Product Sales Incentive Spillovers to the Lending Market: Evidence From Subprime Auto Loan Defaults

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December 2022

ABSTRACT

This paper shows how convex incentives in vertical contracts between manufacturers and retailers can induce sales behavior with costs to consumers. We examine this problem in the automotive sector, where manufacturers commonly motivate new vehicle sales through dealer incentive programs with large discrete bonuses determined by monthly sales targets. Using subprime car loans from over 3,500 dealerships, we document high default rates on new car loans originated at the end of the month—the period when dealerships attempt to secure target-based bonuses by intensifying efforts to sell new cars. We provide evidence consistent with the observed higher default rates resulting from customers purchasing new vehicles at month-end. New car purchases stretch borrower budgets and expose borrowers to rapid depreciation, which consigns the borrower with negative equity through much of the loan term. Our results imply that the quartile of customers with the highest payment-to-income ratio see default rates increase from 13.6% to 19.7% on the last day of the month. Although consumers bear high costs from increased defaults, we find no evidence that lenders who purchase the loans are hurt by the default increase. Our results demonstrate how the behaviors induced by convex incentive schemes for sales are borne by customers.

JEL Classification: D82, G29, G32, G34, L14, R30

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*Jansen: University of Utah, Eccles School of Business; Pierce: Washington University in St. Louis, Olin Business School; Snyder: University of Utah, Eccles School of Business; Nguyen: Foreign Trade University. We are grateful to the management team at the firm that provided the data for this research, and to the Sorenson Center for Discovery and Innovation. This paper was previously titled, "Product sales incentive spillovers to the lending market." For helpful comments, we also thank the seminar participants at Brigham Young University, the University of Maryland, and the University of Utah.

1 Introduction

Incentive structures such as sales compensation plans are commonly designed with a convex relationship between pay and performance (Chung et al. 2021), using kinked accelerators (Larkin and Leider 2012) or stair-step structures (Misra and Nair 2011) to reward personnel within time periods such as months or quarters.[1] Although convex incentives are typically used for individual pay (e.g., Tzioumis and Gee 2013), they are also included in vertical contracts to reward retailers and distributors. For example, car[2] manufacturers often set monthly incentive targets for their franchised dealerships (Pierce et al. 2022). In such cases, the owner of the upstream firm (principal) faces a contract design challenge: to motivate the sales effort of the downstream firm (agent) while limiting actions that are rewarded but costly to the principal (Misra and Nair 2011, Herweg et al. 2010, Chung et al. 2014, Barron et al. 2020). Convex incentive schemes encourage what economists call "gaming" behavior (Baker 1992, Baker et al. 1994), where the agent increases personal earnings by bunching sales within periods, frequently through excessive price discounting that is costly to the principal.[3] Existing research focuses on how agents work with customers to game incentive contracts at the expense of the principal (Healy 1985, Oyer 1998, Larkin 2014, Benson 2015, Frank and Obloj 2014). In this paper, we study how a vertical convex incentive contract between firms can create *negative* spillover costs to the consumers who buy and finance the final product.

We study these vertical contracting costs in automobile sales to "subprime" borrowers: those customers deemed the least creditworthy in debt markets. Subprime borrowers, who we define as having credit scores below 660,[4] constituted over 34% of the $1.4 trillion dollar auto lending market in 2022 (Zabritski 2022). To motivate dealership sales efforts, manufacturers use sales incentives with large bonuses for hitting discrete monthly new-vehicle sales targets.[5] Price competition between local dealerships (Olivares and Cachon 2009) ensures widespread program participation, as earned monthly bonuses frequently represent the majority of direct dealership sales profits. The monthly incentive bonuses studied in Pierce et al. (2022), for example, average over $30,000 per dealer, with the largest dealers earning over $200,000 from the marginal vehicle that precisely

[1]Survey evidence finds that 72% of firms use bonus pay in their compensation structure, and that 76% of the bonus-paying firms use sales relative to a quota as a major determinant of the bonus (Joseph and Kalwani 1998).

[2]Throughout the paper we will interchangeably use "car" and "vehicle" to refer to passenger vehicles that are both traditional cars (e.g., sedans) or light trucks (e.g., pickup and SUVs).

[3]Multitasking problems can also occur when separate schemes for different products create an excessive focus on the product with the highest expected bonus (Obloj and Sengul 2020, Pierce et al. 2022).

[4]This borrower group is also separated as "nonprime," "subprime," and "deep subprime."

[5]Vehicle manufacturers attempt to increase new car sales volume at these dealerships through a variety of other mechanisms, including inventory allocation (Cachon and Lariviere 2005, Cachon et al. 2019) and direct cash rebates to consumers (Busse et al. 2006) that lower sales prices within a given model year (Bennett 2013).

reaches that month's target.[6] This large discrete payoff can motivate intense sales effort at the end of the month (EOM). In these final days, dealers more precisely know which sales are crucial to reach the targets, and can be further motivated by the psychological effect of increasing salience of approaching goals (Chung et al. 2021, Otto et al. 2022).

Automobile dealerships that are affiliated with a car manufacturer such as Ford or Toyota sell both used and new cars. Since manufacturers' monthly incentives apply only to new car sales, dealers direct EOM sales effort toward selling new rather than used cars (Fahey 2003, Wolf 2016). Managers pressure and incentivize salespeople to persuade customers to purchase new rather than used cars, also equipping them with price discounts that they might not offer earlier in the month. Although customers who make this switch might benefit through a lower new-car price at the EOM compared to new car prices at other times of the month, the choice of a new car can severely strain household finances and expose subprime borrowers to significant credit risk (c.f., Diamond and Rajan 2009, Elul et al. 2010, Adams et al. 2009). New cars depreciate rapidly (25%–35%, BlackBook (2019)) within the first year, leaving the borrower with negative equity, which in turn blocks them from selling the vehicle to avoid a loan default (Bhutta et al. 2017). Purchasing a new car in lieu of a used one, even after receiving a price discount, results in higher monthly payments and extended negative equity. If car buyers do not fully understand the implications of their purchase, as prior work has strongly established (Busse et al. 2013, 2015, Lacetera et al. 2012), this choice can create unanticipated future outcomes that financially devastate them.

We illustrate this process using data on subprime loans from over 3,500 car dealerships. Our data provide evidence that consumer loan defaults arise from manufacturer's dealer incentives and the sales activities that they motivate. We show that loans for EOM vehicle purchases have a 10% higher 24-month default probability than loans for vehicle purchases earlier in the month. This holds while controlling for a host of buyer, vehicle, and deal term variables. The positive correlation between EOM sales and defaults is concentrated in new cars, which are the only ones that count toward the monthly targets. We find that the increase in EOM new-car defaults is concentrated among buyers that stretch financially: defaults among new car buyers with the highest payment-to-income (PTI) ratios increase from 13.6% to 19.7% on the last day of the month. Financially-stretched EOM buyers also lower monthly payments by forgoing the purchase of guaranteed asset protection (GAP) insurance—a product that would protect them from default should their negative-equity vehicles be stolen or destroyed. Although the increased EOM default rate produces clear harm to customers, we find no evidence that it harms lenders, whose EOM loan profits are equivalent to those on other days.

[6] Many of these programs were suspended for the COVID-19 pandemic due to supply-chain shortages and reduced customer traffic.

We examine two classes of likely mechanisms through which dealer incentives could increase EOM loan defaults on new cars. We first present evidence that salespeople are able to switch would-be used car buyers to new vehicles through both lower prices and persuasion. New cars are discounted more heavily at EOM than used cars in our data. While this suggests that price is one mechanism used to switch customers into new cars at the end of the month, there is little evidence that these buyers differ on observable characteristics. The evidence is consistent with seemingly similar customers being offered larger discounts and being persuaded to buy new cars at the end of the month, which in turn leads to higher default rate. Many of these customers likely regret their purchase, a common outcome in large consumer purchases (Stango and Zinman 2023).

We use structured interview data from personnel at twelve dealerships to support the claim that salespeople persuade customers to buy vehicles they did not initially desire. Extensive work on consumer behavior and psychology explains how salespeople can affect customer choice by using common decision-making heuristics (Cialdini 1984). These persuasion tactics can range from relatively benign techniques such as converting prices to monthly payments or selectively highlighting features to outright and deliberate deception.[7]

We find little support for a second incentive-program mechanism involving selection, whereby incentive programs attract EOM consumers who are more likely to default. We see few observable differences in EOM purchasers, and our results are consistent when we control for the same borrower, vehicle, and loan characteristics (including price-to-value) that the lender observes.[8] Our interviews of finance managers confirmed our quantitative models in revealing no perceived differences in the creditworthiness of EOM customers. The only EOM customer difference noted by interviewed sales and finance personnel is an increased focus on getting a better deal, which does suggest that some shoppers choose to shop at EOM in anticipation of discounts induced by the incentive programs. There is no clear theoretical implication of such a selection for default rate, however. Customers who negotiate lower prices on vehicle purchases could default *less*, either because of financial conservatism or better negotiation skills; both are known to correlate with financial literacy (Krische and Mislin 2020). In contrast, those seeking deals might do so because of unobservable financial challenges. We cannot definitively identify whether this potential EOM selection affects default, but if it does, it is still a net result of the incentive programs.

Finally, we address the key identification concern about our main finding–selection effects unrelated to the incentive programs. In such an alternative story, EOM customers would need to be different in a way that: a)is unobservable in our data, b)raises default risk, and c)is unrelated to

[7]Sales persuasion is not inherently unethical (Gass and Seiter 2018)., as it can be used to prevent financially irresponsible decisions as well.

[8]The parameter estimates lack sensitivity to the introduction of controls, which is inconsistent with significant omitted variable bias (Oster 2019).

the incentive program. There is no clear rationale why unobservably higher credit risk customers would shop at EOM other than to access incentive-based discounts. Although the robustness of our models to control variables and interview data make this selection story unlikely, we also perform a placebo test in a sample of dealerships without monthly manufacturer incentives–those that only sell used cars. We see no identifiable default increase in this sample at EOM, which suggests that demand-side factors unrelated to manufacturer incentives are unlikely to explain our results.

Our paper makes novel contributions to the literature on vertical relationship contracting. Prior work shows that incentive gaming and other types of moral hazard can generate considerable costs in vertical relationships, which can force firms to employ costly incentive and control mechanisms in suppliers and retail channels (Mortimer 2008, Lafontaine and Slade 2013, Rawley and Simcoe 2010, Bennett et al. 2015, Kalnins 2017, Obloj and Zemsky 2015, Ederer et al. 2018, Narayanan and Raman 2004). This problem is prolific in settings that, like ours, involve diverse retailer networks (Lafontaine 1992, Lafontaine and Shaw 1999, Kalnins and Mayer 2004, Ackermann 2019). We add to this literature by demonstrating that non-linear incentive mechanisms that are meant to address one type of moral hazard (e.g., sales effort) can generate gaming that is harmful to downstream customers' long-run financial health.

