Product sales incentive spillovers to the lending market

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ABSTRACT

We examine how deadline-based convex incentives in physical product markets can affect the credit markets that finance these products. Auto dealerships respond to monthly sales targets in manufacturer incentive programs by shifting borrowers from used to new cars at the end of the month. End-of-month loans default more often, particularly among financially constrained buyers of new cars. At month-end, dealerships sway financially unsophisticated buyers to buy new cars instead of more reliable models that are available as used vehicles. We find no evidence that lenders or dealerships are hurt by this increased default risk from manufacturers' incentives.

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1. Introduction

Incentive structures such as sales contracts are commonly based on a convex relationship between bonus pay and performance achieved before a deadline (Chung et al., 2020).[1] Common examples include kinked commission structures with accelerators (Larkin and Leider, 2012) and stair-step schemes with large bonuses at specific target levels (Misra and Nair, 2011). Although such schemes are most frequently used in individual compensation plans (e.g., Tzioumis and Gee, 2013), they are also designed to reward firms that are suppliers or retailers. The American automotive industry, for example, has long motivated its franchised dealer network through convex monthly incentives based on vehicle sales targets (Pierce et al., 2020). Theoretical work (Oyer, 2000; Misra and Nair, 2011; Herweg et al., 2010; Pierce et al., 2020; Chung et al., 2014; Barron et al., 2020), however, explains why such schemes can motivate individual agents to game the principal's incentive scheme by both lumping sales within specific time periods or concentrating effort on selling only one of many products to exploit the convexity or rewards. The empirical literature broadly supports these predictions for individual agents such as salespeople or managers (Healy, 1985; Oyer, 1998; Larkin, 2014; Benson, 2015), with only recent work showing incentive gaming by firms (Pierce et al., 2020). Nearly all of this literature, however, focuses on the cost of gaming to the principal who writes the incentive contract, often to the benefit of the agent and the customer. But what if the costs of agent gaming are not borne by the principal, but instead by customers and other third-parties such as suppliers and lenders? To date, the existing literature shows little concern for this potential problem.

This paper makes two significant contributions to the literature on incentive gaming. First, we demonstrate that customers do not always benefit from gaming, as they do in most of the existing empirical literature (e.g., Larkin, 2014). Instead, gaming can hurt uninformed

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

customers as salespeople use pressure, deception, or other tactics to sell them products that are of lower quality or present other risks to the customer. Second, we show that although incentive gaming in sales exposes the financial institutions that underwrite the products to default risk, these firms accurately price this additional risk into their loan product portfolio. Consequently, customers bear the vast majority of the cost associated with gaming.

This paper investigates the gaming costs of deadline-based incentives using novel loan data from a leading firm in the American subprime automotive lending market.[2] In this setting, vehicle manufacturers motivate new car sales volume through a variety of mechanisms, including directly offering cash rebates to both consumers and dealers (Busse et al., 2006). But their strongest sales lever is the monthly sales incentives that reward car dealers for hitting discrete sales volume targets in a given calendar month. These monthly incentive systems are nearly universal in the industry and represent the majority of dealership sales profits (Pierce et al., 2020). The incentives motivate both intertemporal and multitasking gaming behaviors when the dealership is close to the target (Pierce et al., 2020). For example, a dealership might either delay or accelerate sales to target monthly targets in the current or subsequent month. Similarly, if a dealership carries multiple car brands, near the end of the month, they might focus attention and resources on the brand most likely to hit its target. Although dealerships have multiple tools to stack sales within months and brands, including pricing, marketing spending, and salesperson assignment, one of their strongest levers is to persuade customers to buy new cars as opposed to used cars, which do not offer the same monthly incentive structure.

The convexity of dealership incentives motivates gaming behaviors that pose potentially significant costs for customers. Dealership managers typically align salesperson incentives through their own deadline-based convex compensation schemes (Fahey, 2003; Wolf, 2016; Pierce et al., 2020), which can conflict with the salesperson's role in matching relatively un-

[2]The loan-level data includes customer and vehicle attributes at the time of purchase and tracks customers over the life of the loan. The data includes sales from over 4,000 dealerships.

informed customers with cars that suit their needs. For example, the salesperson could steer a financially constrained customer away from a car with high maintenance costs. Because vehicle manufacturers' monthly dealer incentives almost always apply only to sales of new cars (Lareau, 2018), dealerships and the salespeople they employ can move customers from used to new cars when the salespeople are just below targets near the end of the month.

We find that loans for end-of-month vehicle purchases have a 10% higher default probability within 24 months, relative to loans made earlier in the month. Moreover, we find little evidence that the finances of buyers at the end of the month differ in observable ways (e.g., credit score and income) from those of buyers at other times. Using a difference-in-difference specification, we find that new-car purchases drive much of the increase in default likelihood. Defaults are 32% higher for new-car loans made at the end of the month, relative to new-car loans made at other times. In contrast, defaults on used-car loans made at the end of the month are just 8% higher *ceteris paribus*.

We examine mechanisms that could explain why new car purchases at the end of the month carry a higher risk of default. The propensity of end-of-month new car buyers to default is concentrated amongst buyers with large payment-to-income (PTI) and debt-to-income (DTI) ratios. New car buyers with greater levels of financial slack who purchase new cars do not exhibit the same likelihood of loan default. Also, buyers may not be fully aware that new vehicles typically depreciate 25% to 35% within the first year after sale, whereas two- to six-year-old vehicles typically depreciate by only 8% to 15% annually (BlackBook, 2019). This high first-year depreciation significantly raises default risk: the new car is worth significantly less than the principal owed on the loan the moment it is driven off the lot. Owners of such cars cannot avoid loan default simply by selling the car. We also find that end-of-month new car buyers are markedly *more* likely to purchase *less* reliable vehicles and *less* likely to buy insurance products that protect them against default should the vehicle suffer significant damage. Although we cannot observe individuals' incentives directly, these factors suggest that moral hazard is a plausible and empirically relevant explanation for the higher default rate among new car buyers.

The findings suggest that financially unsophisticated subprime customers who purchase new cars at the end of the month have an increased likelihood of defaulting.[3] We find little evidence to suggest that lenders or dealers are hurt by the manufacturer's incentives that encourage these purchases. Dealer and lender loan profits on new vehicle sales at the end of the month are indistinguishable from profits at other times.

We employ a variety of robustness checks and controls to rule out alternative explanations for our findings and support our evidence on mechanisms through two-stage least squares (2SLS) models. We show that the percentage of new vehicles sold increases as the end of the month nears and that predicted new vehicle sales coming from this relationship positively correlates with loan defaults. This is consistent with increases in new vehicle sales being the mechanism through which monthly dealer incentives increase defaults. In contrast, we show that the relationship between manufacturer rebates *to consumers* and new car sales does not predict an increase in loan defaults since incentives to customers directly lower the price. Finally, when used-car-only dealerships originate loans at the end of the month, borrowers are no more likely to default than loans originated at other times. Used-car-only dealerships do not qualify for automotive manufacturers' incentives and typically employ piece-rate incentives to drive sales. The absence of a relationship between end-of-month sales and early defaults at these dealerships suggests that automotive manufacturers' incentives meaningfully influence borrower defaults.

Our paper is most closely related to Tzioumis and Gee (2013), which studies the mortgage lending industry. The authors of that paper find that mortgage officers greatly increase their output toward the end of each month to meet minimum monthly quotas. They also find that mortgages originated on the last working day of the month have higher delinquency rates, even when customers' credit-worthiness is controlled for. We build upon Tzioumis and Gee

[3] We cannot determine if the increased default risk is outweighed by the pleasures of new car ownership. As a result, a comprehensive welfare analysis is beyond the scope of this study.

(2013) in three ways. First, we offer an explanation for the high end-of-month delinquencies—specifically, we find that the deadline-based incentives erode the quality of matches between customers and products because of a classic multitasking problem in sales (Holmstrom and Milgrom, 1991; Pierce et al., 2020). Although responsible salespersons can easily make the default risk salient to customers, they are less likely to initiate these conversations at the end of the month. Second, we show that the sales incentives of a durable goods retailer, as opposed to the lender in Tzioumis and Gee (2013), can affect default risk in contracts between two third parties—in this case, the lender and the buyer. Finally, we show that this increased default risk from the retailer is priced into the loan market. Financial institutions recognize the increased default risk of month-end sales, and adjust prices accordingly.

