Product sales incentive spillovers to the lending market

Mark Jansen, Hieu Nguyen, Lamar Pierce, and Jason Snyder*

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ABSTRACT

Automotive manufacturers are known to use deadline-based convex incentives to motivate dealerships to sell new cars. This paper shows that dealerships respond to these incentive targets by pushing customers from used to new cars as the end of the month approaches, and that subprime loans written to finance these end-of-the-month purchases default more often, particularly when written for financially constrained buyers. We also show that the new car buyers at the end of the month are more likely to default because they are sold less reliable models, and are less likely to be covered by insurance that protects them in the event of default. Although consumers undoubtedly bear costs from increased defaults, we find no evidence that the dealerships, or the lenders that purchase these loans, are hurt by the increase in defaults. Our results demonstrate how convex incentives in vertical contract structures can induce gaming behavior with spillover costs to third parties in the supply chain or retail channels.

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

*Jansen: University of Utah, Eccles School of Business; Nguyen: University of Utah, Eccles School of Business; Pierce: Washington University in St. Louis, Olin Business School; Snyder: University of Utah, Eccles School of Business. 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. 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 contracts are commonly based on a convex relationship between pay and performance (Chung et al., 2020).[1] Although convex incentives are most frequently used in individual compensation plans (e.g., Tzioumis and Gee, 2013), they are also included in vertical contracts 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 new 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) explains why such schemes can motivate individual agents to engage in gaming behaviors by, for example, lumping sales within specific time periods or within one rewarded task. The empirical literature broadly supports these predictions for individual agents (Healy, 1985; Oyer, 1998; Larkin, 2014; Benson, 2015; Frank and Obloj, 2014). In addition, recent work demonstrates the existence of incentive gaming by firms in vertical relationships (Pierce et al., 2020).

Much of the literature on convex incentive structures focuses on the cost of gaming to the principal who writes the contract, with the benefit often going to the agent or sophisticated customers who extract price discounts. But what if the costs of agent gaming are not exclusively borne by the principal and instead spill over to customers and other firm stakeholders? To date, the literature has devoted little attention to this question.

Using novel data on subprime automotive loans, this paper demonstrates the externalities arising from convex incentive system gaming in vertical relationships. Our data span over 3,500 U.S. auto dealerships that sell both new and used cars. Vehicle manufacturers increase new car sales volume through a variety of mechanisms, including inventory allocation (Cachon and Lariviere, 2005; Cachon et al., 2019) and direct cash rebates (Busse et al., 2006) that directly control sales prices within a given model year (Bennett, 2013). Of these mechanisms, the strongest might be convex monthly sales incentives, which reward dealerships for hitting discrete new-vehicle sales targets within a calendar month. Because of intense price competition between local dealerships (Olivares and Cachon, 2009), these monthly incentives are nearly universal in the industry and represent the majority of dealership sales profits. The monthly incentive bonuses studied in Pierce et al. (2020)

[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 compensation (Joseph and Kalwani, 1998). 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).

average over \$20,000 per dealer, with the largest dealers earning over \$200,000 from the marginal vehicle (i.e., the vehicle sale that reaches that month's target). The magnitude of the incentives motivates both inter-temporal and multitask gaming behaviors when the dealership is close to the target (Pierce et al., 2020).

Because vehicle manufacturers' monthly dealer incentives apply only to sales of new cars (Lareau, 2018), dealerships profit from moving customers from used to new cars when they are just below the sales target at month's end. Dealership managers typically align salesperson incentives with dealership goals through their own deadline-based convex compensation schemes (Fahey, 2003; Wolf, 2016; Pierce et al., 2020). Such schemes can conflict with the salesperson's role in matching relatively uninformed customers with the cars that best suit the customers' needs. For example, a salesperson could steer a financially constrained customer toward a car that stretches their budget but hits the salesperson's incentive target. Consequently, the gaming behaviors employed at the end of the month could pose potentially significant financial risks to customers instead of benefiting them via lower prices (as they are commonly thought to do).