The broader literature on deadline-based convex incentive contracts suggests that these contracts benefit the firm by attracting high performers (Larkin and Leider 2012) but can also induce costly gaming by agents (Jindal and Newberry 2022). Previous research describes how sales can surge as a deadline approaches (Oyer 1998, Tzioumis and Gee 2013) and customers are offered price discounts for buying immediately (Larkin 2014). We show that customers can be *hurt* by convex incentive schemes despite the discounted prices, because salespeople could direct them to financially inappropriate purchasing decisions.[9]

Finally, our paper contributes to research on sales incentives and loan outcomes. Prior work on sales incentives and consumer debt has focused on how loan officer incentives decrease loan quality (Heider and Inderst 2012, Agarwal and Ben-David 2018, Tzioumis and Gee 2013). Our paper uniquely shows that convex incentive schemes implemented by a durable goods manufacturers (not lenders) can decrease loan quality by encouraging product mismatches between buyers and products that significantly stretch borrower budgets. More generally, we show that vertical contract incentives can generate downstream multitasking problems, resulting in negative externalities to third-party contracts such as consumer loans. These costs are borne by myopic car buyers (Busse et al. 2013, 2015, Lacetera et al. 2012), who fail to anticipate and internalize the increased default risk they face, or lack self-control (Gul and Pesendorfer 2001, Schlafmann 2021) when faced with

[9]This negative customer outcome is similar to the lower-quality work that can be induced by rushing to meet incentive deadlines (Carpenter et al. 2008, 2012, Liebman and Mahoney 2017, Cohen et al. 2021).

consumption. Importantly, our paper shows that sophisticated lenders avoid these externalities. This result contrasts with the originate-to-distribute mortgage market where agency conflicts resulted in loan default costs that were borne by investors (e.g., Keys et al. 2010, 2012, Jiang et al. 2014, Gartenberg and Pierce 2017).[10]

2 Automotive Sales Setting

2.1 Automobile sales and financing at dealerships

In this section, we highlight the car buying and financing process at U.S. car dealerships and explain how monthly sales targets can change product and financing outcomes at the EOM. The description relies on industry and academic publications, the authors' industry experience, and data from formal interviews (using a structured script) of 23 salespeople and finance managers at 12 dealerships. Appendix A.3 describes the interview process and the qualitative data.

When a prospective customer arrives at a dealership, a salesperson is assigned to advise them. Our qualitative interviews suggest that customers often arrive with an idea about which type of vehicle, or even which specific vehicle, they are interested in purchasing. Yet car salespeople are highly capable of persuading customers to consider other vehicles. According to one salesperson that we interviewed, only "about 20% of customers know exactly what they want and drive off in that exact same car." Another stated that "in the past, 90% of the time [the customer] switched." This suggests that when sales incentives are tied to specific vehicle makes (e.g., Dodge) or models (e.g., Dodge Charger), salespeople use persuasion in response to the incentives they face.

A customer who decides to purchase a specific vehicle will typically negotiate the purchase price with the salesperson and sales manager (Bennett 2013). During this negotiation, the sales team considers the profit margin for the vehicle, existing inventory levels, individual and dealer sales target incentives, and the customer's apparent financial capability. The sales team might also consider the dealership's potential to profit from the sale of high-margin add-ons such as extended warranties, insurance products, and service contracts.

After the customer and salesperson agree to a price, a finance manager submits the customer's credit application to multiple lenders in a competitive bidding market through a standardized

[10] Our setting—the indirect lending market which constitutes over 80% of automotive lending—is an originate-to-distribute model similar to the mortgage market Purnanandam (2011). In contrast Einav et al. (2013) document that dealerships attempt to match borrowers to cars based on observable borrower risk characteristics in a sample that comes from a firm that derived its income primarily from the sale of used cars, 99.6% of which were financed in-house. That is, the credit risk of the loans was borne by the same company that sold the cars and originated the loans. In our setting, dealerships face little if any credit risk associated with loan origination, resulting in agency conflicts associated with the sale and financing of the asset.

platform such as *Dealer Track* or *Route One*. Lenders review the application and either deny it or offer terms under which they will acquire the loan from the dealer. The dealership accepts the bid (i.e., the interest rate conditioned on the loan-to-value ratio) that yields the highest profit for the dealership and still has terms acceptable to the customer. The finance manager may then attempt to mark up the interest rate offered by the lender (the buy rate) (Grunewald et al. 2020, Jansen et al. 2021a). Finally, the dealer completes the transaction and originates the loan, and the customer drives off with the vehicle.

Lenders evaluate and price potential loans using credit risk models that account for customer, vehicle, and loan terms, as well as market conditions. All of the risk factors in their models are included in our data. The high historical volume of car loans and loan outcomes allows for a model that has high predictive value in assessing a loan portfolio's delinquency and default rate, even if predicting the outcome on an individual loan is noisy (Jansen et al. 2021b).

2.2 Dealer and salesperson incentives

Automobile manufacturers generate strong monthly sales cycles at dealerships by offering convex incentives both to the dealerships and (directly) to the salespeople. In the dealer incentive programs, the manufacturers typically pay per-unit cash bonuses that are conditional on the dealers reaching certain new vehicle sales targets in a given calendar month. For example, if a dealership's January sales target is ten new vehicles, the dealership may receive no bonus for selling nine vehicles that month but ten times the piece-rate bonus for the sale of the tenth car. An example of a manufacturer threshold-based incentive is Chrysler's dealer "stair-step" program (Sohoni et al. 2011).[11]

Although the structure of these contracts varies across manufacturers and can frequently change across time, nearly all of the contracts involve some type of convexity. The incentives for hitting monthly sales targets are generally strong enough to motivate dealerships to discount and promote new vehicle sales near the end of the month. In Pierce et al. (2022), for example, monthly profits from selling the marginal vehicle—the vehicle that just reaches the target—average \$22,300 in one program and \$12,000 in the other. In their work on that paper, the authors interviewed the top management of Maritz, the largest auto incentives manager and the creator of the first manufacturer incentives program. Maritz confirmed that, at the time of the interview in 2019, every brand with franchised dealers had at least one dealer or direct salesperson incentive program. The vast majority of these programs used monthly targets; a few used quarterly ones. The managers insisted that even within brands with quarterly incentives, dealerships set and focused intently on the monthly

[11] Under the Chrysler program, a dealership received no additional cash for sales below 75% of the monthly sales target, \$150 per car for sales between 75.1% and 99.9% of the target, \$250 per car for sales between 100% and 109.9%, and \$500 per car for sales reaching 110%.

goals needed to hit the quarterly targets and frequently still provided monthly sales targets to their sales forces. All 12 dealerships where we conducted interviews confirmed that they participate in tiered monthly manufacturer incentive programs.

The dealership passes on convex incentives to salespeople to focus them on monthly goals. Each of our interviewed dealerships applied tiered monthly volume bonuses to its sales force. To fully understand the salespeople's motivation to sell new cars at the end of the month, we briefly describe the pay plans that dealerships offer. A pay plan includes some or all of the following components: a base salary, a commission, and a bonus based on units sold (Fahey 2003, Wolf 2016). To encourage more aggressive selling, dealers sometimes integrate nonlinear incentives into the commission. For example, a common commission plan pays 15% of gross profit, increasing to 20% if the salesperson sells ten or more cars in a month. The commission again increases (back to the first car sold) if 15 or more cars are sold (i.e., the incremental compensation for the fifteenth car sold can be more than 15 times larger than the compensation for the fourteenth car sold). Similarly, sales managers may assign each salesperson a monthly sales goal based on the salesperson's ability and the sales volume necessary to hit the dealership's target. Sales managers will typically support these salesperson incentives with greater pricing discretion and, at the same time, increase pressure on the sales force. When asked about the atmosphere at the end of the month, respondents used words like "pressure," "stressful," and "tense." One salesperson noted that "managers bark bark bark!"

Notably, the sales managers may create additional ad hoc salesperson incentives called "spiffs" when the dealership nears its monthly incentive thresholds. Spiffs may take the form of extra bonuses for the sales of cars necessary to reach the threshold, or additional commission to compensate for the low (at times below-cost) prices used to move the last cars in a month. The survey results affirm that franchise dealerships also provide incentives to sales staff on the sale of used cars, and these incentives can be tied to monthly results. Important to our story is that these weaker incentives would tend to work against our result: when sales staff have multiple incentives, they may be less inclined to promote new car sales.[12]

Some car manufacturers have programs that offer direct incentives to salespeople. For example, General Motors' Consultant Performance Program in the 2010s paid salespeople $225 per car if they sold at least 11 Chevrolet vehicles, seven GMCs, or five Buicks in a month (Lareau 2018). These direct convex incentives, combined with the dealerships' own incentives, strongly motivate salespeople to sell new vehicles. Both the dealerships and the salespeople may regularly monitor their progress toward a target throughout the month, but our interviews confirm that sales pressure

[12]We note that the observed increase in loan defaults on new car sales at the end of the month do not manifest at non-franchise car dealerships. This makes sense, since non-franchise dealerships do not enjoy any financial support from automotive manufacturers.

is most intense in the last few days, when the risk of missing the target becomes clear. Managers want to save costly price discounts and spiffs for when they know that the marginal sale is crucial for hitting the target and thus worth the reduced margin.

The pressure to sell new cars at the end of the month alters how customers are matched to vehicles. Importantly, this change in matching has little to do with the selection of customers who arrive at dealership at the EOM. Our data indicate that EOM customers have similar observable characteristics to customers on other days, and our interviewees confirmed this. The interviewees did note that, at EOM, more of the prospective customers arrive believing they can negotiate a better deal, reasonable expectations given how the dealer incentive program motivates EOM discounting. One salesperson noted that "every now and then someone thinks they are getting a better deal. Whatever. It's pretty much the same people."[13] A finance and insurance manager added that "customer demographics don't change from the beginning to end of the month."

At month's end, the salespeople's approach to customers depends on the attainability of their personal monthly target or the dealership's incentive program target. The salespeople we interviewed suggest that if those targets are hopelessly out of reach, they may "sandbag," pushing sales into the next month, when they might count toward achievable bonuses. In such cases, one explained, they "typically kick back and save the transactions for next month." Another put it more succinctly: "I chill." While these months are not common, as Pierce et al. (2022) show, their presence in our data would understate the increased new car sales volume and defaults at the end of the month.

Personal targets are directly tied to compensation and job security. When a target is within reach, the salesperson exerts effort in every way that is likely to help close a new vehicle sale. "Most people get into more of a frenzy trying to hit that next bonus level," one salesperson explained. "They are trying to find anything that will help them hit their goals," noted another. And if the dealership is near a crucial stair-step threshold, managers may use spiffs to further motivate the sales team to close sales. In addition, our interviews confirm that management pressures the sales team to hit dealership targets: "it's a mad scramble."

Salespeople use several tools and strategies to swiftly close customer sales. First, they use price discounts and free add-ons such as floor mats or cargo nets. Appendix Figure A.1 shows that for any given vehicle, customers are paying less at the EOM. At the same time, the average new car in our sample costs $5,000 more than the average used car, a sum that far exceeds the discounts (averaging around $100) that may have influenced customer choice. In other words, a customer purchasing a new vehicle instead of a used one might receive a bigger discount off the listed price yet still pay far more for the car they purchase. Second, salespeople employ common persuasion principles such

[13] We explain in Section 4.4 that such an EOM has ambiguous theoretical implications for default rates.

as reciprocity, liking, or scarcity (Cialdini 1984, Levine 2003) to convince customers to purchase specific cars. When EOM customers arrive intending to purchase a new car, the salesperson tries to convince them to buy immediately. When EOM customers arrive seeking a *used* vehicle, the salesperson attempts to convince them to switch to new. One salesperson described the persuasion message as "free maintenance, better warranty, save money, free [satellite system], etc. Switching [to a new car] is not too hard." Another explained that customers budget based on a maximum monthly payment from vehicle financing, adding, "I'm really good at influencing what they want. Once I know their payment ... I'm good at pushing them in a subtle way in my direction."