This paper also contributes to the broader literature on deadline-based convex incentive contracts. Prior studies have shown that these types of contracts are subject to gaming by agents. The previous works in this literature (Oyer, 1998; Tzioumis and Gee, 2013; Larkin, 2014) describe a surge in sales as a deadline approaches. A mechanism proposed in Larkin (2014) is collusion between buyers and salespeople: salespeople lower the price of a product at quarter-ends (benefiting consumers) in order to induce buyers to purchase by specific deadlines (benefiting salespeople). While these contract structures may seem inefficient, they may benefit the firm by inducing selection of the desired type of salesperson (Larkin and Leider, 2012). Finally, multiple papers conclude that deadlines induce lower-quality work (Carpenter et al., 2008, 2012; Liebman and Mahoney, 2017; Cohen et al., 2019) by making agents rush to finish on time. We show how deadline-based incentives induce salespeople to distort their recommendations to financially unsophisticated buyers.

This paper also contributes to the literature on how incentives lead to market distortions. Our paper sheds light on how sales incentives create negative externalities for borrowers. The extant literature in this area shows that when loan officers are incentivized to prospect for new loans in addition to their normal tasks of screening and pricing loan applications, they increase loan volume by relying less on soft information, leading to a decrease in loan quality (Heider and Inderst, 2012; Agarwal and Ben-David, 2018). The practice of securitization also reduces the lender's incentive to process customers' soft information, so mortgage officers are more likely to originate lower-quality loans (Keys et al., 2010) and misrepresent the related financial documents (Griffin and Maturana, 2016). Finally, this paper adds to the literature on the risks and incentives arising from convexity in managerial pay (Guay, 1999; Coles et al., 2006; Bettis et al., 2018; Benson, 2015).

2. Overview of the auto financing and sales incentives

2.1. Automobile sales and financing at dealerships

In this section, we highlight aspects of the car buying and financing process at car dealerships in the United States. When a customer walks into a dealership to buy a vehicle, a salesperson advises her on available options that suit her needs. If she is interested in purchasing a vehicle, the customer typically negotiates the purchase price with the salesperson, with final price approval granted by the sales manager. During this negotiation, the salesperson and sales manager consider the profit margin for the specific vehicle, existing inventory levels, individual and dealer sales targets, and the customer's apparent financial capability. They 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.[4]

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

[4]Our measure of dealer profits is at the transaction level at the time of sale and does not represent the lifetime profits from the customer. Dealers are reported to make 50% of their profits from their service departments. If defaults reduce the profitability of a customer seeking service, then our results would, if anything, be biased downwards, since dealerships would try to dilute incentives to steer customers to financially inappropriate vehicles.

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 financing agent can attempt to mark up the interest rate that the lowest-bidding lender offers (the buy rate). At this point, the dealer completes the transaction, originates the loan, and the customer drives off with the vehicle.

Over the next several days, the winning lender verifies customer information such as employment and income. If there are no problems in this screening process, the lender buys the loan from the dealer on the agreed-upon terms. If the verification process flags any problems with the information (e.g., customer's income cannot be verified), the lender renegotiates with the dealer and typically buys the loan at a discount reflecting the higher risk. The dealer may seek recourse directly from the customer, though this rarely happens in practice.

2.2. Dealer and salesperson incentives

Automobile manufacturers generate strong monthly sales cycles at dealerships by offering convex incentives to dealerships, and directly to salespeople. Dealer incentive programs typically involve the manufacturers paying per-unit cash bonuses that are conditional on reaching certain sales targets or thresholds in a given calendar month. For example, if a dealership's January sales target is ten vehicles, they 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 the "stair-step" program that Chrysler offers to dealers (Sohoni et al., 2011).[5]. Under this program, a dealer receives 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%. Although the structure of these contracts varies

[5]Pierce et al. (2020) provides a detailed description of the structure and implications of stair-step incentives in the automotive industry

across manufacturers and can frequently change across time, they nearly all use some type of convex structure.

These convex dealer incentives are subsequently passed on by the dealership to the salesperson to motivate their focus on monthly goals. To understand the salespeople's motivation to push car sales 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, commission, and bonus based on units sold (Fahey, 2003; Wolf, 2016). Dealers may integrate nonlinear incentives into the commission to encourage more aggressive car selling. For example, a common commission plan pays 15% of gross profit, but the commission increases to 20% if the salesperson sells 10 or more cars in a month. The commission again increases if 15 or more cars are sold. Similarly, sales managers may assign each salesperson a monthly sales goal based on their ability and the sales volume necessary to hit the dealership target. Notably, the salesperson may face strong additional incentives when the dealership is near its monthly incentive thresholds. Sales managers commonly pay extra bonuses for the sale of cars necessary to reach the threshold, or may still pay and additional commission to the sales person to compensate for the low and often below-cost price needed to move the last cars in a month. Sales managers will typically support these salesperson incentives with greater pricing discretion, marketing effort, and increased attention and pressure on the sales force.

In addition, some car manufacturers have promotion programs that offer direct incentives to salespeople to sell more new cars. For example, General Motors' Consultant Performance Program pays a salesperson $225 per car, provided that they sell at least eleven Chevrolet vehicles, seven GMCs, or five Buicks in a month (Lareau, 2018). These direct convex incentives, combined with those offered by the dealerships, provide strong motivation for salespeople to sell new vehicles at the end of the month.

In sum, the design of both dealer and salesperson incentives schemes align them to focus on monthly sales levels. The stakes are highest at the end of the month if monthly sales are approaching a threshold. This is especially important in the case of new cars, since manufacturers' incentives do not apply to most used vehicles.

3. Data and descriptive statistics

3.1. Data

Over 65,000 financial institutions, including banks and non-bank lenders, finance auto loans across the U.S. The market is highly competitive, with no single firm holding more than 6% market share (Baines and Courchane, 2014). Our data provider is among the twenty largest auto finance companies. The data provider buys subprime loans from over 4,000 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, while twenty percent only sell used cars.

Our novel dataset includes all loans that the data provider acquired between 1995 and 2017—more than 247,000 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. Moreover, we observe the price at which the loan trades between the dealership and the lender. 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.

3.2. Descriptive statistics

In Table I, we summarize buyer, loan, and vehicle characteristics for all loans in our sample. Variables are winsorized at 1% and 99% levels to avoid extreme values affecting the results.

The borrowers' profiles reflect the fact that the lender operates in the subprime auto lending market. The average buyer in our sample has credit score of 532 and a monthly income of $3,600. By comparison, the average credit score for a national sample of new car buyers is 719; for used car buyers, the average score is 661 (Zabritski, 2019). Borrowers with credit scores below 660 constitute 27% of new car buyers and 49% of used car buyers.

The average interest rate on loans in the sample is 19.3%. The mean opening principal balance is $16,900, with an average term of 67 months. Sixty percent of loans in the sample have a 72-month term. On average, borrowers in our sample spend 11% of their reported monthly income on their car payment. About 7% of auto purchases are new cars. Dealership add-ons are popular among subprime borrowers—43% of customers buy insurance against default.

Our findings about the end of the month (EOM) depend on there being no significant economic differences among customers across different days of the month. Appendix Table A.1 shows that observable attributes across the customer groups are almost identical in terms of borrower risk characteristics.[6] Panel A compares EOM customers with other customers within the sample of new car loans. Panel B compares EOM customers with other customers within the sample of used car loans. If anything, customers at the end of the month are getting better deals on their cars, which might suggest that borrowers face a lower likelihood of default. This is shown in Appendix Figure A.1

After acquiring the loan, the lender alone bears the consequences of default. The dealership's objective is to sell cars at the highest margin conditioned on their ability to sell the loan. The profit the dealership earns from the transaction includes the difference between the vehicle's selling price and its cost, a portion of the APR markup, and any profit from

[6]While some of the differences in Panel B are statistically significant due to the large sample size, the differences are not economically meaningful. For example, there is a statistically significant difference in credit score in Panel B, but this difference amounts to just 1.3 points. This 0.2% difference in credit score is orders of magnitude smaller than the reported error rate on FICO scores (Axelrod, 2013).

add-ons such as service contracts. The lender collects payments from the customer, so its loan-level profit is only fully realized when the loan is paid off or the collections on a defaulted loan have ceased. When bidding, the lender weighs price competition from other lenders against pricing to compensate for the risk of default loss. While there are multiple bidders for each application, all lenders face a cost of capital that is correlated with the risk of default.

4. Results

4.1. Loan originations at the end of month

We examine the trend in the daily number of loans that are originated across days of the month. We calculate the daily average number of loans for thirteen days before, and thirteen days after, the last day of a month. Figure 1 plots this measure against a timeline variable that indicates the number of days relative to the end of the month.[7] The number of loans signed on the last day of the month is 55% higher than the number signed on each of the first five days of the following month. Our data is consistent with the car sales patterns that are generally observed at dealerships: lower at the beginning of the month, higher during the second half, and peaking on the last day. Further, we examine the composition of car sales (new or used) during the month. Figure 2 depicts the percentage of new car sales on the timeline. New car sales increase by 30% as the end of the month approaches.

