second, we investigate the complex setting of

external sales forces, which, unlike internal sales forces, have access to competitors' offerings in addition to those of the focal firm. With this regard, we include an outside competitor option within the pricing optimization algorithm to ensure that the optimal price reflects competitive pressures. By ignoring the outside option from the competitors, the optimal price (and profits) would be overstated. Third, we simultaneously optimize price and commission to account for the impact of commission on the salesperson's pricing decision.

The results suggest that analytics-driven discriminatory pricing based on risk leads to an increase of 34% in the firm's profits compared with sales force price delegation. This extends the literature by empirically demonstrating that centralized analytics-based pricing is superior to price discretion when there is a lack of strong information asymmetry between the firm and sales representative, confirming the expectations derived from the analytical and survey-based research (Lal, 1986; Mishra and Prasad, 2004; Frenzen *et al.*, 2010). Moreover, the results indicate that optimized commissions increase with gross margin and are higher for more profitable customers. This finding provides empirical insight into the optimal commission/pricing structure and supports the analytical and survey-based research claim that pricing discretion is more likely to be profitable when commissions are based on gross margin or price (Homburg *et al.*, 2012; Bhardwaj, 2001; Weinberg, 1975). Extending the literature, we demonstrate that, even when sales force price delegation is based on gross margin or price, as in our setting (i.e. commissions increase with price on the rate sheet), centralized analytics-based pricing is superior in driving bottom-line performance.

In addition, by accounting for the interdependencies between the firm, salesperson and customer, we formally allow for forward-looking behavior of salespeople who make their pricing decisions based on the expected commission, balancing the trade-off between closing the sale and generating a large commission. The findings, indeed, support this forward-looking behavior of the agents, showing that the odds of a salesperson selecting a specific price option increase by 24.42% for every \$100 increase in expected incentives assigned to that price option. This demonstrates that external sales representative decisions are driven by forward-looking behavior through consideration of customers' (Yang *et al.*, 2019) and the firm's reactions to their decision. Thus, we extend the list of factors that impact sales force decisions, providing a more nuanced understanding of salesperson behavior.

With respect to the latter, we contribute to the price discrimination literature by demonstrating customer risk as a basis for price discrimination, using a context that involves an aftermarket good (i.e. loans). We provide overwhelming evidence that risk is a strong factor affecting access to financing and price sensitivity, which, if considered together, could benefit both the firm and the customer. Specifically, we demonstrate that the odds of a firm approving a loan application are over 80% lower for the high-risk segments compared with low-risk segments. This points out the welfare implications of risk-based discriminatory pricing, as it would allow a marginalized segment access to loans, which they otherwise do not have. Moreover, we find that, on average, riskier customers are less price-sensitive. Particularly, the odds of a low-risk customer accepting a loan offer decrease by 68.07% for every 1% increase in price, while the decrease in odds of purchase is almost five percentage points smaller, at 63.81%, for the segment that is one tier up in terms of risk group. This result provides support for the profitability of risk-based segment-level centralized pricing.

While marketing literature has examined many variables for segmentation and price discrimination purposes, including various demographics (Frank *et al.*, 2014; Gary-Bobo and Larribeau, 2004), risk has generally been overlooked (Zhao *et al.*, 2009). Thus, we extend the marketing literature by demonstrating that customer risk is a powerful means to both segment and price discriminate. Finally, our results speak to price discrimination for loans, which is an aftermarket good that augments the core product and differs in ways that have

important implications for customer price sensitivity (Gil and Hartmann, 2009). Unlike core products, aftermarket goods have received little attention in the literature but are important for several industries such as insurance, warranty and financing. Thus, we extend the price discrimination literature by demonstrating the potential profit lift associated with centralized optimized discriminatory pricing for aftermarket goods.

6.2 Managerial contributions

The findings from this study provide ample evidence for the benefits of leveraging analytics and AI to deliver customized prices, considering both the cost of service and customer WTP. In our empirical application, switching to centralized discriminatory pricing and optimizing salesperson incentives collectively led to a 34% lift in firm profits. We also find that the optimal price increases proportional to the riskiness of the segment, whereas the optimal salesperson commission decreases for higher risk segments. As such, the dual optimization helps firms balance customer risk with higher prices and lower sales force commission leading to increased profitability.