First, EOM customers may come to regret purchasing a car they had not intended to purchase, particularly if it stretches their budget. Despite new cars being more heavily discounted at the end of the month, customers who switch to a new car are more likely to stretch their budget due to the higher retail price. Consumer regret is widely documented (Simonson 1992), particularly after impulsive purchases Stango and Zinman (2023). Second, due to the rapid depreciation of new vehicles, EOM customers who were persuaded to buy a new car are more "underwater" financially (i.e., have negative loan equity) than if they had purchased a used car. Since underwater loans cannot be paid off simply by selling the vehicle, default risks rise. Customers who are persuaded to purchase more expensive vehicles might also compensate for the higher purchase price by forgoing GAP insurance. Standard motor vehicle accident or theft insurance pays the value of the car—not the principal of the loan—so loans on destroyed or stolen vehicles cannot be fully repaid with an insurance settlement. This constitutes another trigger for default.

To summarize, manufacturers' incentive programs focus both dealership staff on reaching discrete monthly sales targets. At the end of the month, the financial stakes for selling new vehicles rise when important targets are within reach. During these critical periods, salespeople have the tools and skills to increase overall sales and shift customers to vehicles that count toward monthly targets.

3 Data and descriptive statistics

3.1 Data and identification strategy

Over 65,000 financial institutions, including banks and non-bank lenders, finance auto loans across the United States. The market is highly competitive, with no single firm holding more than 6% market share (Baines and Courchane 2014). Our data provider, which is among the 20 largest auto finance companies, buys subprime loans from over 3,500 auto dealerships across 40 U.S. states and has been in the business for several decades. As a result, our sample is ideally suited to provide insights into the differences in loan outcomes across U.S. dealerships that sell cars to subprime customers. Eighty percent of dealerships in this sample sell both new and used cars; the remainder only sell used cars.

Our data includes all loans that the data provider acquired between 2005 and 2016 for which we observe loan, borrower, and vehicle characteristics—188,517 loans in all. We conduct our analysis on loans originated before 2017 to ensure that we observe at least 24 months of payment history.

We observe key features of each transaction from the credit application, including borrower attributes, vehicle characteristics, and financing terms. Our data also shows the borrower payment history (or the absence thereof) and whether a default has taken place as of July 2019. Finally, we have information on the loan-level profits of the dealerships and the lender. In Table 1, we summarize buyer, loan, and vehicle characteristics for all loans in our sample. Variables are winsorized at the 1% and 99% levels to prevent extreme values from affecting the results.

The borrowers' profiles reflect that the lender operates in the subprime auto lending market. The average buyer in our sample has a credit score of 531 and a monthly income of $4,295, with 99% of our sample below 660. By comparison, the average credit score for a 2017 national sample (Zabritski 2022) of new car buyers was 727; for used car buyers, the average score was 660. Borrowers with credit scores below 660 constitute 27% of new car buyers and 49% of used car buyers.[14]

The average interest rate on loans in the sample is 18.7%. The mean opening principal balance is $16,900, with an average term of 69 months. Sixty-nine percent of loans in the sample have a 72-month term. On average, borrowers in our sample spend 11% of their reported (pre-tax) monthly income on their car payment. About 8% of auto purchases are new cars. Dealership add-ons are popular among subprime borrowers—48% of customers buy GAP insurance.

3.2 Identification strategy

Our empirical analysis seeks to establish that EOM loans are more likely to default because convex incentive systems change EOM selling and lending behavior. To accomplish this, we first implement linear probability models to establish that loan defaults are predicted by origination on the last day of the month. Next, we support multiple likely causal mechanisms: dealerships use price discounts and persuasion to convince customers to buy new vehicles that depreciate more quickly; the loans for these vehicles stretch customer budgets and repayment ability; to compensate for being financially stretched, buyers fail to insure loans against accidental loss. We then provide

[14] Subprime borrowers predominantly purchase used vehicles and are more likely to default than prime borrowers (Zabritski 2022). Our sample of subprime and deep subprime auto loans is comparable to the overall market as described in Experian's State of the Automotive Market report (Zabritski 2022), which covers the entire U.S. auto loan market.

additional quantitative and qualitative evidence that buyer characteristics are unlikely to generate our main effect. Some price-conscious buyers may come to the dealership at EOM hoping for the price discounts resulting from the dealer incentive program, but this poses no clear implication for default rate. More importantly, we see no evidence of the principal identification threat–that EOM selection on unobservables that might be unrelated to the incentive program. Finally, we provide evidence that EOM defaults do not hurt lender profitability and discuss why customers likely fail to account for the long-term implications of EOM purchases.

4 Results

4.1 Loan volume at the end of month

We first show that loan origination volume across the average month is consistent with typical sales patterns under convex monthly sales incentives (Larkin 2014). In Figure 1, we calculate and plot the daily average number of loans for 13 days before and after the last day of a month. The loan volume signed on the last day of the month is 55% higher than the volume signed on each of the first five days of the following month. Our data are consistent with the general car sales patterns observed at dealerships under monthly sales incentives: lower at the beginning of the month, higher during the second half, and peaking on the last day.

4.2 Loan defaults for end-of-the-month purchases

We next establish that loans signed at the end of the month have higher default rates than those on other days. Our measure of loan default, *Early Default*, is an indicator that equals 1 if the loan defaults within 24 months of origination, and 0 otherwise. It is a common industry practice to evaluate loan portfolio performance using early loan default because these defaults yield the largest costs for lenders.[15] As mentioned in Section 3, we restrict our sample to loans originated before 2017 to ensure an uncensored view of loan status for 24 months after origination. We estimate the effect using the OLS regression:

$$Early\ Default_{lt} = \beta_0 + \beta_1 MonthEndlt + \gamma Controls_{lt} + \epsilon_{lt} \tag{1}$$

In Equation (1), all variables are at the loan level l. *Month End* is an indicator that equals 1 if the contract is signed on the last day of a month, and 0 otherwise. We control for time trend with origination year fixed effects. Since loans within a dealership are interrelated and reflect

[15] In Section A.2, we report results for early default measures with time horizons spanning 18 to 30 months after origination. The results are quantitatively similar to the main results.

organizational practices (e.g., similar sales practices, customer demographics, and vehicle types), robust standard errors are clustered by dealership.

Table 2, column 1 presents coefficient estimates and t-statistics from an analysis that includes year fixed effects without controls. In this specification, the coefficient on *Month End* (β_1) is positive and significant ($p < 0.01$). The estimated β_1 of 110 basis point increase means that the EOM loans' early default rate is 9.8% higher than the mean default rate of 10.8% of all non-EOM loans. As we introduce buyer attributes (column 2), price-to-value (i.e., the ratio of the retail price to the wholesale price) and vehicle type (column 3), and loan and vehicle attributes (column 4), the coefficient value is consistently around 110 basis points and precisely estimated ($p < 0.01$). Furthermore, the EOM effect is not significantly changed by the inclusion of dealership fixed effects (column 5), or day of the week and vehicle make fixed effects (column 6). The stability in coefficients across models with different controls in Table 2 is consistent with higher EOM default levels not being caused by omitted customer variables correlated with both default and the end of the month.

Column (7) conducts a placebo test by repeating the fully-controlled model for the sample of dealerships that sell only used cars. The used-only dealers are unaffected by manufacturers' incentives and typically employ piece-rate incentives to motivate their salespeople. If the manufacturer incentives are driving EOM defaults, then we should not observe an EOM default effect in used-car dealerships. Indeed, we see a far smaller and imprecise EOM effect for these dealers, although we caution that the smaller sample size makes this difference statistically indistinguishable.

Taken together, these results suggest that our main finding—that EOM new car loans are 9%–10% ($p < 0.01$) more likely to default than those issued on other days of the month—is not driven by unobserved buyer heterogeneity across purchase dates. We note that we do not observe the monthly dealership targets. Not having these works against our finding as we only observe the average monthly effect. As the surveys point out, dealers that are far from their targets sandbag (shirk) near the end of the month. This suggests that the observed effect is much stronger at the marginal dealership.

4.3 Sales mechanisms behind EOM defaults

Shift from used to new vehicles. Our belief that manufacturer incentive schemes drive increased default risk hinges on the idea that, at the end of the month, dealerships convince customers to purchase new vehicles through price discounts and persuasion, exposing them to higher depreciation rates and a higher liquidity risk (associated with the higher payments on new vehicles). In this section, we provide evidence in support of this idea. We first show that the EOM sales are accompanied by a shift from used to new vehicles. Then, we show that nearly all of the increased default rate is driven by end-of-month new car sales, particularly those involving the most financially stretched customers. We then provide evidence that this shift can be partly explained by dealers discounting new car prices at EOM, but it is likely the case that salesperson persuasion also facilitates this switch.

Figure 2 presents the composition of new vs. used car sales by the day of the month. The resulting fraction of all sales that are new vehicles increases by 30% as the end of the month approaches, which is consistent with salespeople shifting customer purchases from used to new cars. Borrowers who are observably similar (e.g., same income) and would typically buy used cars are 25% more likely to purchase new cars at the end of the month.

There are a number of potential explanations for why dealers wait until EOM to focus so heavily on the target. First, uncertainty about the value of the marginal sale decreases as the dealer approaches the end of the month. In the middle of the month, the dealer is highly uncertain about whether the cost of moving a customer from a used to new car is justified by importance of that car to target attainment. At the end of the month, the dealer is far more certain about the marginal value. Second, the extensive literature on "goal gradients" (described in Chung et al. (2021)) explains how people become more motivated as they near a goal, which would also be consistent with the patterns we observe. Third, desk-clearing behavior (as described in Cohen et al. (2021)) may explain the observed higher default rate on the last day as dealership personnel rush to meet incentive deadlines and finalize loan paperwork.

New vehicle sales not only increase relative to used vehicle sales but also drive most of the increased default risk. Figure 3 presents a binned scatter plot of 24-month default likelihood for both new and used cars using the same controlled regression approach above. The figure shows a spike in the default rate for new car loans signed on the last day of the month, compared with new car loans signed on other days. Used cars show only a very small increase on the last day, if at all. This finding is consistent with the hypothesis that manufacturers' incentives for new cars are driving the result.

Next, we demonstrate this new-car effect through regression. We define *New* as an indicator that equals 1 if the purchased vehicle is new and 0 if the purchased vehicle is used. We estimate the regression of *Early Default* on *Month End*, *New*, and their interaction:

$$Early\ Default_{lt} = \beta_0 + \beta_1 MonthEnd_{lt} + \beta_2 New_{lt} + \beta_3 MonthEnd_{lt} \times New_{lt} + \gamma Controls_{lt} + \epsilon_{lt} \quad (2)$$

Table 3, column 1 shows that the higher default rate at month's end is mainly driven by new cars. EOM new car sales are 35% (the effect of $\beta_1 + \beta_3$ over the baseline new car non-EOM default rate of 10.7%) more likely to default than new car sales at other times. The coefficient on the interaction term (β_3) is positive and precise across all specifications, and the economic magnitude remains stable when we control for buyer characteristics (columns 2–4), loan characteristics (columns 3–4), and vehicle attributes (columns 3–4). Including fixed effects for dealership, make, and intra-week sales patterns (column 4) does not change the interaction estimate.