Surges in transaction volumes as deadlines approach have been documented in previous studies (Tzioumis and Gee, 2013; Cohen et al., 2019). In housing finance, Tzioumis and Gee (2013) provide evidence that mortgage officers greatly increase their output towards the end of each month. Cohen et al. (2019) find that drug approvals by regulators surge at the end of each month and each year, even though the regulators have no explicit quota

[7]The last day of a month has a value of 0, the day before the last day has a value of -1, and the first day of next month has a value of 1.

or financial incentives. The authors hypothesize that workers rush to complete projects because the psychological costs of delay outweigh the benefits (i.e., "desk-clearing behavior"). Such behavior is less relevant in our setting because dealership salespeople are paid for each transaction and can accelerate their commissions by passing monthly sales thresholds, particularly for new-car sales.

4.2. Loan defaults for end of the month purchases

In this section, we compare the default rates of loans that are signed at the end of the month against the default rates of loans signed at other times. Our measure of loan performance, *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. As mentioned in Section 3, we restrict our sample to loans originated before 2017 to ensure that we have an uncensored view of loan status for 24 months after origination. We estimate the effect using the OLS regression:

$$Early\ Default = \beta_0 + \beta_1 Month\ End + \gamma Controls + \epsilon \tag{1}$$

In Equation (1), *Month End* is a dummy that equals 1 if the contract is signed on the last day of a month, and 0 otherwise. We control for time trend across vintage years with year fixed effects. Since loans within a dealership may be autocorrelated (e.g., similar sales practices, customer demographics, and vehicle types), robust standard errors are clustered by dealership.

Table II, column 1 presents the results 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 104 basis points means that the EOM loans' early default rate is 9.7% higher than the mean default rate of 10.7% for non-EOM loans. The relation of end-of-month loans and subsequent default is generally unaffected as we add more controls. β_1 remains consistently positive and significant ($p < 0.01$) across all specifications.

As we introduce buyer attributes (column 2) and loan and vehicle attributes (column 3), the coefficient value is approximately 80 to 90 basis points. Furthermore, the end-of-month effect is not determined by state fixed effects (column 4), dealership fixed effects (column 5), or the relative business of the dealership within a week. Finally, using a sample of dealerships that sell only new and used cars, we find the results are unchanged (column 6). Taken together, these results suggest that our main finding is not driven by unobserved buyer heterogeneity across purchase dates (Oster, 2019). Overall, EOM loans are 7% to 10% ($p < 0.01$) more likely to default than loans issued on other days of the month.[8]

To further unpack the end-of-the-month default puzzle, we explore whether the effect is driven by auto manufacturers' new-car sales incentives, which induce sales efforts at the end of the month. Consistent with this idea, Figure 2 shows that new-car sales increase proportionally as the month's end approaches.

To examine the impact of auto manufacturer's incentives, we construct a binned scatter plot, by first regressing loan defaults on the loan risk characteristics the lender observed at the time of origination. This include loan, borrower, and vehicle characteristics, as well as year fixed effects. We then group the residuals from this regression into bins for each day of the month, and compute the mean of the default rate for each bin to create a scatterplot of these data points. Figure 3 plots the 24-month default rate for each day of the month. The figure shows a stark spike in the default rate for loans signed on the last day of the month for new cars, compared with loans signed on other days.

Next we examine this more formally in a multi-variate regression. We define *New Car* as a dummy that equals 1 if the purchased vehicle is new, and 0 if used. We estimate the

[8]In Appendix Table A.3, 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.

regression of *Early Default* on *Month End*, *New Car*, and their interaction:

$$Early\ Default = \beta_0 + \beta_1 Month\ End + \beta_2 New\ Car + \beta_3 Month\ End \times New\ Car + \gamma Controls + \epsilon \tag{2}$$

We continue to restrict our sample to loans originated at dealerships that sell both new and used cars. Dealerships that only sell used cars are not pertinent to this analysis, but we later examine them as a placebo group.

Table III, column 1 shows that the higher default rate at month's end seems to be mainly driven by new cars. End-of-month new-car sales are 32% (the effect of $\beta_1 + \beta_3$ over the baseline new-car default rate of 10.4%) more likely to default than new-car sales at other times. The coefficient on the interaction term (β_3) is positive and significant across all specifications, and the economic magnitude remains stable when we control for buyer characteristics (column 2 to 6), loan characteristics (column 3 to 6), and vehicle attributes (column 3 to 6). Further, when we include fixed effects for state (column 4), dealership (column 5 and 6), and intra-week sales patterns (column 6), the results remain consistent.

These findings are consistent with our hypothesis that at the end of the month, the car manufacturers' convex incentives for new-car sales influence salespeople's behavior more strongly. In marginal cases, salespeople influence the trade-off that car buyers make between the immediate gratification of new-vehicle purchase and the long-term financial ramifications of this choice. This result differs from Larkin (2014), who finds that salespeople game deadline-based convex incentives by lowering product prices in a way that *benefits* customers. Our results suggest that manufacturers' incentives not only have the expected effect of encouraging more new-car sales but also induce salespeople to match financially unsophisticated car buyers with new cars that they might struggle to afford.

4.3. Two-stage least squares approach

Auto manufacturers have a menu of options with which they can influence consumers' buying behaviors. Whether these options increase the likelihood of loan default among subprime borrowers is ex ante unclear. Using two-stage least squares (2SLS) approach, we investigate this directly by comparing the effects, on loan default rates, of direct cash rebates to new-car buyers and of manufacturers' incentives for dealerships.

We first test whether cash rebates nudge customers toward choosing a new car instead of a comparable used vehicle and, if so, whether the resulting customer-vehicle matching leads to a higher default rate. According to this explanation, dealership salespeople do not play an important role in the customer's choice. To test this hypothesis, we estimate the 2SLS regression of *Early Default* on the customer's new-car/used-car choice (*New Car*), using the size of the cash rebate (*Model Rebate*) of a vehicle model that the manufacturer offers in the month of the transaction to predict *New Car* in the first stage. Here, *New Car* is an indicator that equals 1 if the loan defaults within 24 months of origination, and 0 otherwise. We include controls for buyer attributes and fixed effects for car models, years, and U.S. states. The first- and second-stage equations are:

$$New\ Car = \delta_0 + \delta_1 Model\ Rebate + \lambda Controls + \mu \tag{3}$$

$$Early\ Default = \beta_0 + \beta_1 \widehat{New\ Car} + \gamma Controls + \epsilon \tag{4}$$

Table IV describes these results. In column 1, the first-stage (equation 3) shows that a customer is more likely to choose a new car as the model rebate increases (the coefficient on *Model Rebate* is positive and significant with $p < 0.01$). In column 2, the second-stage regression (equation 4) shows that the coefficient on the predicted *New Car* from the first stage is *not* positive (it is negative and significant at the 10% level). This result indicates that new-car purchases influenced by cash rebates do not lead to a higher default rate. Rather, it suggests that new-car buyers, even in the subprime population, are generally less likely to default.

Next, we test the salespeople's deadline-based incentive channel, which we discussed in previous results. From Figure 2, we know that the percentage of new-car sales increases as the end of the month approaches. If riskier borrowers who prefer new cars are more likely to purchase them at the end of the month, the exclusion restriction would be violated. We show in Appendix Table A.1 that there are no economically significant observable differences among buyers across different days of the month. Moreover, the manufacturer's cash rebates do not vary from day to day. The natural interpretation of the increase in new-car sales as a percentage of total sales (as shown in Figure 2) is that salespeople exert more effort to persuade customers to buy new cars as the end of the month approaches. The number of days until the month's end can be used as a proxy both for the salespeople's effort to sell new cars and for their incentives to do so.