To better understand the role of data-driven pricing models in the financial sector, we had discussions with several C-suite executives. Through these conversations, it was clear that data-driven analytics approaches are not used to the extent that they are in other industries, such as the airline industry, a point that has also been raised in the academic literature (Phillips, 2013). Instead, indirect lenders delegate pricing decisions to the sales force who decide on the price to offer customers using their expertise and customer interactions. However, there is clearly an appetite for improving pricing decisions using AI and data analytics approaches, as highlighted by the following quote from an executive at the focal firm:

our approach to pricing has not evolved at the same pace of technology [...] we empower our sales force to make pricing decisions even though we collect and store data that can probably be utilized to better inform our pricing decisions.

Even still, there are legal and ethical considerations that limit the types of data analytics tools that C-suite executives at financial institutions are willing to implement. Although the potential for machine learning approaches such as neural networks to predict optimal prices have been commonly acknowledged by the C-suite executives, concerns regarding the “black box” nature of neural networks are widespread – an issue that has been mentioned in the academic literature as well (Baesens *et al.*, 2003). This is especially problematic within the context of financial loans because there are laws, including The Equal Credit Opportunity Act in the USA, that prohibit the use of certain customer characteristics, including age, gender and marital status, in making decisions related to credit. AI can exhibit many of the same biases as humans (Townson, 2020), and the following quote from a manager confirms this: “we prefer to use models that are based on more traditional statistical methods to make sure we are able to explain the reasons behind the decisions of the algorithm being implemented and avoid legal action.”

As such, we propose a modeling approach that can be used by indirect retailers (e.g. indirect lenders, travel agents, real estate agents, insurance brokers, talent agents, department stores, supermarkets, etc.) to better understand the benefits of data-driven analytics compared with traditional pricing delegation within their particular use case. To implement the modeling approach proposed in this study, firms should implement a four-step approach. First, practitioners must select the price discrimination criterion that the firm will use to segment the customer base. In the context of lending, we propose that firms use the risk profile of the customer, which is measured by the partner lender using a proprietary method that groups customers into three risk classes based on the customer’s credit score.

The chosen price discrimination criterion should replace the risk-related variables that are present on the right-hand side of [equation \(11\)](#). Specifically, the selected price discrimination criterion should be included both on its own and as an interaction term with price to capture differences in price sensitivity across the levels of this chosen price discrimination variable. Second, the practitioner should collect data for variables that are relevant for each of the decisions that are made by the stakeholders within the indirect retail channel. In this study, we highlight the key variables that pertain to the empirical context of indirect auto loans; however, these variables, outside of price, can be replaced by other variables that better fit the empirical context under question. These new variables should replace, or be added to, the variables on the right-hand side of [equation \(1\)](#) for the salesperson decision, [equation \(6\)](#) for the firm decision and [equation \(11\)](#) for the customer decision. Third, the practitioner should estimate the impact of the chosen variables on the decision of the firm, sales representative and customer, using the approach described in Section 3. Fourth, using the parameter estimates from the third step, the practitioner should run the optimization, again described in Section 3, to determine the optimal price and commission across the various levels of the price discrimination variable that was selected.

6.3 Welfare implications

With advances in machine learning/AI and increasing amounts of available data, many companies across various industries, including financial institutions, are increasingly relying on sophisticated tools to improve corporate decisions ([Townson, 2020](#)). However, the customer welfare outcomes of using such techniques within the financial sector are not very clear to regulators. On the one hand, benefits of AI and machine learning could remove inherent biases that are involved when employees make loan approval and pricing decisions. On the other hand, many algorithms are “black boxes” that could perpetuate current biases within the system ([Waters and Foster, 2021](#)). As such, regulation regarding the use of such tools, especially when it comes to decisions regarding customer financing, is in a state of flux, leaving policymakers in a position where they must decide how much leeway organizations should have when it comes to using AI and machine learning techniques ([Burt, 2021](#)).

This study contributes to this debate by developing a modeling approach that provides support for the use of AI/data analytics while also mitigating the concerns voiced by various policymakers. The findings suggest that using an AI/data analytics-driven approach that is based on risk as a price discrimination criterion not only improves firm profits but also allows customers from a high-risk group, who have traditionally been a marginalized customer segment, access to loans. These loans are much more affordable than pay day loans, which unfortunately are a last resort for these marginalized customers. This points out the customer welfare impact of risk-based discriminatory pricing and how firms can create a win-win by leveraging the WTP of less price-sensitive segments. Moreover, our approach is based on traditional statistics, rather than relying on a neural network approach, ensuring that the algorithm’s recommendations are transparent and can be explained to regulators.