If the manufacturer's incentive programs focus only on new cars, why do we observe small increases in used-car defaults at month-end at these new car dealerships? Our qualitative interviews confirmed that franchise dealerships that sell new and used cars sometimes employ monthly incentives to motivate sales staff to sell used cars as well, primarily to improve uniformity across the entire sales staff and perhaps to reduce envy (see Nickerson and Zenger (2008)). In some cases, these incentives will be spiffs to sell certain cars before month-end. Consistent with our argument (i.e., that dealerships respond to manufacturer's incentives), these results are not significant in the case of used-car-only dealerships, and substantially weaker for the sale of used cars at franchise dealerships. We note that these weaker incentives would tend to work against our result: when sales staff have multiple incentives, they may be less inclined to promote new car sales.

In summary, these findings support the argument that manufacturer incentives motivate salespeople to convert used car shoppers to new vehicle buyers, and suggest that this conversion is a key mechanism in explaining the higher EOM default rates.

Increased payment-to-income ratios We next show that the customers whose budgets are stretched the most drive the EOM increases in new car defaults. A key industry measure of financial constraint is the ratio of monthly car payment to income (PTI). Borrowers with high *PTI* use a larger portion of monthly income to repay loan debt. Higher payments, which are predictive of short-term liquidity risks associated with loan default (Argyle et al. 2020, Brown and Jansen 2019), often contribute to increases in PTI. Table 4 represents models regressing *PTI* on *Month End*, *New*, and their interaction, and confirms that PTI is higher for EOM new car buyers than for new car buyers on other days, regardless of which set of controls is included. The table affirms that payments are generally higher for new cars, reflecting their higher prices. Consistent with our argument, the interaction term of *Month End* and *New* (β_3) is positive and significant ($p < 0.05$) across all four specifications, emphasizing how new car buyers stretch their budgets at EOM. Notably, the estimate is nearly identical after the introduction of controls and fixed effects.

We next examine how the higher PTI ratios result in higher defaults. We estimate Equation (2) separately for transactions in which the customers are in 1) the top quartile of *PTI* or 2) the bottom quartile of *PTI*. The results are reported in Table 5. Columns 1–4 and columns 5–8 present the results for customers in the top and bottom quartiles, respectively. For customers in the top quartile of *PTI* (i.e., those that are stretching their budgets), the coefficient on the interaction term of *Month End* and *New* (β_3) is positive and significant ($p < 0.05$) across all four specifications. This result is unaffected by buyer attributes (column 2), loan and vehicle attributes (column 3), and dealership fixed effects (column 4). At the same time, in columns 5–8, the coefficient on the interaction term of β_3 is economically and statistically insignificant, indicating that new car buyers in the bottom quartile of PTI are no more likely to default if their loans are signed at month's end (relative to on other days). Overall, these results are consistent with our argument that increased EOM default rates result from monthly incentives that motivate salespeople to persuade customers to stretch their budgets and purchase new cars.

One concern is that dealerships could misrepresent income in the loan application. Although we cannot empirically disprove this, we conducted several common fraud detection tests used in forensic auditing and found no evidence of increased misrepresentation. Specifically, we found no EOM difference in reported incomes with either round numbers (e.g., $4500 rather than $4512) or repeating digits, nor correlations between these fraud identifiers and default.

Failure to insure EOM loans. Next, we examine whether customers who purchase new cars at the end of the month are more or less likely to buy guaranteed asset protection insurance (GAP). Since the cost of GAP insurance (which ranges from $200 to $900) is financed, the lender's PTI limits might prevent financially stretched EOM borrowers from buying this coverage, or customers may voluntarily eschew it to reduce monthly payments that already stretch their budgets. Because primary auto insurance only covers the car's fair market value, borrowers who have negative-equity loans but lack GAP insurance must pay the remaining debt out of pocket if their car is lost or destroyed. In our setting, the absence of GAP insurance is likely to be particularly consequential due to the rapid depreciation on new vehicles. New cars typically depreciate 25%–35% in the first year after the sale (BlackBook 2019), meaning that the modal 6-year loan in our sample will have negative equity for the first four to five years. In contrast, two- to six-year-old vehicles typically depreciate in the 8%–15% range annually, significantly reducing the time that the borrower is underwater. We use the variable *GAP Indicator* to indicate whether a loan includes GAP insurance, and regress this variable on the same set of variables as above and report the results in Table 6. Consistent with our expectation, the coefficient on the interaction term of *Month End* and *New* is negative and significant ($p < 0.01$), indicating that new-car buyers at the end of the month are *less* likely to buy GAP insurance, relative to other new-car buyers. While the change in GAP coverage purchases alone cannot explain the positive association between EOM and default, it does suggest that buyers are financially-stretched, consistent with the finding that EOM loan defaults in new car buyers is concentrated in borrowers with high payment-to-income ratios.

Price discounts to induce switching. We next provide evidence that intended used car buyers are at least partly convinced to buy new cars because of price discounting. As our qualitative interviews support, salespeople have substantial ability to convince customers to purchase cars different from what they were originally intending, and use a variety of persuasive tactics to do so, but perhaps their most straightforward tool is to simply discount price. Table 7 reports the results for the price-to-value ratio that the dealers command. The negative coefficients on the main effect of *Month End* and the interaction term in columns (1–4) show that dealerships are discounting new vehicles at over twice the rate as used ones at EOM, which likely induces some customers to switch to higher-risk new cars. While statistically significant, the magnitude of the average price discounts we see is small. The average EOM price discounts are less than 1% for used vehicles and 2% for new vehicles.

As we noted earlier, the use of monthly salesperson targets for used cars likely explains their smaller discounts at month-end. Importantly, column (5) examines pricing in dealerships that only sell used cars, and finds no effect. This placebo test supports the argument that dealerships for which the incentive programs are irrelevant seem unmotivated to decrease prices at month-end. We note that although this result suggests that dealerships experience a negative impact on their transaction-level profit margin when they sell EOM new cars, the overall impact is ambiguous since we do not observe the incentive payments made to the dealer.

Summary of mechanisms. Though descriptive in nature, these results on possible mechanisms underlying EOM default rates are consistent with manufacturer incentive structures and with the incentives that are passed on to the dealership sales force. Together, they suggest that when subprime borrowers purchase new cars at the end of the month, they stretch their budget and expose themselves to additional risk from rapid depreciation, and the risk of default from accident or theft. These findings are consistent with subprime borrowers who are influenced to purchase new cars being myopic in considering the higher likelihood of a loan default with these vehicles.

4.4 Customer selection mechanisms

There are two ways in which customer selection mechanisms might potentially explain EOM higher default rates. The first is selection induced by the incentive program, where certain types of customers shop at the end of the month because they perceive the potential for better prices. This type of selection is not a threat to our argument that incentive programs increase loan defaults, but rather represents a different mechanism than the used-to-new car switching induced by price discounts and persuasion. The second is EOM selection based on factors other than the incentive program, where some independent factor leads customers with unobservably higher credit risk to shop at the end of the month. This type of selection represents a true identification challenge to our story, and is important for us to dispel.

Quantitative evidence on selection. We first search for possible evidence that EOM customers are different, regardless of the reason. We first test for differences on observable characteristics across all customers that arrive at dealerships, then address possible unobservable differences.

In Appendix Table A.2, for both used and new vehicle buyers, we compare customer profiles at the end of the month with customer profiles on other days. The differences over time generally lack statistical and economic significance in both the used and new vehicle groups. Although the differences in EOM credit scores and bankruptcy rates are statistically significant, they are not economically meaningful. There is a statistically significant decrease in customer credit scores for used car buyers at the end of the month (relative to used car buyers earlier in the month), but the magnitude amounts to just 1.6 points, as shown in Appendix Table A.2.[16] This difference in credit score is orders of magnitude smaller than the reported error rate on FICO scores (Axelrod 2013) and translates to only a 0.05-percentage-point greater default probability, relative to a mean of 10.2%, compared to the 90-110 basis point increase that occurs at EOM. We note that the statistically imprecise 1.2 point credit score increase among new car buyers is similarly small in magnitude, with their opposite signs consistent with some switching across samples. Appendix Table A.3, which examines loan applications, supports this similarity: it shows that customers applying for loans on the last day of the month are nearly indistinguishable from customers who apply on other days with the exception of a similarly tiny 1 point credit score decrease. We also note that loan terms are similar at EOM on new car sales as shown in Appendix Table A.4.

We next examine whether there is any evidence of unobservable differences in customers at EOM. For an omitted variable to bias our results, the characteristic would need to (1) be different at the end of the month in a way that increases loan defaults, and (2) not be captured by observables such as credit score and income. We first note that Section 4.2 showed our results to hold after controlling for the same borrower, vehicle, and loan characteristics that the lenders observe. The fact that the coefficient estimates in Table 2 lack sensitivity to the introduction of customer characteristics and other observable controls is inconsistent with significant omitted variable bias (Oster 2019). The control variables are important predictors of default, but they do not significantly change the magnitude of the *Month End* coefficients. This suggests that the addition of any unobservable characteristics would, similarly, have little impact on the higher EOM default rates.

We also observe no evidence that lenders have looser standards at EOM that would allow riskier customers to purchase on those days. Figure A.1 shows that loan approvals have lower sale prices relative to the vehicle wholesale price. Stated differently, the loan-to-value ratio of approved loans is *lower* at the end of the month. This suggests that either credit conditions tightened or dealers simply sold cars for lower prices. Neither of these explanations are empirically consistent with lax loan approval standards at the end of the month. We also note that new car loans approved at

[16]Moreover, when examining the distribution of incomes and credit scores for EOM and non-EOM buyers, we find that they looking quite similar as shown in Appendix Figure A.3.

the end of the month are similarly profitable for lenders as those originated at other times of the month (as we show later). This is consistent with lenders maintaining, rather than loosening their lending standards. This provides further evidence that lender behavior is not the explanation for the observed phenomenon of higher default rates at the end of the month.[17]

Finally, we note again that our placebo test in Section 4.2 showed a much smaller default effect for dealerships that only sell used cars and therefore lack convex incentives from manufacturers. The absence of a relationship between EOM sales and early defaults at these dealerships is inconsistent with selection effects based on the general demand for car purchases at EOM.

Qualitative evidence on selection. The lone evidence supporting selection is from our qualitative interviews with dealership personnel at 12 dealerships, but their reports of deal-seeking customers seems unlikely to explain higher EOM default rates. Our structured interview asked, "How does the customer mix change [at the end of the month]?" Of the 20 respondents who answered this question, five said that there was no difference; 14 explained that more EOM customers arrive looking for deals; and one said the EOM customers "tend to be tighter," meaning they are more conservative and negotiate harder.[18]

Although this qualitative evidence suggests some selection induced by expected price discounts, there no definitive argument for how this might impact default rates. It is possible that these customers seek deals because of some financial challenges that are unobservable both to lenders and in our data, or even that deal-seekers might be more likely to strategically default. Perhaps stronger argument can be made that such deal-seekers would present a lower default risk because they are more financially conservative and more skilled at negotiation. Financially conservative customers are less likely to stretch their budgets and more likely to take on loans that they can safely repay. If conservatism reflects financial literacy, it is almost certain to reduce delinquencies (Agarwal et al. 2010). Similarly, stronger negotiators typically pay less for the car and the loan interest rate (which dealers try to mark up), which reduces their monthly payments and the associated liquidity risk. The default risk will be further reduced if the conservative behavior carries over to other financial decisions that might affect the borrower's ability to repay a car loan. As we showed earlier in Table 7, the Price-to-Value of cars is lower for all cars at EOM, and particularly so for new cars, which reduces default risk. Table 2 column (3) shows that price discounts are associated with

[17] To complete the picture on loan profitability from the lender, recall that the prices of cars are lower at the end of the month, which results in a lower loan-to-value (LTV) ratio. When borrowers with lower LTVs default, the lender's recovery of the collateral is higher which helps to offset the higher default rate of the month-end loans.