We estimate the 2SLS regression of *Early Default* on *New Car Percentage* (the daily percentage of new car sales) by first predicting *New-Car-Percentage* with *Days to Month End* (the number of days until the month's end) in the first stage. The first- and second-stage equations have the form:

$$New\ Car\ Percentage = \delta_0 + \delta_1 Days\ to\ Month\ End + \lambda Controls + \mu \tag{5}$$

$$Early\ Default = \beta_0 + \beta_1 New\ \widehat{Car\ Percentage} + \gamma Controls + \epsilon \tag{6}$$

The results in Table V, column 1 show the first stage regression (equation 5) of *New Car Percentage* on *Days to Month End*. The coefficient of *Days to Month End* is negative and significant ($p < 0.01$), confirming the correlation between new-car sales and the end of the month—the composition cars sold that are new increases as the end of the month approaches. Column 2 describes the second-stage results (equation 6). The positive and significant coefficient on *New Car Percentage* indicates that defaults are more likely for new-car sales that are influenced by salespeople's end-of-month sales incentives. A 10% increase in the percentage of new cars sold leads to a 3% increase in the early default rate.[9]

In a falsification test, we regress *Early Default* on *Days to Month End* for the sample of dealerships that sell only used cars. These dealerships do not qualify for automotive manufacturers' incentives (since they only sell used cars) and typically employ piece-rate incentives to motivate salespeople. If defaults are higher at the end of month in the sample of used-car dealerships, then the manufacturers' incentives are likely correlated with an unobserved factor that is also related to defaults (i.e., an endogeneity concern with the 2SLS model). In Table V, column 3, the coefficient on *Days to Month End* is not significant, indicating that loans originated at used-car dealerships are *not* more likely to default as the month's end approaches. This contrasting finding promotes our interpretation that automobile manufacturers' incentives influence subprime loan outcomes.

In summary, the findings in this section support the hypothesis that convex incentives at car dealerships—manufacturers' incentives in particular—are the mechanism underlying the higher default rate associated with loans at the end of the month.

4.4. Loan performance of financially constrained borrowers who buy new cars at the end of month

In this section, we examine whether the customers who default on new-car purchases at month's end are more financially constrained, relative to other month-end buyers. If vehicle-customer mismatches are prevalent in month-end new-car sales, then financially constrained customers should be impacted the most, and the default rates will be higher for these customers. We measure the level of financial constraint by the ratio of monthly car payment

[9]In unreported results, we use the square of the number of days until the month's end in the first stage, because the new-car portion of daily sold cars rises at an increasing rate as the end of the month approaches. The second-stage result from this test is quantitatively similar to our main specification.

to income (*PTI*) and the ratio of total monthly debt payment to income (*DTI*). Borrowers with high *PTI* (or *DTI*) use a larger portion of their monthly income to repay their loan debt.

We estimate Equation (2) separately for 1) transactions in which customers are in the top quartile of *PTI*, and 2) transactions in which customers are in the bottom quartile of *PTI*. We use several specifications, which have different combinations of controls and fixed effects. The results are reported in Table VI. Columns 1–4 present results for customers in the top quartile of *PTI*, and columns 5–8 present results for customers in the bottom quartile of *PTI*.

For customers in the top quartile of *PTI*, the coefficient on the interaction term of *Month End* and *New Car* (β_3) is positive and significant ($p < 0.05$) across all four specifications. Within the top PTI quartile customer group, new-car loans at month's end are 44% more likely to default (column 1) than new-car loans signed at other times (a 6 percentage points increase from the mean default rate of 13.6% on new-car loans signed at other times). This result is unaffected as we introduce buyer attributes (column 2) and loan and vehicle attributes (column 3), and dealership fixed effects (column 4). At the same time, the results in columns 5 to 8, β_3 show the interaction is economically and statistically insignificant, indicating that new-car buyers who purchase cars at the end of the month do not default at a higher rate if they are less financially stretched (i.e., if they are in the bottom quartile of *PTI*).

We repeat the tests using samples of top and bottom *DTI* quartiles and report the results in Table VII. The results are similar to those in Table VI—new car buyers in the top *DTI* quartiles (i.e., those that are most financially constrained) are more likely to default if they purchased their cars at month's end, while bottom *DTI* quartile customers do not experience higher default rates. Overall, these results are consistent with the mismatching hypothesis. In particular, when salespeople persuade customers to purchase new cars at the end of the month, financially constrained customers are the most likely to default.

4.5. Characteristics of vehicles sold at the end of month

To further understand how the mismatch between customer and vehicle (in terms of the choice of new or used cars) leads to higher default rates, we examine the features of vehicles sold at month's end. One vehicle attribute that is relevant to loan defaults is the reliability of the vehicle. If a car breaks down frequently and becomes a liability, the borrower may need to replace the vehicle. Importantly, borrowers are responsible for the repayment of the loan even if the car breaks down, is damaged, or is repossessed (i.e., the loans are full recourse), so they must contend with outstanding debt on the vehicle even if a replacement vehicle is purchased. Using vehicle reliability scores (*Reliability* spans 0 to 100) from Consumer Reports (Consumer Reports, 2017), we regress *Reliability* on *Month End*, *New Car*, and their interaction term.

The results are reported in Table VIII. The coefficient on *New Car* is positive and significant ($p < 0.01$), suggesting that customers who buy new cars on days *not* at the end of the month select vehicles with *higher* reliability ratings. The significantly negative coefficient of the interaction term on *Month End* x *New Car* indicates that customers who buy new cars at month's end are more likely to select less reliable vehicles. This finding suggests that buyers sometimes choose between a new car and a more reliable model that is used.

Next, we examine whether customers are more likely to buy guaranteed asset protection insurance (GAP), which covers the difference between what a vehicle is worth and the amount owed if default occurs. The absence of insurance coverage seems more consequential when one considers the rapid depreciation on new vehicles, which can put borrowers underwater early in the loan term. A buyer who has been persuaded to purchase a new car may not realize that new cars typically depreciate 25% to 35% in the first year after the sale (BlackBook, 2019). In contrast, two- to six-year-old vehicles typically depreciate in the 8% to 15% range annually. We use the variable *GAP Dummy* to indicate if a loan includes GAP insurance. We conduct a test econometrically similar to that of *Reliability* and report the results in

Table IX. The coefficient on the interaction term of *Month End* and *New Car* 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.

Taken together, these results suggest that when subprime borrowers purchase new cars at the end of the month, they are making economic trade-offs that have longer term consequences. More specifically, these trade-offs increase their likelihood of default through more rapid vehicle depreciation, reducing insurance coverage against mechanical failure, and, at the same time, exposing buyers to vehicles with more mechanical problems. These findings are consistent with these same subprime borrowers being myopic in considering the higher likelihood of a loan default when influenced to purchase a new car.

4.6. Individual-loan profits of dealers and the lender

We have provided evidence that salespeople respond to convex incentives by persuading customers to buy new cars at month's end, and that, in doing so, they create customer-vehicle mismatches that ultimately lead to defaults. Now we investigate whether the dealerships and lenders suffer financially from this distortion, or if borrowers bear the full weight of these frictions. Using loan-level data on dealer and lender profits, we estimate the effect of month-end new-car sales on the dealers' and lenders respective profit margins.

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.

We calculate loan-level profitability for the dealer as the sum of (1) the amount received from the lender; (2) the down payment from the customer (this can be a negative amount if the customer has negative equity in an existing vehicle); and (3) commissions from selling add-ons such as insurance and service contracts, less the acquisition cost of the vehicle (i.e., the book value of the vehicle).[10] The dealer's loan-level profit margin is equal to the profit divided by the book value of the vehicle.

We estimate the regressions of profit margins on *Month End*, *New Car*, and their interaction term, controlling for borrower, loan, and vehicle characteristics, as well as fixed effects described in earlier specifications. Table X reports the results for the dealers' profit margin. The coefficient on the interaction term is insignificant across all specifications. This result suggests that dealerships do not experience a negative impact on their transaction-level profit margin when they sell more new cars at month's end, and might actually benefit from it. More generally, month-end incentives for sales representatives do appear to reduce transaction-level profitability. Although dealerships make less money at the end of the month at the transaction level, this loss is not attributable to the customer-vehicle mismatches. The finding in our context is thus markedly different from Larkin (2014), who finds that salespeople exploit the high-powered incentives and cause revenue losses to the firm.

Table XI reports the results for the lender's profit margin on completed loans. The coefficient on *Month End* is not significant, indicating that higher month-end new-car sales do not affect the lender's profit margin. The coefficient on the interaction term is also not significant. Like the dealerships, the lender is not hurt by the higher realized default rates on month-end new-car sales. As mentioned in Section 2, the lender bids for loans in a highly competitive market. The lender appears to price the risks associated with deadline-based convex incentives and the resultant mismatching that occurs at month's end.

4.7. Robustness checks

In this section, we perform several robustness checks to alleviate concerns about the choice of measurement of default. First, we estimate Equations (1) and (2) using default rates of different time horizons (i.e., defaults that occur within 18 or 30 months of origination). In

[10]This profitability measure does not include manufacturers' rebates that dealerships might receive as they are not observable.

these tests, we include controls and fixed effects identical to what was previously described. We report the result in Appendix Table A.3. In Panel A, the coefficient on *Month End* is positive and significant across the 18- and 30-month time horizons. In Panel B, the coefficient on the interaction term of *Month End* and *New Car* is also significant across all time horizons. These findings are consistent with our main finding (in Table III) that higher default rates are attributable to month-end new-car sales.