We find that loans for end-of-month vehicle purchases have a 10% higher 24-month default probability, relative to loans made earlier in the month. While we observe an increase in the number of deals closing at the end of the month, there is no evidence that the composition of the customer population changes. Customers at the end of the month do not differ in observable ways (e.g., credit score and income) from customers 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.

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 among buyers with large payment-to-income (PTI) and debt-to-income (DTI) ratios. In short, these are the customers that are the most financially stretched. The new car buyers may not be fully aware that new vehicles typically depreciate 25%–35% within the first year after sale, whereas two- to six-year-old vehicles typically depreciate by only 8%–15% annually (BlackBook, 2019). Consequently, owners of new 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 loan deficiencies in case of default. These choices expose customers to a higher risk and consequence of default.

Together, the findings suggest that financially unsophisticated subprime customers who purchase new cars at the end of the month have an increased likelihood of defaulting.[2] We find little evidence to suggest that the manufacturer's incentives that encourage these purchases harm the dealers or lenders themselves, as the dealers' and lenders' loan-level profits on new vehicle sales at the end of the month are indistinguishable from those at other times.

The key identification concern of our main finding (i.e., that dealerships match borrowers with unsuitable vehicles, resulting in higher loan default rates) is that unobserved borrower heterogeneity explains our results. However, we observe the same set of borrower, vehicle, and loan characteristics that the lenders observe, and the lenders' profitability appears to be unaffected by dealership gaming. This suggests that our controls adequately capture the end-of-month gaming, because if the lenders had failed to observe, and therefore to price, a risk factor, then this risk factor would have adversely affected their profitability on end-of-month loans. We find that this is not the case.

We employ a variety of robustness checks and controls to rule out alternative explanations for our findings and to support our evidence on mechanisms. We show that the percentage of new vehicles sold increases as the end of the month approaches, and that the predicted new vehicle sales from this relationship are positively correlated with loan defaults. This result is consistent with increases in new vehicle sales being the mechanism through which monthly dealer incentives increase defaults, although it does not rule out alternative mechanisms. Furthermore, we show that the relationship between manufacturers' rebates *to consumers* and new car sales does not predict an increase in loan defaults. These incentives, unlike the end-of-month incentives for dealers, directly lower the price to customers.

In a placebo test, we consider used-car-only dealerships. We find that, at these dealers, borrowers are no more likely to default on loans originated at the end of the month than on loans originated at other times. Used-car-only dealerships do not qualify for 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 demand-side factors attributable to end-of-month borrower behavior are unlikely to explain our results. Instead our results are consistent

[2] 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.

with automotive manufacturers' incentives, which are absent for used-car-only dealers but present for new car dealers, influencing borrower defaults.

Our paper provides several unique contributions to the literature on vertical relationship contracting, incentive gaming, and consumer finance. Incentive gaming and other types of moral hazard can generate considerable costs in vertical relationships, which can shift the efficient boundary of the firm (Williamson, 1979; Gartenberg, 2014; Gartenberg and Pierce, 2017). Firms can employ a variety of incentive and control devices to reduce moral hazard 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), but vertical contracts frequently misalign incentives, generating dramatic costs in supply chain management (Narayanan and Raman, 2004). Franchisors (such as the manufacturers in our setting) face particular challenges in managing wide networks of retailers (Lafontaine, 1992; Lafontaine and Shaw, 1999; Kalnins and Mayer, 2004; Ackermann, 2019). Our contribution to the literature in this area is to demonstrate the gaming of non-linear incentives in vertical relationships, its negative consequences to customers, and its potential impacts on other stakeholders.

This paper also contributes to the broader literature on deadline-based convex incentive contracts. Such contracts benefit the firm by attracting high performers (Larkin and Leider, 2012) but can also induce costly gaming by agents. Previous works in this literature (Oyer, 1998; Tzioumis and Gee, 2013; Larkin, 2014) describe a surge in sales as a deadline approaches. Larkin (2014) argues that this surge results from pricing collusion between salespeople and buyers, which ultimately benefits both parties. Deadlines can also induce lower-quality work (Carpenter et al., 2008, 2012; Liebman and Mahoney, 2017; Cohen et al., 2019) by incentivizing agents to 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. 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 and decrease 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). Our paper sheds additional light on how sales incentives create negative externalities for borrowers.