[18] Two interviewees also mentioned that more cash transactions take place at month's end. Cash-only vehicle purchases are not in our data, and would affect our findings only if dealers were pushing customers with an unobservable default-reducing borrower trait to substitute cash for subprime loans. This seems highly unlikely, given that very few subprime borrowers would be able to pay cash for a new vehicle. And because loan originations generate additional profit for the dealership, it is unlikely that dealers would push customers to pay cash.

decreased likelihood of default conditional on observable borrower risk characteristics.

We conclude that although more deals get closed at the end of the month, EOM customers as a group, on average, have substantively identical observable characteristics to customers on other days, and that the only EOM customer selection perceived by dealership personnel (i.e., deal-seeking) is both driven by the incentive program and unlikely to increase default.

4.5 Lender profits

We next investigate whether lenders suffer financially from the increased defaults. As we noted earlier, the profit impact on dealers is ambiguous, since we cannot know if the decreased margins due to lower prices are justified by the incentive program bonuses that are unobservable in our data. However, our data allow us to estimate the effect of month-end new car sales on the profit margins of the lenders who might be hurt by higher default rates.

Table 8 reports the results for the lender's profit margin on completed loans. We define the lender's profit as the total payments received from the borrower, including payments prior to default, collections payments after default, and any net proceeds arising from the sale of the repossessed vehicle, minus the acquisition cost of the loan. The profit margin is the ratio of profit to the acquisition cost of the loan. The coefficient on both *Month End* and its interaction term are small and imprecise, indicating no correlation between the lender's profit margin and month-end defaults. The lender is not hurt by the higher realized default rates on month-end new-car sales, likely for several reasons. First, month-end loans have lower loan-to-value ratios due to the lower pricing, which in turn improves the collateral coverage, and in the case of defaults, leads to higher recoveries for the lender. Another likely reason is that the lenders are paying the dealers a discounted price for the loans after origination, understanding the increased EOM risk. Regardless, lenders do not appear to be hurt by the increased defaults generated from the incentive program.

5 Discussion and Conclusion

Although much ink has been devoted to the agency conflicts arising in mortgage lending, the connection between financial services and durable product sales in other industries remains under-explored. The importance of consumer financing to the profitability of the automotive industry raises important questions about how sales incentives in that industry spill over into loan origination and loan outcomes.

The customers we examine are buying not only a car but a bundle that includes financing. Financially unsophisticated customers may be able to weigh some of the trade-offs between new and used vehicles but are unlikely to fully comprehend the financial implications or associated risks of the loan contracts. The borrowers at the end of the month appear to suffer the brunt of the consequences of loan default. We find little evidence that lenders are harmed. These results contrast with those of Larkin (2014), who shows that sophisticated buyers collude with salespeople to get better deals. Our result that lender profitability is unaffected by these agency conflicts contrast with the mortgage market where agency conflicts resulted in loan default costs that were borne by investors (e.g., Keys et al. 2010, 2012, Jiang et al. 2014).

Are these decisions to purchase new cars at the end of the month mistakes for some consumers? A definitive answer is beyond the scope of this study. Consumer regret over past purchases is widely documented in psychology and consumer behavior research (Bell 1982, Landman 1987, Simonson 1992). Customers frequently make impulsive and misguided purchase decisions due to both cognitive and emotional biases (Fitzsimons et al. 2002, Stango and Zinman 2023), producing regret that is common enough to have motivated common "cooling off period" regulations that give purchasers the right to return recently acquired products (Sparks et al. 2014). While these regulations are not common in the United States in relationship to automobile purchases, this lack of regulation could be due to political economy considerations. Further research on the decision-making relating to high stakes purchases is merited.

Additional research on how manufacturer incentives create negative externalities for borrowers in the $1.5 trillion auto loan market is merited. One possible area for future research is the welfare implications of buying a new car at month's end. We do not consider whether customers are truly worse off due to the increased default risk or whether the risk is outweighed by the joys of new car ownership. Our data does strongly suggest that many consumers who buy new cars at month's end substantially damage their credit through undisciplined borrowing behavior (Charles et al. 2008, Jagtiani and Lemieux 2019, Garmaise and Natividad 2017). We also note that the manufacturers that use convex dealer incentive designs may suffer unexpected long-term costs from the associated loan defaults even without underwriting the loans: Borrowers who default are unlikely to be approved for future new car loans or to return to the brand that ruined their credit. In increasing their current sales volume, manufacturers may be cannibalizing their pool of *future* customers. Such a pattern would not be without precedent: Pierce (2012) argues that auto manufacturers choose to boost immediate sales revenue and earnings through lower lease payments that will inevitably force them to write off large residual value losses when the leases end many years into the future. He argues this unprofitable, myopic behavior is driven by managerial agency problems and weak accounting rules.

We note that although our data only cover a subset of sales at our 3,500 dealers, this does not detract from the internal validity or importance of our results. Each new car sold counts equally toward the sales target regardless of borrower financial status. These subprime new car sales are very important at the margin because of the discrete target and bonus. The subprime population we study is large, financially vulnerable, and economically important on its own, and our sample is comparable to Experian's data on the overall subprime car buyer population (Zabritski 2022). That being said, the external validity of the effect on prime borrowers is unknown but is likely to be much lower, given the lower propensity of prime borrowers to default. We caution readers not to freely apply our results to *prime* EOM buyers.

Our study's implications extend beyond the design of vertical contracts to other convex incentive structures in finance. Deadline-based convex incentives are ubiquitous in firms that offer discontinuous rewards for meeting quarterly profitability targets and analyst estimates (Degeorge et al. 1999, Roychowdhury 2006). Similar problems exist on the reward for beating the inclusion threshold for equity indexes (Shleifer 1986, Chang et al. 2015) and for reaching performance thresholds in hedge fund compensation (de Figueiredo et al. 2023). Achieving discrete performance targets tends to reward executives, but the convex incentives used to do so have implications both for the firm and for stakeholders such as employees, investors, suppliers, and vendors. Managers who ignore the spillover costs to third parties are likely to overestimate the net benefits associated with the deadline-based incentives.

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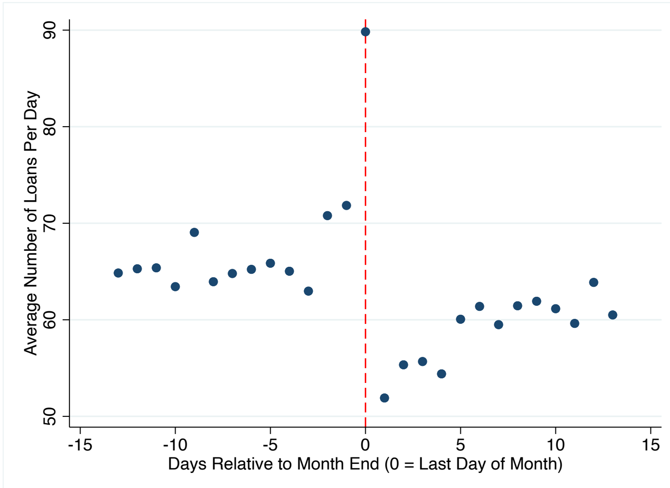
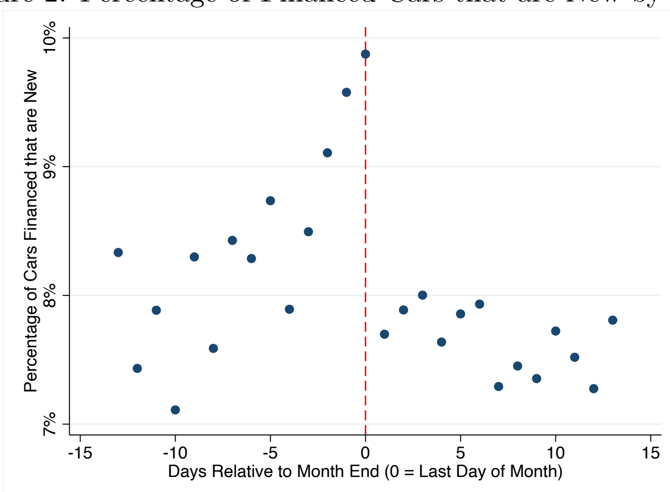
Figure 1: Average Number of Loans per Day of the Month.



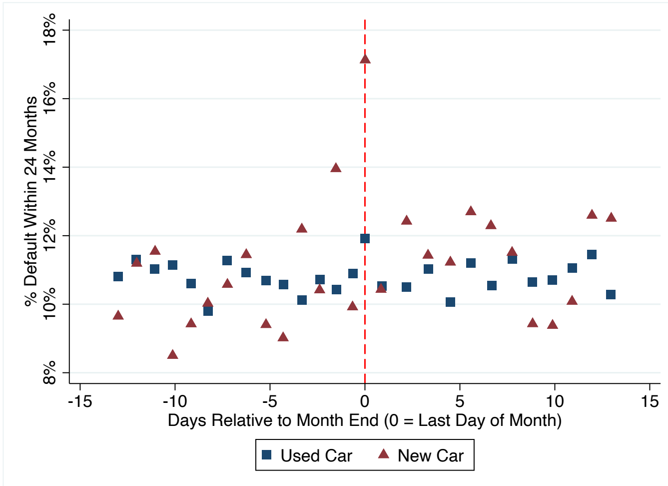
This figure is a binned scatter plot of the total number of loans in our sample signed on the same day each month versus the number of days relative to the end of the month. The vertical dashed line represents the last day of the month.

Figure 2: Percentage of Financed Cars that are New by Day.



This figure is a scatter plot of the percentage of new cars that are financed of the total deals that are signed on the same day each month versus a variable that indicates the number of days relative to the end of the month. The vertical dashed line represents the last day of month.

Figure 3: Default Rate for New and Used Cars on Each Day of the Month.



This figure is a binned scatter plot of the percentage of loans that default within 24 months of origination for each day of the month relative to the end of the month. Blue squares (red triangles) represent used (new) car sales. The vertical dashed line is the last day of the month. To construct the binned scatter plot, we first regressed y- and x-axis variables on a set of control variables consistent with column (2) of Table 3. We then grouped the x-variables into bins and computed the mean of the x-variable and y-variable residuals within each bin, creating a scatter plot of these data points.