Next, we use a modified definition of *Month End* in the tests. Many states ban car sales on Sunday (Lareau, 2015), and many dealerships close on certain holidays. We modify our month-end measure as follows: *Adj. Month End* is equal to 1 if the loan is originated on the last day of a month or on a Saturday immediately before the last day. Similar adjustments are made to accommodate holidays that fall on the month's end. We estimate Equations (1) and (2) with *Adj. Month End* and report the results in Appendix Table A.4. Panel A shows the adjusted month-end results, and Panel B shows the results with the interaction between *Adj. Month End* and *New Car*. Consistent with the results in Tables II and III, the coefficient on *Adj. Month End* in Panel A is positive and significant, as is the coefficient on the interaction term in Panel B.

Finally, we address the concern that customer heterogeneity across the month is correlated with the loan default rate. Suppose that a segment of customers purposely shop at the end of the month because they anticipate better deals. This group of customers may differ from other customers (for example, they may be more financially constrained) in ways that result in the higher default rate for month-end loans. We control for these observable differences directly in our specifications. However, unobservable heterogeneity may still be present, and this heterogeneity could confound our specifications. At the same time, if there is little observable heterogeneity across customers, it would appear more likely than on observable dimensions these customers are also similar (Oster, 2019). We investigate this here.

Using loan application data for a four-year sample period, we depict the average number of loans per day relative to the last day of a month in Appendix Figure A.2.[11] The visualization shows that the number of applications received is 5% higher in the last week of a month than in the preceding week. We compare customer characteristics (i.e., income, vehicle payment to income ratio, credit score, and home-ownership status) for applications on the last day of the month with other days in Appendix Table A.2. Comparing the two groups side by side, 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.1 and helps to address the concern that customer heterogeneity that is correlated with month-end defaults drives our results. There is no observable evidence that this is the case.

5. Conclusion

Although much ink has been devoted to the agency conflicts that arise in lending, the connection between financial services and physical product sales remains underexplored in certain industries. The importance of financing to the profitability of the automotive industry raises important questions about how sales incentives spill over into automotive loan origination and the outcomes of those loans.

Our study examines how deadline-based convex incentives relate to the outcomes of subprime auto loans. We find that auto dealers push borrowers into new cars at the end of the month. At month's end, new-car buyers are markedly more likely to purchase less reliable vehicles and are less likely to buy insurance products that protect them against default (should the vehicle become damaged). These results are particularly important for the most financially constrained car buyers.

[11] The four-year sample includes 1.77 million loan applications, 3.5% of which were received by the lender on the last day of the month. The limited time span of the application data is problematic for studying long-term loan outcomes. Consequently, the use of this data is limited to the comparison of customer characteristics across days of the month.

In fact, customers are buying not just a car but a bundle that includes financing. Financially unsophisticated customers may be able to weigh some of the trade-offs of new versus used vehicles, but they may not fully comprehend the financial implications of the loan contracts or the associated risks. We interpret these results as evidence that automotive manufacturers' incentives to dealerships encourage salespeople to match financially unsophisticated car buyers with loan contracts that are more likely to end in default. We find little evidence to suggest that lenders or dealers are harmed by these incentives.

Additional research on how manufacturer's incentives create negative externalities for borrowers in the \$1.3 trillion auto loan market is merited. Our data does not offer the opportunity to address the welfare implications of buying a new car at month's end. Are customers truly worse off with the increased default risk, or are these risks outweighed by the joys of owning a new car? Also, our finding that borrowers appear similar on ex ante observable dimensions, and differ greatly on ex post loan performance raises important questions about the validity of the application information submitted by dealerships.

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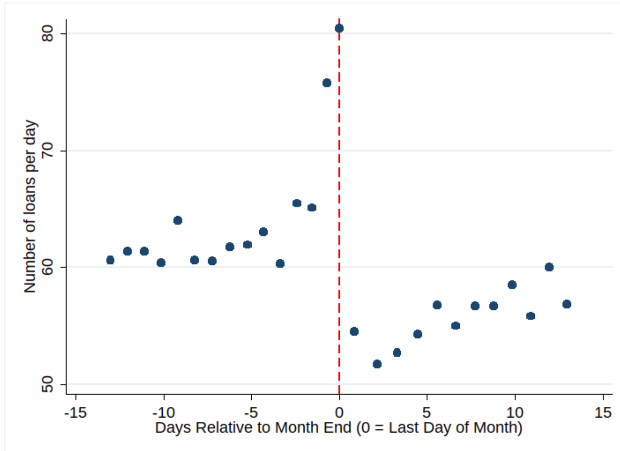

Figure 1. Number of loans per day of the month. This figure is a binned scatter plot of the number of loans that are signed on the same day each month versus a variable that indicates the number of days relative to the end of the month. The vertical dashed line represents the last day of month.

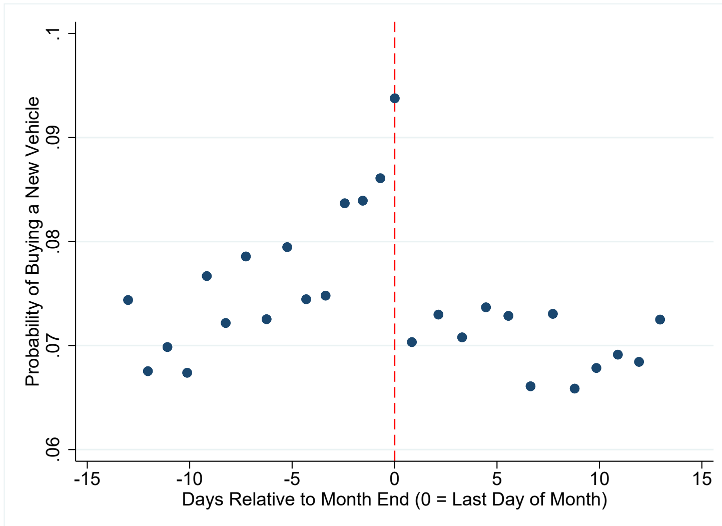

Figure 2. The composition of new versus used car sales. This figure is a binned scatter plot of *New Car* (an indicator that equals 1 if the vehicle is new) of deals that are signed on the same day each month versus a variable that indicates the number of days relative to the end of the month. The vertical dashed line represents the last day of month. 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 dummies), and generated the residuals from those regressions. We then grouped the residualized x-variable into 27 equal-sized bins, computed the mean of the x-variable and y-variable residuals within each bin, and created a scatterplot of these data points.

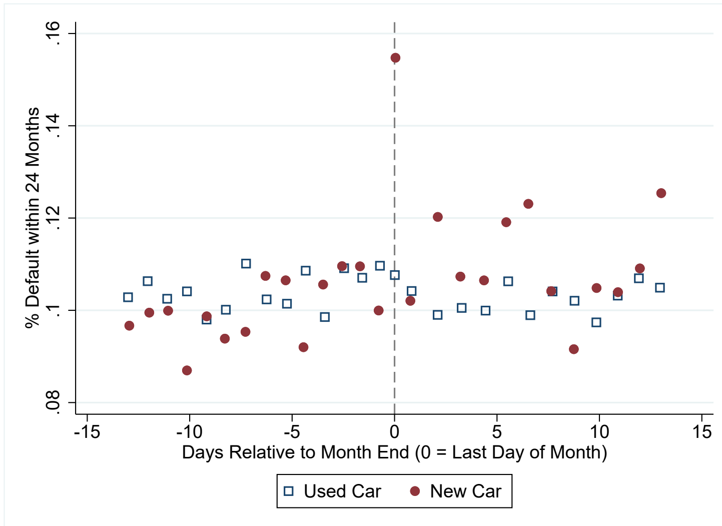

Figure 3. Default rate by day of the month for new and used cars. This figure is a binned scatter plot of the early default rate (default within 24 months) of loans that are signed on the same day each month versus a variable that indicates the number of days relative to the end of the month. Blue squares (red circles) represent used (new) car sales. The vertical dashed line represents the last day of 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 dummies), and generated the residuals from those regressions. We then grouped the residualized x-variable into 27 equal-sized bins, computed the mean of the x-variable and y-variable residuals within each bin, and created a scatterplot of these data points.

Table I. Summary statistics. This table reports summary statistics for loans originated from 1995 to 2017. The number of observations, mean, median, and standard deviations are reported for buyer characteristics, loan characteristics, vehicle characteristics, and loan outcomes.