Considering the results of this study, we recommend that regulatory agencies and policymakers across the world – including The Financial Conduct Authority (FCA) in the UK, Office of the Superintendent of Financial Institutions (OSFI) and Financial Consumer Agency of Canada (FCAC) in Canada, The Office of the Comptroller of the Currency (OCC), The Federal Reserve, The Federal Deposit Insurance Corporation (FDIC), The Office of Thrift Supervision (OTS) and The National Credit Union Administration (NCUA) in the USA – promote the use of data-driven analytics and AI that are based on traditional statistical methods to reduce some of the biases that are present within current systems that

rely on human decision-making, such as pricing delegation, and avoid potential biases that could be reinforced by “black box” approaches such as neural networks.

6.4 Limitations and future research

Although these are significant contributions to the marketing literature, practice and customer welfare, this study has several limitations, most of which relate to the lack of data availability. Specifically, we do not have information on loans that are submitted by the salespeople to the competitors. While we take competition into account as an outside option to reflect competitive pressures in the optimization stage, the absence of loan applications sent to competing firms limits our ability to explicitly model the sales representative’s choice of lender. Particularly, this limits our ability to isolate how competitor decisions about pricing and incentives impact salespeople’s demand allocation. Future research on the topic should therefore more explicitly account for competition by including competitor pricing options within the estimation stage of the analysis, specifically within [equation \(1\)](#) in Section 3. By explicitly accounting for competition within the estimation stage, future research can better understand competitor’s reactions to pricing and commission decisions in the marketplace ([Gallego and Talebian, 2014](#)), using an empirical approach. Moreover, if additional data regarding the customer (e.g. demographics) and lenders (e.g. quality of relationship between sales representative and lender) is available, then these variables should again be included in [equation \(1\)](#) to determine their impact on the salesperson’s demand allocation decision. In doing so, future research can use our methodological approach to answer questions such as: is price and commission more important than relationship quality in determining which option the salesperson selects for offer to the customer? Do customer characteristics, such as gender or race, have an impact on the salesperson’s choice of option?

Another immediate extension of this research relates to understanding the negotiation process between the salesperson and the customer, and how this impacts the former’s pricing decision. Given that we focus on an aftermarket good (i.e. auto loans), negotiation is less relevant for our context because most of the customer’s negotiation effort is exerted during the purchase of the core product (i.e. the automobile). Because customer WTP is generally higher for aftermarket goods than core products ([Gil and Hartmann, 2009](#)), the dynamics of negotiation is likely to be different between these two. Specifically, we expect negotiation, and thus sales force pricing authority, to be more critical for contexts involving the purchase of a core good. If this, indeed, is the case, then future research can use field and lab experiments to tap into the effects of moderators of the negotiation process, such as the tenure of the salesperson ([Jindal and Newberry, 2022](#)), customer characteristics ([Frenzen et al., 2010](#)) and product characteristics (e.g. premium vs economy) on salesperson’s decision regarding price.

Understanding the effect of the degree of information asymmetry on the profit discrepancy between pricing authority and centralized pricing is also a relevant and important topic for future empirical research. Because the benefits of AI and analytics rely on having access to high-quality data, we expect these benefits to be less prominent in the case of high information asymmetry because the sales force has access to information that is not available to the firm. This could include private information about customer’s motives, needs, financial capabilities/liabilities and behavior ([Kim et al., 2019](#)), as well as information about the customer’s outside options ([Kim et al., 2022](#)).

Last but not the least, future research is necessary to understand the effectiveness of AI and data analytics when other indirect retail channel coordination methods, outside of incentives and commissions, are used. The most cited methods for channel coordination within the academic literature include profit sharing ([Yan, 2011](#)), joint ownership ([Jeuland and Shugan, 2008](#)), quantity discounts ([Raju and Zhang, 2005](#)) and simple contracts ([Jeuland and Shugan, 2008](#)). However, it is unclear if the impact of AI and data analytics on firm profits will be as strong when other channel

coordination mechanisms, outside of commissions, are in place. Building on our methodological framework and altering the payoffs to the salesperson [i.e. equation (1)] and firm [i.e. Equation (15)] according to the various channel coordination methods, future research can investigate how prominent the benefits of centralized pricing (vs price delegation) are when channels use profit sharing, joint ownership and/or quantity discounts, rather than commissions.

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