Table 1: **Summary Statistics.**

	Count	Mean	Median	SD
Early Default Indicator	188,516	0.11	0	0.31
Month End Indicator	188,516	0.051	0	0.22
Credit Score	188,516	530.8	530	49.0
Prior Ch.7 Bankruptcy Indicator	188,516	0.32	0	0.47
Homeownership Indicator	188,516	0.068	0	0.25
Monthly Income	188,516	4,295.0	3,855.4	1,834.0
New Car Indicator	188,516	0.080	0	0.27
Luxury Indicator	188,516	0.028	0	0.17
Reliability Rating	188,516	48.6	45	19.9
Vehicle Miles (10,000s)	188,516	3.77	3.69	2.14
Age (years)	188,516	2.43	2	1.83
Vehicle Payment/Income	188,516	0.11	0.11	0.036
Loan-to-Value	188,516	1.31	1.30	0.18
Price-to-Value	188,516	1.28	1.29	0.14
Price (in 10,000s of Dollars)	188,516	1.76	1.72	0.43
Amount Financed (in 10,000s of Dollars)	188,516	1.79	1.75	0.43
Vehicle Book Value (in 10,000s of Dollars)	188,516	1.40	1.34	0.40
Downpayment (in 10,000s of Dollars)	188,516	0.099	0.060	0.13
APR	188,516	18.7	18.9	2.43
Term (months)	188,516	69.0	72	5.31
GAP Indicator	188,516	0.48	0	0.50
Service Contract Indicator	188,516	0.45	0	0.50

This table reports summary statistics for loans originated from 2005 to 2016. The number of observations, mean, median, and standard deviations are reported for buyer characteristics, loan characteristics, vehicle characteristics, and loan outcomes.

Table 2: **Loan Defaults for Vehicles Sold at the End of the Month**

DV: Early Default	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Month End	0.011^{***}	0.011^{***}	0.011^{***}	0.011^{***}	0.0090^{***}	0.0086^{***}	0.0037
	(3.38)	(3.20)	(3.30)	(3.32)	(2.82)	(2.69)	(0.44)
Credit Score		-0.00057^{***}	-0.00058^{***}	-0.00032^{***}	-0.00032^{***}	-0.00032^{***}	-0.00042^{***}
		(-30.11)	(-30.58)	(-15.00)	(-16.20)	(-16.18)	(-7.54)
Prior Ch.7 Bankruptcy Indicator		-0.037^{***}	-0.037^{***}	-0.025^{***}	-0.017^{***}	-0.017^{***}	-0.022^{***}
		(-12.52)	(-12.33)	(-8.54)	(-6.35)	(-6.40)	(-3.99)
Homeownership Indicator		0.0063^{*}	0.0063^{*}	0.012^{***}	0.0059^{**}	0.0060^{**}	0.0037
		(1.82)	(1.86)	(3.89)	(2.05)	(2.06)	(0.51)
Ln(Income)		-0.045^{***}	-0.044^{***}	-0.052^{***}	-0.050^{***}	-0.050^{***}	-0.059^{***}
		(-21.25)	(-21.18)	(-20.84)	(-19.11)	(-18.95)	(-10.46)
Price-to-Value			0.046^{***}				
			(5.70)				
New Car Indicator			0.013^{***}	0.026^{***}	0.018^{***}	0.018^{***}	
			(3.20)	(6.00)	(5.53)	(5.50)	
Luxury Indicator				0.011^{**}	0.00039	0.00029	
				(2.53)	(0.08)	(0.06)	
Reliability Rating				-0.00017^{***}	-0.000038	-0.000038	
				(-3.45)	(-0.84)	(-0.84)	
Vehicle Miles 10000				0.0031^{***}	0.0013^{**}	0.0013^{**}	0.0037^{**}
				(4.51)	(2.32)	(2.31)	(2.46)
Age (years)				-0.0023^{***}	0.00017	0.00015	0.0018
				(-3.50)	(0.29)	(0.25)	(1.41)
APR				0.012^{***}	0.012^{***}	0.012^{***}	0.016^{***}
				(23.81)	(24.44)	(24.49)	(13.05)
Ln(Price)				-0.051^{***}	-0.093^{***}	-0.094^{***}	-0.093^{***}
				(-4.24)	(-6.86)	(-6.87)	(-2.68)
Ln(Amount Financed)				0.25^{***}	0.24^{***}	0.24^{***}	0.31^{***}
				(20.68)	(20.62)	(20.72)	(11.26)
Ln(Vehicle Book Value)				-0.11^{***}	-0.072^{***}	-0.073^{***}	-0.11^{***}
				(-10.38)	(-6.00)	(-6.05)	(-4.66)
Term (months)				-0.0015^{***}	-0.0016^{***}	-0.0016^{***}	-0.0012^{**}
				(-7.23)	(-8.73)	(-8.71)	(-2.35)
Ln(Down Payment)				-0.00100^{***}	-0.0014^{***}	-0.0014^{***}	-0.0025^{***}
				(-2.71)	(-4.28)	(-4.31)	(-2.74)
GAP Indicator				-0.021^{***}	-0.0099^{***}	-0.0099^{***}	-0.015^{***}
				(-8.49)	(-4.48)	(-4.47)	(-3.83)
Service Contract Indicator				-0.012^{***}	-0.014^{***}	-0.014^{***}	-0.024^{***}
				(-5.32)	(-6.71)	(-6.70)	(-4.26)
Adjusted R^2	0.006	0.018	0.018	0.028	0.038	0.039	0.041
Year FE	YES	YES	YES	YES	YES	YES	YES
Dealer FE	NO	NO	NO	NO	YES	YES	YES
Day of Week FE	NO	NO	NO	NO	NO	YES	YES
Vehicle Make FE	NO	NO	NO	NO	NO	YES	YES
Only Used Dealer	NO	NO	NO	NO	NO	NO	YES
Observations	188,516	188,516	188,516	188,516	188,516	188,516	32,729

This table reports estimates from regressions of early default on whether the sales contract is signed on the last day of the month. The regressions in columns 1–5 include the full sample. Column 7 is restricted to a sample of loans originated in dealerships that sell only used vehicles. *Early Default* is an indicator that equals 1 if a loan defaults within 24 months of origination, and 0 otherwise. *Month End* is an indicator that equals 1 if the loan is signed on the last day of a month, and 0 otherwise.Robust standard errors are clustered by dealership, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 3: **Loan Defaults for New Vehicles Sold at the End of the Month**

DV: Early Default	(1)	(2)	(3)	(4)
Month End	0.0083**	0.0075**	0.0080**	0.0057*
	(2.40)	(2.18)	(2.34)	(1.68)
New Car	−0.0048	0.0035	0.024***	0.016***
	(−1.04)	(0.87)	(5.63)	(4.82)
Month End × New Car	0.029**	0.030***	0.029**	0.029***
	(2.57)	(2.62)	(2.51)	(2.60)
Adjusted R^2	0.006	0.018	0.028	0.039
Year FE	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES
Loan Controls	NO	NO	YES	YES
Dealer FE	NO	NO	NO	YES
Vehicle Make FE	NO	NO	NO	YES
Day of Week FE	NO	NO	NO	YES
Observations	188,516	188,516	188,516	188,516

This table reports estimates from regressions of early default on whether the sales contract is signed on the last day of the month and whether the vehicle is new or used. *Early Default* equals 1 if a loan defaults within 24 months of origination, and 0 otherwise. *Month End* equals 1 if the loan is signed on the last day of the month, and 0 otherwise. *New Car* equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, Ln(Income), and Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price). Loan Characteristics include APR, Ln(Price), Ln(Loan Amount), Terms, Ln(Down Payment), GAP Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 4: **Payment-to-Income Ratio at the End of the Month**

DV: PTI	(1)	(2)	(3)	(4)
Month End	-0.00055	-0.00057	-0.00074^{**}	-0.00071^{**}
	(-1.48)	(-1.55)	(-2.00)	(-2.00)
New Car	0.0052^{***}	0.0054^{***}	0.0028^{***}	0.0015^{***}
	(8.30)	(9.69)	(4.67)	(2.63)
Month End $\times$ New Car	0.0028^{**}	0.0029^{**}	0.0029^{**}	0.0026^{**}
	(2.15)	(2.30)	(2.27)	(2.11)
Adjusted R^2	0.015	0.033	0.059	0.082
Year FE	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES
Loan Controls	NO	NO	YES	YES
Dealer FE	NO	NO	NO	YES
Vehicle Make FE	NO	NO	NO	YES
Day of Week FE	NO	NO	NO	YES
Observations	188,516	188,516	188,516	188,516

This table reports estimates from regressions of payment-to-income (PTI) ratio on whether the loan is signed on the last day of the month and whether the vehicle is new or used. *Month End* equals 1 if the loan is signed on the last day of a month, and 0 otherwise. *New Car* equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, and Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price). Loan Characteristics include APR, Terms, Ln(Down Payment), Gap Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 5: **New Car Loan Default at End of the Month for Top and Bottom PTI Quartile**

Sample:	PTI top quartile				PTI bottom quartile			
DV: Early Default	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Month End	0.0049	0.0040	0.0040	0.0010	0.016**	0.015**	0.014**	0.012*
	(0.64)	(0.52)	(0.53)	(0.13)	(2.47)	(2.40)	(2.18)	(1.79)
New Car	−0.0054	−0.0052	0.032***	0.021***	−0.0053	0.0080	0.020***	0.021***
	(−0.87)	(−0.88)	(4.46)	(2.89)	(−0.94)	(1.44)	(3.21)	(3.29)
Month End × New Car	0.061**	0.060**	0.058**	0.059**	0.00077	0.0036	0.0064	0.0068
	(2.45)	(2.42)	(2.38)	(2.40)	(0.03)	(0.16)	(0.28)	(0.29)
Adjusted R^2	0.004	0.012	0.023	0.033	0.005	0.022	0.033	0.041
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES	NO	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES	NO	NO	YES	YES
Loan Controls	NO	NO	YES	YES	NO	NO	YES	YES
Dealer FE	NO	NO	NO	YES	NO	NO	NO	YES
Vehicle Make FE	NO	NO	NO	YES	NO	NO	NO	YES
Day of Week FE	NO	NO	NO	YES	NO	NO	NO	YES
Observations	47,129	47,129	47,129	47,034	47,129	47,129	47,129	47,078

This table reports estimates from regressions of early default on whether the sales contract is signed on the last day of the month and whether the vehicle is new or used. The samples in columns 1–4 include customers in the top quartile of *PTI* (the ratio of monthly car payment to income). The samples in columns 5–8 include customers in the bottom quartile of *PTI*. *Early Default* is an indicator that equals 1 if a loan defaults within 24 months of origination, and 0 otherwise. *Month End* is an indicator that equals 1 if the loan is signed on the last day of the month, and 0 otherwise. *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, Ln(Income), and Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price). Loan Characteristics include APR, Ln(Price), Ln(Loan Amount), Terms, Ln(Down Payment), GAP Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 6: **GAP Insurance at the End of the Month.**

DV: GAP Indicator	(1)	(2)	(3)	(4)
Month End	-0.020^{***}	-0.019^{***}	-0.012^{**}	-0.012^{***}
	(-3.03)	(-2.88)	(-2.07)	(-2.62)
New Car	0.026^{*}	0.019	0.042^{***}	0.021^{***}
	(1.69)	(1.29)	(3.17)	(3.36)
Month End × New Car	-0.036^{*}	-0.038^{**}	-0.044^{**}	-0.041^{**}
	(-1.87)	(-1.99)	(-2.43)	(-2.30)
Adjusted R^2	0.006	0.010	0.189	0.301
Year FE	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES
Loan Controls	NO	NO	YES	YES
Dealer FE	NO	NO	NO	YES
Vehicle Make FE	NO	NO	NO	YES
Day of Week FE	NO	NO	NO	YES
Observations	188,516	188,516	188,516	188,516