	N	Mean	Median	SD
Buyer Characteristics				
Credit Score	247706	531.8	531	50.1
Homeownership Indicator	247706	0.067	0	0.25
Monthly Income	247706	3597.8	3511.9	2178.4
Prior Ch.7 Bankruptcy Indicator	247706	0.28	0	0.45
Loan Characteristics				
APR	247706	19.3	19.5	2.91
Loan-to-Value	247701	1.28	1.28	0.18
Loan Amount	247706	16872.5	16796.6	4667.9
Discount	247706	610.0	548	367.4
Term (months)	247706	67.2	72	7.43
Down Payment	247441	1070.0	1000	1155.6
Vehicle Payment/Income	209840	0.11	0.11	0.035
Debt Payments/Income	209802	0.39	0.39	0.078
Price-to-Value	247436	1.35	1.35	0.18
Vehicle Characteristics				
New Car Indicator	247706	0.074	0	0.26
Luxury Indicator	247706	0.028	0	0.16
Mileage	245468	37983.0	37101	21549.6
Reliability Rating	247706	46.2	45	21.1
Book Value	247701	13414.6	12975	4144.7
GAP Indicator	243595	0.43	0	0.49
Service Contract Indicator	247706	0.44	0	0.50
Loan Outcomes				
Dealer Profit Margin	243434	0.36	0.34	0.21
Lender Profit Margin	209168	0.35	0.39	0.31
Early Default Indicator	247706	0.11	0	0.31

Table II. Car sales on the last day of the month and loan default. 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 6 is restricted to a sample of loans originated in dealerships that sell both new *and* 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, and t-statistics are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Var: Early Default	(1)	(2)	(3)	(4)	(5)	(6)
Month End	0.010***	0.0080***	0.0090***	0.0082***	0.0074***	0.0082***
	(3.51)	(2.74)	(3.09)	(2.86)	(2.59)	(2.59)
Ln(Credit Score)		-0.38***	-0.25***	-0.24***	-0.24***	-0.23***
		(-36.32)	(-22.22)	(-21.50)	(-21.11)	(-18.32)
Homeownership Indicator		-0.011***	0.0040	0.0016	0.0029	0.0023
		(-3.91)	(1.39)	(0.54)	(1.04)	(0.77)
Ln(Income)		-0.015***	-0.016***	-0.015***	-0.015***	-0.013***
		(-8.24)	(-8.01)	(-8.04)	(-7.76)	(-6.92)
Prior Ch.7 Bankruptcy Indicator		-0.059***	-0.056***	-0.051***	-0.047***	-0.046***
		(-26.20)	(-24.37)	(-24.43)	(-25.38)	(-22.35)
APR			0.011***	0.011***	0.011***	0.010***
			(24.93)	(25.01)	(26.76)	(23.35)
Loan-to-Value			0.15***	0.14***	0.13***	0.13***
			(21.62)	(22.99)	(20.07)	(17.39)
Ln(Amount Financed)			0.059***	0.055***	0.052***	0.049***
			(13.60)	(13.11)	(12.99)	(11.78)
Ln(Discount)			0.0081***	0.0063***	0.0064***	0.0062***
			(4.41)	(3.62)	(4.89)	(4.31)
Ln(Terms)			-0.061***	-0.060***	-0.060***	-0.059***
			(-7.59)	(-7.44)	(-7.27)	(-6.72)
Ln(Down Payment)			-0.0021***	-0.0018***	-0.0027***	-0.0025***
			(-6.83)	(-6.28)	(-9.08)	(-7.71)
Luxury Indicator			0.010***	0.0092**	0.0052	0.0056
			(2.89)	(2.51)	(1.23)	(1.11)
Ln(Mileage)			0.00026	0.000097	0.000076	-0.000055
			(0.40)	(0.15)	(0.12)	(-0.08)
Ln(Reliability Rating)			-0.017***	-0.018***	-0.013***	-0.016***
			(-4.17)	(-5.48)	(-3.77)	(-4.05)
Reliability Rating Indicator			0.061***	0.066***	0.049***	0.060***
			(3.80)	(4.99)	(3.59)	(3.87)
New Car Indicator			0.025***	0.022***	0.021***	0.019***
			(4.87)	(4.51)	(4.39)	(3.96)
GAP Indicator			-0.020***	-0.017***	-0.010***	-0.0099***
			(-8.88)	(-7.36)	(-5.10)	(-4.22)
Service Contract Indicator			-0.016***	-0.016***	-0.015***	-0.014***
			(-6.65)	(-6.55)	(-7.60)	(-6.48)
Year FE	YES	YES	YES	YES	YES	YES
State FE	NO	NO	NO	YES	NO	NO
Dealer FE	NO	NO	NO	NO	YES	YES
Day of week FE	NO	NO	NO	NO	YES	YES
N	247706	247706	241188	241188	240741	192342
Adj-R2	0.0081	0.022	0.035	0.038	0.043	0.043

Table III. New car sales on the last day of the month and loan default. 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 sample is restricted to loans originated in dealerships that sell both new *and* 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 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 Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Dep Var:	Early Default					
	(1)	(2)	(3)	(4)	(5)	(6)
Month End	0.0081**	0.0056	0.0066*	0.0058*	0.0054	0.0049
	(2.33)	(1.63)	(1.93)	(1.72)	(1.59)	(1.46)
New Car	-0.0043	-0.0021	0.022***	0.018***	0.017***	0.017***
	(-0.98)	(-0.53)	(4.11)	(3.71)	(3.56)	(3.55)
Month End x New Car	0.026**	0.028***	0.028***	0.028***	0.029***	0.029***
	(2.51)	(2.74)	(2.71)	(2.74)	(2.78)	(2.81)
Controls:						
Buyer Characteristics	NO	YES	YES	YES	YES	YES
Loan Characteristics	NO	NO	YES	YES	YES	YES
Vehicle Characteristics	NO	NO	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State FE	NO	NO	NO	YES	NO	NO
Dealer FE	NO	NO	NO	NO	YES	YES
Day of week FE	NO	NO	NO	NO	NO	YES
N	197983	197983	192342	192342	192342	192342
Adj-R2	0.0095	0.023	0.036	0.038	0.043	0.043

Table IV. Manufacturer's cash rebates for new cars and loan default. This table reports estimates from the instrumental variables (IV) regression of early default on whether the vehicle underlying the loan is new or used. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. *Early Default* is an indicator that equals 1 if a loan defaults within 24 months of origination, and 0 otherwise. Column 1 reports the first-stage regression of *New Car* on the manufacturer's rebate (*Model Rebate*) of the car model in a year-month. Column 2 reports the second-stage regression of *Early Default* on *New Car.* Robust standard errors are clustered by model, and t-statistics are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Var:	New Car	Early Default
	(1)	(2)
Model Rebate	0.000031***	
	(6.47)	
New Car		-0.066*
		(-1.69)
Ln(Credit Score)	0.098***	-0.35***
	(6.90)	(-34.48)
Homeownership Indicator	0.017***	-0.011***
	(5.66)	(-3.98)
Ln(Income)	0.026***	-0.0095***
	(8.02)	(-6.55)
Prior Ch.7 Bankruptcy Indicator	-0.017***	-0.052***
	(-6.47)	(-27.65)
Model FE	YES	YES
Year FE	YES	YES
State FE	YES	YES
N	197910	197910
Adj-R2	0.17	0.0090

Table V. Dealership incentives and loan default. This table reports estimates from the instrumental variables (IV) regression of early default on the percentage of new cars in all sold cars each day. The sample in columns 1 and 2 is restricted to loans originated in dealerships that sell both new *and* used vehicles. The sample in column 3 is restricted to 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. *New Car Percentage* is the proportion of all cars sold daily that are new. *Days to Month End* is the number of days from the date of sales contract until the last day of month. Column 1 reports the first-stage regression of *New Car Percentage* on *Days to Month End*. Column 2 reports the second-stage regression of *Early Default* on *New Car Percentage*. Robust standard errors are clustered by dealership and *Days to Month End*. t-statistics are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Var:	New Car Percentage	Early Default	
	(1)	(2)	(3)
Days to Month End	-0.00049***		0.00012
	(-4.10)		(0.68)
New Car Percentage		0.33**	
		(2.12)	
Ln(Credit Score)	0.000034	-0.35***	-0.40***
	(0.36)	(-29.39)	(-16.89)
Homeownership Indicator	0.000030	-0.011***	-0.0040
	(1.01)	(-3.81)	(-0.44)
Ln(Income)	-0.000013	-0.012***	-0.031***
	(-0.77)	(-7.19)	(-6.75)
Prior Ch.7 Bankruptcy Indicator	-0.000021	-0.047***	-0.054***
	(-0.71)	(-21.36)	(-14.79)
Year FE	YES	YES	YES
Dealer FE	YES	YES	YES
N	197983	197983	49229
Adj-R2	0.47	0.011	0.027