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).

Our paper is most closely related to Tzioumis and Gee (2013), who find that mortgage officers increase their output to meet minimum monthly quotas and that mortgages originated on the last working day of the month have higher delinquency rates. We build upon Tzioumis and Gee (2013) by showing that deadline-based incentives erode the quality of matches between customers and products through multitasking problems (Holmstrom and Milgrom, 1991; Pierce et al., 2020; Obloj and Sengul, 2020). We also show that the sales incentives of a durable goods retailer can affect default risk in contracts between two third parties—in this case, the lender and the buyer. Finally, we show that the increased default risk from the retailer is priced into the loan. Financial institutions recognize the increased default risk of month-end sales and adjust their prices accordingly.

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, and a final price is approved 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.[3] The two 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

[3] Pricing used vehicles also involves considerable learning about the idiosyncratic quality of the individual car (Huang et al., 2019).

[4] Our measure of dealer profits is at the transaction level at the time of the sale and does not represent the lifetime profits from the customer. 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 any incentives that steer customers to financially inappropriate vehicles.

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.[5] 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 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.[6]

Over the next several days, the winning lender verifies customer information such as employment and income. If this screening process uncovers no problems, 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., the customer's income cannot be verified), the lender renegotiates with the dealer and typically buys the loan at a discount that reflects 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 both to dealerships and directly to salespeople. In the dealer incentive programs, the manufacturers typically pay per-unit cash bonuses that are conditional on the dealers' reaching certain sales targets or thresholds 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 the "stair-step" program that Chrysler offers to dealers (Sohoni et al., 2011).[7]. Under that program, a dealership 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

[5] Phillips et al. (2015) show that centralized, data-driven pricing strategies improve loan performance for lenders in this setting.

[6] See Pierce (2009, 2012) for a discussion of the similar but more complex process of lease origination and pricing.

[7] Pierce et al. (2020) provides a detailed description of the structure and implications of stair-step incentives in the automotive industry. The authors interviewed the top management of Maritz, the largest auto incentives manager and the creator of the first manufacturer incentives program. Since they either manage or bid to manage programs for every car brand. They confirmed that every brand has at least one dealer or direct salesperson incentive program. The vast majority of these use monthly targets, while a few use quarterly targets. The managers insisted that even within brands with quarterly incentives, dealerships set and focus intently on the monthly goals needed to hit the quarterly targets, and frequently still provide monthly sales targets to their sales force.

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 strong, motivating dealerships to heavily discount and promote new vehicle sales near the end of the month. In Pierce et al. (2020), 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.

The dealership subsequently passes convex incentives on to salespeople to motivate their focus on monthly goals. To 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). Dealers sometimes integrate nonlinear incentives into the commission to encourage more aggressive car selling. 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 if 15 or more cars are 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. Notably, the salesperson may be given strong additional incentives when the dealership nears its own monthly incentive thresholds. Sales managers commonly pay extra bonuses for the sales of cars necessary to reach the threshold, and may pay an additional commission to the salesperson to compensate for the low (often below-cost) prices used 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. For example, General Motors' Consultant Performance Program pays a salesperson \$225 per car, provided they sell at least 11 Chevrolet vehicles, seven GMCs, or five Buicks in a month (Lareau, 2018). These direct convex incentives, combined with those offered by the dealerships, should strongly motivate salespeople to sell new vehicles at the end of the month.

In sum, the design of both dealer and salesperson incentive schemes are aligned in that they focus on monthly sales levels. The stakes are highest at the end of the month, if the monthly sales are approaching a threshold. This is mainly 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 United States. 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 20 largest auto finance companies. The data provider 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 rest only sell used cars.

Our data 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 1, 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 a 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.[8]

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 the customer groups are almost identical in terms of observable borrower risk characteristics.[9] 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.