This table reports estimates from regressions on the use of GAP insurance on whether the loan is signed on the last day of the month and whether the vehicle is new or used. *GAP Indicator* equals 1 if the buyer gets GAP insurance, and 0 otherwise. *Month End* is an indicator that equals 1 if the loan is signed on the last day of a month, and 0 otherwise. *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, Ln(Income), and Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price). Loan Characteristics include APR, Ln(Price), Ln(Loan Amount), Terms, Ln(Down Payment), and Service Contract Indicator. Robust standard errors are clustered by dealership, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 7: **PTV for New Cars Sold at the End of the Month**

Sample:	Full Sample				Used Only
DV: PTV	(1)	(2)	(3)	(4)	(5)
Month End	-0.0082^{***}	-0.0080^{***}	-0.0069^{***}	-0.0065^{***}	-0.0021
	(-4.26)	(-4.13)	(-3.63)	(-4.39)	(-0.80)
New Car	-0.17^{***}	-0.17^{***}	-0.10^{***}	-0.11^{***}	
	(-25.40)	(-25.61)	(-15.04)	(-30.83)	
Month End × New Car	-0.010^{**}	-0.011^{**}	-0.0087^{*}	-0.0091^{**}	
	(-2.11)	(-2.32)	(-1.84)	(-2.20)	
Adjusted R^2	0.129	0.135	0.212	0.351	0.333
Year FE	YES	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES	YES
Loan Controls	NO	NO	YES	YES	YES
Dealer FE	NO	NO	NO	YES	YES
Vehicle Make FE	NO	NO	NO	YES	YES
Day of Week FE	NO	NO	NO	YES	YES
Only Used Dealer	NO	NO	NO	NO	YES
Observations	188,516	188,516	188,516	188,516	32,729

This table reports estimates from regressions of price to value (PTV) on whether the loan is signed on the last day of the month and whether the vehicle is new or used. PTV is the ratio of the retail price to the wholesale price for each vehicle. *Month End* equals 1 if the loan is signed on the last day of a month, and 0 otherwise. *New Car* equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, and Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, and Vehicle Age. Loan Characteristics include APR, Terms, Ln(Down Payment), Gap Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 8: **Lender Loan Profitability**

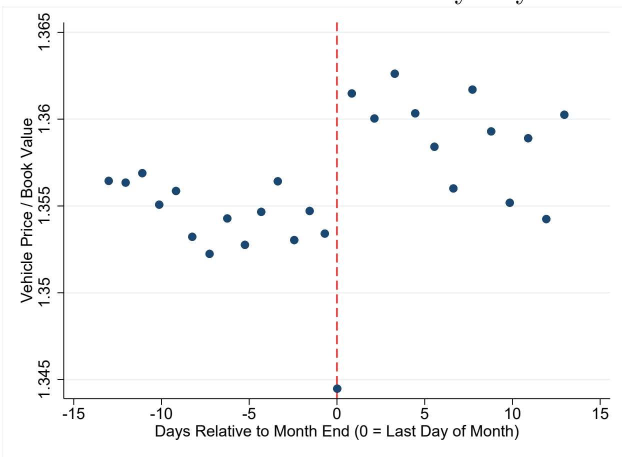
DV: Loan Profitability	(1)	(2)	(3)	(4)
Month End	−0.00053	−0.00094	−0.0017	−0.00075
	(−0.12)	(−0.21)	(−0.38)	(−0.18)
New Car	−0.028***	−0.029***	−0.021***	−0.023***
	(−6.97)	(−7.08)	(−4.43)	(−4.91)
Month End × New Car	−0.011	−0.011	−0.0093	−0.0098
	(−0.90)	(−0.86)	(−0.75)	(−0.81)
Adjusted R^2	0.074	0.079	0.088	0.100
Year FE	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES
Loan Controls	NO	NO	YES	YES
Dealer FE	NO	NO	NO	YES
Vehicle Make FE	NO	NO	NO	YES
Day of Week FE	NO	NO	NO	YES
Observations	186,181	186,181	186,181	186,181

This table reports estimates from regressions of loan profitability on whether the sales contract is signed on the last day of the month and whether the vehicle is new or used. *Loan Profitability* is the margin earned on the loan by the lender. *Month End* is an indicator that equals 1 if the loan is signed on the last day of the month, and 0 otherwise. *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, and Vehicle Age. Loan Characteristics include APR, Terms, Ln(Down Payment), GAP Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, with t-statistics in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

A Online Appendix

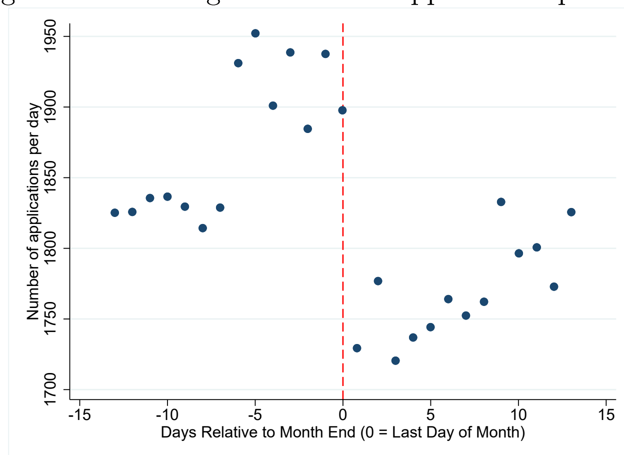
A.1 Figures and Tables

Figure A.1: Vehicle Price-to-Value Ratio by Day of the Month.



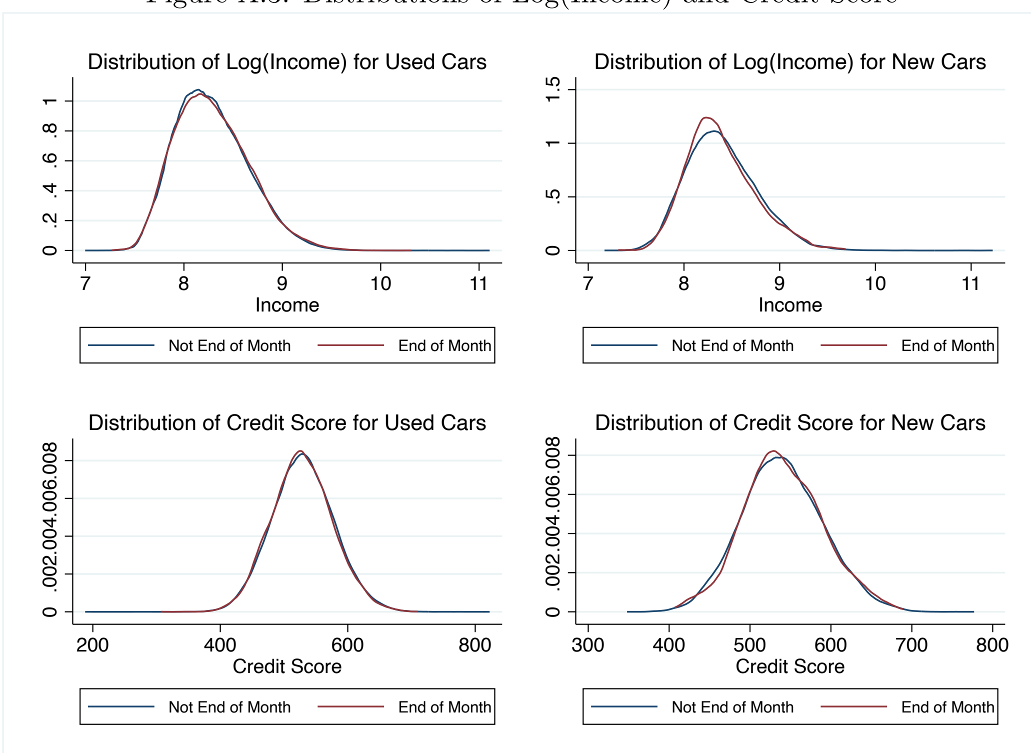
This figure is a binned scatter plot of the vehicle retail price to wholesale price ratio (PTV) for loans signed on the same day of the month, relative to the end of the month. To construct the binned scatter plot, we first regressed y- and x-axis variables on a set of control variables (loan characteristics, borrower characteristics, vehicle characteristics, and year indicators) and generated the residuals from those regressions. We then grouped the residualized x-variables into 27 equal-sized bins, computed the mean of the x-variable and y-variable residuals within each bin, resulting in the scatter plot of these data points.

Figure A.2: Average Number of Applications per Day.



This figure is a binned scatter plot of the average number of applications that the lender receives each day versus a variable that indicates the number of days relative to the end of the month. The vertical dotted line represents the last day of the month.

Figure A.3: Distributions of Log(Income) and Credit Score



These are the kernel densities of Log(Income) and Credit Scores by new vs. used cars and EOM vs. non-EOM.

Table A.1: **Alternative Default Definitions**

DV: Default at	18mth (1)	24mth (2)	30mth (3)	36mth (4)
Month End	0.0033	0.0057*	0.0010	0.0025
	(1.25)	(1.68)	(0.27)	(0.61)
New Car	0.012***	0.016***	0.024***	0.030***
	(4.37)	(4.82)	(5.78)	(6.21)
Month End × New Car	0.029***	0.029***	0.036***	0.027**
	(2.83)	(2.60)	(2.89)	(2.09)
Adjusted R^2	0.028	0.039	0.050	0.059
Year FE	YES	YES	YES	YES
Buyer Controls	YES	YES	YES	YES
Vehicle Controls	YES	YES	YES	YES
Loan Controls	YES	YES	YES	YES
Dealer FE	YES	YES	YES	YES
Vehicle Make FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Observations	188,516	188,516	188,516	188,516

This table reports estimates from regressions of default rate measures on whether the loan is signed on the last day of the month. The dependent variables in columns 1–4 are indicators that equal one if a loan defaults within 18 months, 24 months, 30 months, and 36 months, respectively. *Month End* is an indicator that equals 1 if the loan is signed on the last day of a month, and 0 otherwise. *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. The regressions use specification (4) from table 3. Buyer Characteristics include Credit Score, Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price). Loan Characteristics include APR, Ln(Price), Ln(Loan Amount), Terms, Ln(Down Payment), GAP Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, and t-statistics are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.2: **Borrower Profiles.**

Panel A: New-Vehicle Sample

	Non-EOM Customer			EOM Customers				
	N	Mean	SD	N	Mean	SD	Difference	*p*-value
Income	14,196	4,768.2	2,134.1	944	4,674.5	1,902.4	−93.7	0.146
Credit Score	14,196	540	50.5	944	541.2	49.6	1.2	0.72
Homeownership Indicator	14,196	0.079	0.27	944	0.0847	0.279	0.005	0.57
Bankruptcy Indicator	14,196	0.215	0.411	944	0.230	0.421	0.015	0.30

Panel B: Used-Vehicle Sample

	Non-EOM Customer			EOM Customers				
	N	Mean	SD	N	Mean	SD	Difference	*p*-value
Income	164,760	4,252.6	1,799.3	8,616	4,285.4	1,837.4	32.8	0.106
Credit Score	164,760	530.1	48.8	8,616	528.5	48.0	−1.6	0.003
Homeownership Indicator	164,760	0.066	0.249	8,616	0.068	0.253	0.002	0.75
Bankruptcy Indicator	164,760	0.331	0.470	8,616	0.338	0.473	0.008	0.11

This table reports separate summary statistics for borrowers who purchase their cars at the end of the month (EOM) and at other times of the month (Non-EOM). The number of observations, mean, and standard deviations are reported. Panel A includes only new-vehicle transactions. Panel B includes only used-vehicle transactions.