Table VI. Loan default on new cars at month-end, customers in the top quartile of PTI versus the bottom quartile. 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 sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. 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 Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Dep Var:	Early Default							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	PTI top quartile				PTI bottom quartile			
Month End	0.0049	0.0022	0.0042	0.0016	0.011	0.0090	0.0089	0.0085
	(0.59)	(0.27)	(0.52)	(0.19)	(1.58)	(1.34)	(1.27)	(1.20)
New Car	0.0014	-0.0019	0.047***	0.040***	0.000024	0.012**	0.0038	0.0051
	(0.22)	(-0.34)	(3.65)	(3.16)	(0.00)	(2.15)	(0.36)	(0.48)
Month End x New Car	0.055**	0.056**	0.054**	0.055**	-0.0033	-0.0021	0.0014	0.0041
	(2.31)	(2.36)	(2.30)	(2.28)	(-0.16)	(-0.10)	(0.07)	(0.18)
Controls:								
Buyer Characteristics	NO	YES	YES	YES	NO	YES	YES	YES
Loan Characteristics	NO	NO	YES	YES	NO	NO	YES	YES
Vehicle Characteristics	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Dealer FE	NO	NO	NO	YES	NO	NO	NO	YES
N	42051	42051	40949	40752	40280	40280	39340	39168
Adj-R2	0.0047	0.017	0.027	0.033	0.0050	0.025	0.037	0.041

Table VII. Loan default on new cars at month-end, customers in the top quartile of DTI versus the bottom quartile. 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. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. The samples in columns 1-4 include customers in the top quartile of *DTI* (the ratio of monthly debt payment to income). The samples in columns 5-8 include customers in the bottom quartile of *DTI*. *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 Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Dep Var:	Early Default							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	DTI top quartile				DTI bottom quartile			
Month End	-0.0027	-0.0061	-0.0042	-0.0069	0.011	0.0086	0.0080	0.0051
	(-0.38)	(-0.85)	(-0.57)	(-0.94)	(1.50)	(1.16)	(1.08)	(0.68)
New Car	0.0041	0.0071	0.020	0.015	0.0059	0.014**	0.032***	0.032***
	(0.61)	(1.15)	(1.37)	(1.00)	(0.92)	(2.28)	(3.37)	(3.34)
Month End x New Car	0.046*	0.049*	0.050*	0.054**	0.016	0.016	0.019	0.025
	(1.80)	(1.92)	(1.96)	(2.12)	(0.77)	(0.80)	(0.90)	(1.16)
Controls:								
Buyer Characteristics	NO	YES	YES	YES	NO	YES	YES	YES
Loan Characteristics	NO	NO	YES	YES	NO	NO	YES	YES
Vehicle Characteristics	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Dealer FE	NO	NO	NO	YES	NO	NO	NO	YES
N	40771	40771	39597	39407	40528	40528	39718	39538
Adj-R2	0.0050	0.019	0.031	0.042	0.0069	0.021	0.033	0.042

Table VIII. Vehicle reliability rating on different days of the month. This table reports estimates from regressions of the vehicle reliability rating on whether the loan is signed on the last day of the month and whether the vehicle is new or used. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *Reliability* is the reliability rating of the make of the vehicle. *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 Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Dep Var:	Vehicle Reliability			
	(1)	(2)	(3)	(4)
Month End	-0.090	0.13	0.055	0.21
	(-0.48)	(0.70)	(0.32)	(1.29)
New Car	4.40***	7.44***	7.39***	6.27***
	(5.24)	(8.14)	(8.60)	(7.92)
Month End x New Car	-1.24**	-1.46***	-1.50***	-1.00***
	(-2.33)	(-2.88)	(-2.99)	(-2.64)
Controls:				
Buyer Characteristics	NO	YES	YES	YES
Loan Characteristics	NO	YES	YES	YES
Vehicle Characteristics	NO	YES	YES	YES
Year FE	YES	YES	YES	YES
State FE	NO	NO	YES	NO
Dealer FE	NO	NO	NO	YES
N	177192	175379	175379	175362
Adj-R2	0.055	0.11	0.13	0.30

Table IX. GAP insurance on different days of the month. This table reports estimates from regressions of the GAP insurance Indicator on whether the loan is signed on the last day of the month and whether the vehicle is new or used. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *GAP Indicator* is an indicator that equals 1 if the buyer purchases GAP insurance for the vehicle, 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 Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Dep Var:	GAP Indicator			
	(1)	(2)	(3)	(4)
Month End	-0.016***	-0.0024	0.0015	-0.0026
	(-2.71)	(-0.46)	(0.30)	(-0.58)
New Car	0.017	0.031**	0.025**	-0.0032
	(1.10)	(1.98)	(1.99)	(-0.33)
Month End x New Car	-0.044**	-0.044***	-0.047***	-0.043***
	(-2.50)	(-2.73)	(-2.92)	(-2.70)
Controls:				
Buyer Characteristics	NO	YES	YES	YES
Loan Characteristics	NO	YES	YES	YES
Vehicle Characteristics	NO	YES	YES	YES
Year FE	YES	YES	YES	YES
State FE	NO	NO	YES	NO
Dealer FE	NO	NO	NO	YES
N	194533	192342	192342	192342
Adj-R2	0.086	0.23	0.25	0.33

Table X. Dealer profitability of loans signed on the last day of the month. This table reports estimates from regressions of dealer profit margin on whether the loan is signed on the last day of the month and whether the vehicle is new. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *Dealer Profit Margin* is the profit margin that a dealer receives from each transaction. *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 Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Dep Var:	Dealer Profit Margin			
	(1)	(2)	(3)	(4)
Month End	-0.018***	-0.0034***	-0.0036***	-0.0043***
	(-6.81)	(-3.23)	(-3.36)	(-4.27)
New Car	-0.20***	-0.016***	-0.017***	-0.016***
	(-26.90)	(-5.00)	(-5.96)	(-5.81)
Month End x New Car	-0.0044	-0.0017	-0.0015	-0.0023
	(-0.74)	(-0.47)	(-0.42)	(-0.62)
Controls:				
Buyer Characteristics	NO	YES	YES	YES
Loan Characteristics	NO	YES	YES	YES
Vehicle Characteristics	NO	YES	YES	YES
Year FE	YES	YES	YES	YES
State FE	NO	NO	YES	NO
Dealer FE	NO	NO	NO	YES
N	194379	192337	192337	192337
Adj-R2	0.099	0.82	0.83	0.83

Table XI. Lender profitability of loans signed on the last day of the month. This table reports estimates from regressions of lender profit margin on whether the loan is signed on the last day of the month and whether the vehicle is new. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *Lender Profit Margin* is the ratio of the net money collected to the initial investment. *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 Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Dep Var:	Lender Profit Margin			
	(1)	(2)	(3)	(4)
Month End	0.0010	0.0012	0.0021	0.0018
	(0.25)	(0.31)	(0.54)	(0.47)
New Car	-0.026***	-0.025***	-0.020***	-0.019***
	(-5.65)	(-4.21)	(-3.56)	(-3.46)
Month End x New Car	-0.014	-0.010	-0.010	-0.014
	(-1.08)	(-0.80)	(-0.79)	(-1.11)
Controls:				
Buyer Characteristics	NO	YES	YES	YES
Loan Characteristics	NO	YES	YES	YES
Vehicle Characteristics	NO	YES	YES	YES
Year FE	YES	YES	YES	YES
State FE	NO	NO	YES	NO
Dealer FE	NO	NO	NO	YES
N	146270	143481	143481	143441
Adj-R2	0.12	0.14	0.15	0.15

Appendix A.

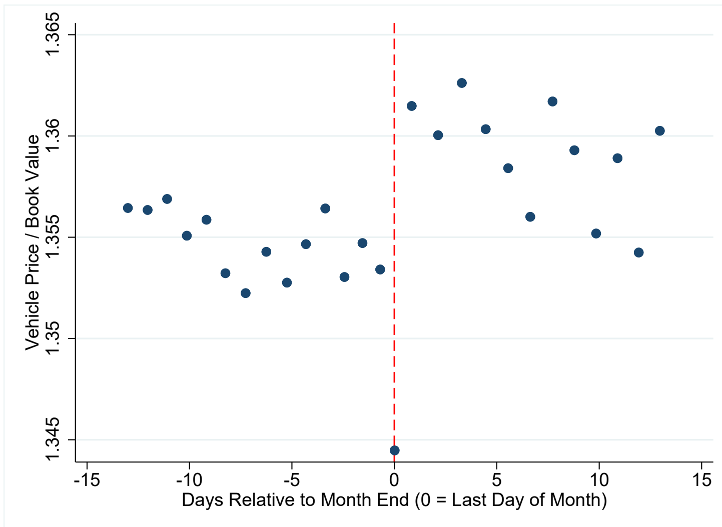

Figure A.1. Vehicle price-to-value ratio by day of the month. This figure is a binned scatter plot of the vehicle price to book value ratio of loans that are signed on the same day each month versus a variable that indicates the number of days relative to the end of the month. To construct the binned scatter plot, we first regressed y- and x-axis variables on a set of control variables (loan characteristics, borrower characteristics, vehicle characteristics, and year dummies), and generated the residuals from those regressions. We then grouped the residualized x-variable into 27 equal-sized bins, computed the mean of the x-variable and y-variable residuals within each bin, and created a scatterplot of these data points.