Table A.3: Application Profiles.

	Non-EOM applications		EOM applications			
	Mean	SD	Mean	SD	Difference	*p*-value
Monthly Income	3,473.5	1,586.0	3,468.3	1,584.1	−5.20	0.42
Credit Score	533.7	52.34	532.7	52.23	−1.00***	0.00
Homeownership Indicator	0.0704	0.256	0.0693	0.254	0.00	0.29
Observations	1,708,227		62,162			

This table reports separate summary statistics for loan applications that occur at the end of the month (EOM) and at other times of the month (Non-EOM). This sample of loan applications is for the period 2015–2019. The number of observations, mean, and standard deviations are reported.

Table A.4: Loan Terms

Panel A: *APR (Interest Rate)*

DV: APR	(1)	(2)	(3)	(4)
Month End	0.038	0.0050	−0.0039	−0.011
	(1.41)	(0.21)	(−0.17)	(−0.60)
New Car	−1.08***	−0.82***	−0.20*	−0.20***
	(−8.62)	(−8.80)	(−1.91)	(−4.86)
Month End × New Car	−0.066	−0.026	−0.041	−0.013
	(−0.82)	(−0.38)	(−0.62)	(−0.22)
Adjusted R^2	0.062	0.292	0.331	0.439
Observations	188,516	188,516	188,516	188,516

Panel B: *Term Length*

DV: Term	(1)	(2)	(3)	(4)
Month End	0.036	0.036	0.057	0.090*
	(0.58)	(0.58)	(1.13)	(1.86)
New Car	2.94***	2.81***	−3.39***	−3.99***
	(25.56)	(25.18)	(−31.58)	(−33.94)
Month End × New Car	−0.070	−0.057	−0.042	−0.011
	(−0.74)	(−0.60)	(−0.41)	(−0.11)
Adjusted R^2	0.033	0.038	0.449	0.504

Panel C: *Down Payment*

DV: Down payment	(1)	(2)	(3)	(4)
Month End	0.084*	0.087**	0.11***	0.035
	(1.90)	(2.04)	(2.85)	(1.23)
New Car	0.32***	0.23**	0.68***	0.51***
	(2.77)	(2.07)	(5.80)	(7.35)
Month End × New Car	−0.047	−0.058	0.10	0.067
	(−0.45)	(−0.55)	(1.02)	(0.71)
Adjusted R^2	0.023	0.046	0.242	0.358

Panel D: *Loan to Value*

DV: Down payment	(1)	(2)	(3)	(4)
Month End	−0.011***	−0.011***	−0.0064***	−0.0049***
	(−5.64)	(−5.51)	(−3.98)	(−3.56)
New Car	−0.18***	−0.18***	−0.097***	−0.10***
	(−28.50)	(−29.18)	(−17.22)	(−29.56)
Month End × New Car	−0.0018	−0.0026	0.0026	0.0049
	(−0.29)	(−0.45)	(0.47)	(0.93)
Adjusted R^2	0.098	0.104	0.417	0.492

This table reports estimates from regressions of APR (Panel A), Term (Panel B), Down Payment (Panel C), and Loan to Value (Panel D) on whether the sales contract is signed on the last day of the month and whether the vehicle is new or used. *APR* is the annual percentage rate on the loan. *Loan Term* is the length of the loan in months. *Down payment* is the size of the down payment in dollars. *Loan to Value* is the loan to value. *Month End* is an indicator that equals 1 if the loan is signed on the last day of the month, and 0 otherwise. *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. Controls and fixed effects are consistent with Table 8 as described hereunder. Controls for buyer characteristics (Credit Score, Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator) are included in columns 2, 3, and 4. Controls for vehicle characteristics (Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price)) are included in columns 3 and 4. Controls for loan characteristics (APR, Ln(Price), Ln(Loan Amount), Terms, Ln(Down Payment), GAP Contract Indicator, and Service Contract Indicator) are included in columns 3 and 4. All panels include year fixed effects, and column 4 also includes dealership, vehicle make, and day-of-the-week fixed effects. When the dependent variable is listed as a control, that variable is dropped as a control variable in the regression. The number of observations for all regressions across the four panels and columns is 188,516. Robust standard errors are clustered by dealership, and t-statistics are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A.5: **Alternative End of Month Definition**

DV: Early Default	(1)	(2)	(3)	(4)
Month End (adj)	0.0028	0.0022	0.0028	0.0018
	(1.22)	(0.95)	(1.20)	(0.80)
New Car	−0.0058	0.0026	0.023***	0.016***
	(−1.18)	(0.59)	(5.26)	(4.53)
Month End (adj) × New Car	0.019**	0.019**	0.016**	0.015*
	(2.34)	(2.32)	(1.97)	(1.83)
Adjusted R^2	0.006	0.018	0.028	0.039
Year FE	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES
Loan Controls	NO	NO	YES	YES
Dealer FE	NO	NO	NO	YES
Vehicle Make FE	NO	NO	NO	YES
Day of Week FE	NO	NO	NO	YES
Observations	188,516	188,516	188,516	188,516

This table reports estimates from regressions of early default on whether the loan is signed on the last day of the month and whether the vehicle is new or used. *Early Default* is an indicator that equals 1 if a loan defaults within 24 months of origination, and 0 otherwise. *Adj. Month End* is an indicator that equals 1 if the loan is signed on the last day three days of a month. *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price). Loan Characteristics include APR, Ln(Price), Ln(Loan Amount), Terms, Ln(Down Payment), GAP Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, and t-statistics are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A.6: **Loan Defaults for New Vehicles Sold at the End of the Month with Placebo**

DV: Early Default	(1)	(2)	(3)	(4)	(5
Month End	0.0083**	0.0075**	0.0080**	0.0057*	0.0039*
	(2.40)	(2.18)	(2.34)	(1.68)	(0.47)
New Car	−0.0048	0.0035	0.024***	0.016***	
	(−1.04)	(0.87)	(5.63)	(4.82)	
Month End × New Car	0.029**	0.030***	0.029**	0.029**	0.029***
	(2.57)	(2.62)	(2.51)	(2.60)	(2.14)
Adjusted R^2	0.006	0.018	0.028	0.039	0.039
Year FE	YES	YES	YES	YES	YES
Buyer Controls	NO	YES	YES	YES	YES
Vehicle Controls	NO	NO	YES	YES	YES
Loan Controls	NO	NO	YES	YES	YES
Dealer FE	NO	NO	NO	YES	YES
Vehicle Make FE	NO	NO	NO	YES	YES
Day of Week FE	NO	NO	NO	YES	YES
Observations	188,516	188,516	188,516	188,516	188,516

This table reports estimates from regressions of early default on whether the sales contract is signed on the last day of the month and whether the vehicle is new or used. *Early Default* equals 1 if a loan defaults within 24 months of origination, and 0 otherwise. *Month End* equals 1 if the loan is signed on the last day of the month, and 0 otherwise. *New Car* equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Credit Score, Homeowner Indicator, Ln(Income), and Bankruptcy Indicator. Vehicle Characteristics include Luxury Indicator, Vehicle Reliability, Vehicle Mileage, Vehicle Age, and Ln(Wholesale Price). Loan Characteristics include APR, Ln(Price), Ln(Loan Amount), Terms, Ln(Down Payment), GAP Contract Indicator, and Service Contract Indicator. Robust standard errors are clustered by dealership, and t-statistics are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

A.2 Robustness checks

In this section, we perform several robustness checks to alleviate concerns about our choice of measurement of default. First, we estimate Equation 2 using default rates over different time horizons (i.e., defaults that occur within 18 or 30 months of origination). In these tests, we include controls and fixed effects identical to those previously described. We report the result in Appendix Table A.1 The coefficient on the interaction term of *Month End* and *New* is significant across all time horizons. These findings are consistent with our main finding (in Table 2) that higher default rates are attributable to month-end new-car sales.

We next use a modified definition of *Month End* that is equal to 1 if the loan is originated on the last *three* days of the month. We estimate Equation 2 with *Adj. Month End* and report the results in Appendix Table A.5. Consistent with the results in Table 2, the coefficient on the interaction between *Adj. Month End* and *New* is positive and significant. Not surprisingly, it is smaller than when we use just the last day (our main definition), since dealerships are less certain about the impact on the bonus of he marginal sale. Consistent with this, Figure 1 shows that the last day is when the most intense sales activity occurs.

In our final robustness check, we use loan application data for a four-year sample period to depict the average number of loans per day relative to on the last day of a month as shown in Appendix Figure A.2. Loan applications are substantially higher than actual loans in our data because lenders are competitively bidding for contracts.[19] The visualization shows that the number of applications received is 5% higher in the last week of the month than in the preceding week. When, in Appendix Table A.3, we compare customer characteristics (i.e., income, credit score, and home-ownership status) for applications on the last day of the month with customer characteristics for applications on other days, we observe no economically significant difference in the mean of each characteristic. This evidence is consistent with the comparison of borrower characteristics reported in Appendix Table A.2 and helps to allay concerns that customer heterogeneity is driving the month-end loan defaults. There is no evidence that this is the case.

[19] The four-year sample includes 1.77 million loan applications, 3.5% of which were received on the last day of the month.

A.3 Structured Dealership Interviews

We conducted structured interviews of 23 employees at 12 new car dealerships. The participants included 18 salespeople and 5 finance and insurance managers. The interview script and process were approved by the authors' institutional review boards (IRB), and the interviews were conducted with the explicit consent of dealership management and the participants.

The interviews were intended to gather qualitative data for several important parts of the paper. First, we sought to better understand the sales and lending process, particularly with regard to monthly sales incentives and dealership operations and strategy at the end of the month. We also wanted to understand the ease with which salespeople could persuade customers to buy vehicles that they had not originally intended to purchase.

Second, we sought to understand how salesperson incentives were tied to monthly sales cycles, and how this relationship differed between new and used vehicles. For new car sales, we wanted to verify that the end of the month produced high managerial pressure that would motivate sales effort.

Finally, we sought to identify any differences in the mix of customers that arrive at the end of the month, compared to on other days. In particular, we were looking for customer characteristics that would be both unobservable in our data *and* positively correlated with loan default, in case an omitted variable was biasing our main results.

The exact anonymized responses are provided as supplemental material. The formal interview script is listed below.

Dealership Interview Script

1. Could you please walk us through the transaction of the last vehicle you sold before the end of the month?
2. What sort of bonuses or incentives are tied to month-end new car volume? Is this different from used?
3. What happens toward the end of the month when dealer or salesperson targets are in reach?
   a Do any comp components change?
   b How does the atmosphere change?
   c How does the customer mix change? (push on any possible unobservables)
   d How close to the end of the month does this start to change?
   e What happens when monthly incentive thresholds are out of reach?
   f What tactics or strategies do you use to try to increase volume at the end of the month?

4. Why is there an end of the month surge? Why don't dealers spread the work out during the month?
5. How much ability do you have to influence which vehicles customers buy? What percentage know exactly what they want? New vs. used? How narrow is the price range? Vehicle type, make, model?