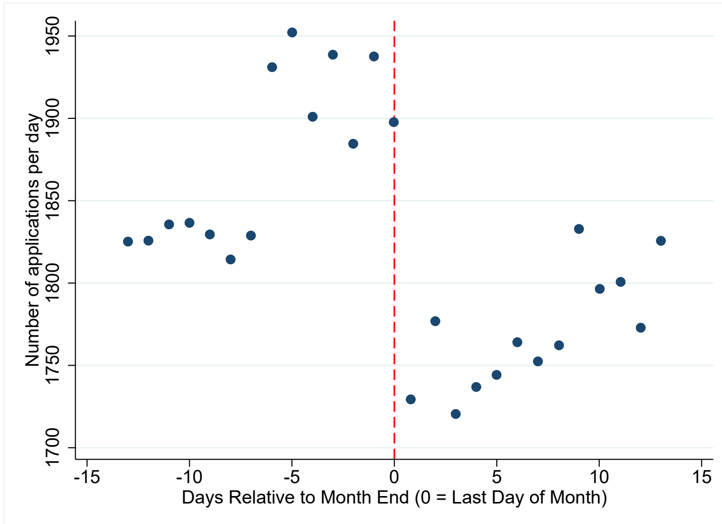

Figure A.2. Average number of applications per day. This figure is a binned scatter plot of the average number of applications that the lender receives each day versus a variable that indicates the number of days relative to the end of the month. The vertical dotted line represents the last day of the month.

Table A.1. Customer profiles. 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.

Panel A: New-vehicle sample

	Non-EOM Customer			EOM Customers				
	N	Mean	SD	N	Mean	SD	Difference	p-value
Monthly Income	17123	4275.2	2191.2	1127	4227.7	2113.2	-47.5	0.48
Vehicle Payment/Income	15532	0.11	0.036	1030	0.11	0.035	0.0016	0.18
Debt Payments/Income	15529	0.38	0.079	1030	0.38	0.078	0.0026	0.31
Credit Score	17123	540.4	50.5	1127	541.8	49.2	1.48	0.34
Ch.11 Bankruptcy	17123	0.25	0.43	1127	0.25	0.43	-0.0046	0.73
Ch.7 Bankruptcy	17123	0.17	0.38	1127	0.15	0.36	-0.018	0.11
Homeownership Indicator	17123	0.087	0.28	1127	0.089	0.28	0.0018	0.84

Panel B: Used-vehicle sample

	Non-EOM Customers			EOM Customers				
	N	Mean	SD	N	Mean	SD	Difference	p-value
Monthly Income	218219	3541.4	2168.3	11237	3596.7	2178.8	55.3***	0.01
Vehicle Payment/Income	183734	0.11	0.035	9544	0.10	0.036	-0.00029	0.43
Debt Payments/Income	183701	0.39	0.078	9542	0.39	0.077	0.0034***	0.00
Credit Score	218219	531.2	50.0	11237	529.9	49.1	-1.30***	0.01
Ch.11 Bankruptcy	218219	0.36	0.48	11237	0.36	0.48	-0.0026	0.58
Ch.7 Bankruptcy	218219	0.29	0.45	11237	0.26	0.44	-0.026***	0.00
Homeownership	218219	0.066	0.25	11237	0.068	0.25	0.0020	0.41

Table A.2. Application profiles. 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 to 2019. The number of observations, mean, and standard deviations are reported.

	Non-EOM applications		EOM applications			
	Mean	S.D	Mean	S.D	Difference	p-value
Monthly Income	3473.5	1586.0	3468.3	1584.1	-5.20	0.42
Vehicle Payment/Income	0.345	0.125	0.345	0.125	0.00	0.10
Credit Score	533.7	52.34	532.7	52.23	-1.00***	0.00
Homeownership	0.0704	0.256	0.0693	0.254	-0.00	0.29
Observations	1,708,227		62,162			

Table A.3. Car sales on the last day of the month and different default horizons. This table reports estimates from regressions of default rate measures on whether the loan is signed on the last day of the month. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. The dependent variables in columns 1–3 are indicators that equal one if a loan defaults within 18 months, 24 months, and 30 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. Buyer Characteristics include Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Panel A: *Effect of Month End*

Dep Var:	18M	24M	30M
	(1)	(2)	(3)
Month End	0.0057**	0.0079***	0.0058*
	(2.49)	(2.75)	(1.80)
Controls:			
Buyer Characteristics	YES	YES	YES
Loan Characteristics	YES	YES	YES
Vehicle Characteristics	YES	YES	YES
Year FE	YES	YES	YES
Dealer FE	YES	YES	YES
N	240741	240741	240741
Adj-R2	0.032	0.043	0.054

Panel B: *Effect of choosing new car at Month End*

Dep Var:	18M	24M	30M
	(1)	(2)	(3)
Month End	0.0044	0.0054	0.0041
	(1.63)	(1.59)	(1.09)
New Car	0.012***	0.017***	0.027***
	(2.65)	(3.56)	(4.60)
Month End x New Car	0.022**	0.029***	0.031***
	(2.38)	(2.78)	(2.82)
Controls:			
Buyer Characteristics	YES	YES	YES
Loan Characteristics	YES	YES	YES
Vehicle Characteristics	YES	YES	YES
Year FE	YES	YES	YES
Dealer FE	YES	YES	YES
N	192342	192342	192342
Adj-R2	0.033	0.043	0.053

Table A.4. Car sales on the last day of the month and loan default, with different end of month definition. 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. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *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 of a month. If the actual last day of a month is a Sunday or a national holiday, the previous day is considered the last day (*Adj. Month End*=1). *New Car* is an indicator that equals 1 if the purchased vehicle is new, and 0 if used. Buyer Characteristics include Ln(Credit Score), Homeowner Indicator, Ln(Income), and Prior Ch. 7 Bankruptcy Indicator. Loan Characteristics includes APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics includes Luxury Indicator, Ln(Mileage), Reliability Rating, Reliability Rating Indicator, GAP 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.

Panel A: *Effect of Month End*

Dep Var:	Early Default					
	(1)	(2)	(3)	(4)	(5)	(6)
Adj. Month End	0.0085***	0.0067**	0.0072***	0.0062**	0.0068**	0.0077**
	(3.07)	(2.41)	(2.65)	(2.28)	(2.52)	(2.54)
Controls:						
Buyer Characteristics	NO	YES	YES	YES	YES	YES
Loan Characteristics	NO	NO	YES	YES	YES	YES
Vehicle Characteristics	NO	NO	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State FE	NO	NO	NO	YES	NO	NO
Dealer FE	NO	NO	NO	NO	YES	YES
Day of week FE	NO	NO	NO	NO	YES	YES
N	247706	247706	241188	241188	240741	192342
Adj-R2	0.0080	0.022	0.035	0.038	0.043	0.043

Panel B: *Effect of choosing new car at Month End*

Dep Var:	Early Default					
	(1)	(2)	(3)	(4)	(5)	(6)
Adj. Month End	0.0070**	0.0051	0.0057*	0.0046	0.0043	0.0053*
	(2.12)	(1.57)	(1.77)	(1.45)	(1.35)	(1.65)
New Car	-0.0041	-0.0018	0.022***	0.019***	0.018***	0.017***
	(-0.92)	(-0.46)	(4.15)	(3.75)	(3.61)	(3.59)
Adj. Month End x New Car	0.020**	0.021**	0.021**	0.021**	0.021**	0.021**
	(2.01)	(2.16)	(2.15)	(2.13)	(2.16)	(2.18)
Controls:						
Buyer Characteristics	NO	YES	YES	YES	YES	YES
Loan Characteristics	NO	NO	YES	YES	YES	YES
Vehicle Characteristics	NO	NO	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State FE	NO	NO	NO	YES	NO	NO
Dealer FE	NO	NO	NO	NO	YES	YES
Day of week FE	NO	NO	NO	NO	NO	YES
N	197983	197983	192342	192342	192342	192342
Adj-R2	0.0094	0.023	0.036	0.038	0.043	0.043