In addition, we regress each borrower characteristic on day-of-the-month indicators, including year-month fixed effects and dealer fixed effects. In all regressions, the coefficients on these indicators are economically small and generally not statistically significant (see Appendix Figure A.3 for the visualization of these coefficients). Although more deals get closed at the end of the month, the customers' observable characteristics are not different at month's end than on non-EOM days. If anything, the main difference is that customers at the end of the month are getting better deals on their cars. This suggests that EOM borrowers face a lower likelihood of default, which would work against our finding. 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 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 that will 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.

Note that the American automotive industry has some institutional details that limit the manufacturers' vertical contracting options. First, manufacturers cannot vertically integrate into dealerships either through acquisition or direct entry. Second, the incentive contracts presented here

[8] Subprime borrowers predominantly purchase used vehicles and are more likely to default than prime borrowers (Zabritski, 2019). Consequently, our findings will be limited to subprime borrowers, for whom we have a representative sample.

[9] 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).

treat each sold vehicle identically, possibly forgoing important gains from value-based incentives determined by revenue or earnings (Hagiu and Wright, 2019b). Furthermore, the manufacturers' inability to terminate franchise agreements with specific dealerships weakens their ability to substitute initial condition requirements for direct monitoring of the franchisee. Instead, they must use other levers, such as inventory allocation and cash payments or marketing support, to motivate compliance and performance (Kosová and Sertsios, 2018). Finally, manufacturers cannot directly control retail price negotiations or other dealership decisions, and this restricts their ability to manage the important controlling vs. enabling trade-offs in principal-agent relationships (Hagiu and Wright (2019a)).

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 13 days before, and 13 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.[10] 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.

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

[10] 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 the next month has a value of 1.

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 2, 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-the-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 80–90 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 both new and used cars, we find that the results are unchanged (column 6). Consistent with Oster (2019), the parameters are relatively unchanged as controls are added. Taken together, these results suggest that our main finding is not driven by unobserved buyer heterogeneity across purchase dates. Overall, EOM loans are 7%–10% ($p < 0.01$) more likely to default than loans issued on other days of the month.[11]

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 manufacturers' incentives, we construct a binned scatter plot. We do this by first regressing loan defaults on the loan risk characteristics that the lender observed

[11] 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.

at the time of origination. This includes 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, creating a scatterplot of these data points. Figure 3 plots the 24-month default rate for each day of the month. 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. This finding suggests that the demand-side effect is not the mechanism that drives the higher default rate for loans originated at the end of the month. While dealerships enjoy increasing numbers of customers as the end of the month approaches (as shown in Figure 1), the impact of the manufacturer's incentives is identifiable only on the last day. This likely results from dealerships understanding precisely the marginal profit from these last-day cars.

Next, we examine this relation more formally in a multivariate regression. We define *New Car* as a dummy that equals 1 if the purchased vehicle is new, and 0 if used. We estimate the 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 3, column 1 shows that the higher default rate at month's end seems to be mainly driven by new cars. End-of-the-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 (columns 2–6), loan characteristics (columns 3–6), and vehicle attributes (columns 3–6). Further, when we include fixed effects for state (column 4), dealership (columns 5–6), 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. The salespeople, in turn, affect the trade-off that car buyers, in marginal cases, make between the immediate gratification of a new-vehicle purchase and the long-term financial ramifications of this choice. Unlike Larkin (2014), who finds that salespeople game deadline-based convex incentives by lowering product prices in a way that *benefits* customers, we suggest that manufacturers' incentives induce salespeople to match financially unsophisticated car buyers with new cars that they might struggle to afford.

4.3. Direct-to-consumer cash rebates

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. 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. If the cash rebates by themselves encourage the customers to choose a new car, the dealership salespeople may play a less important role in the customer's choice, and this, in turn, may be reflected in the default rate. 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 4 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.[12]

[12] We note that this result is not indicative of a causal result, since the exclusion restriction could have been violated. It is simply an indication that a priori, new-car sales do not result in a higher rate of loan default.

4.4. Deadline-based manufacturer's incentives to dealerships

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. As discussed earlier in Appendix Table A.1, 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 month-end 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:

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

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

The results in Table 5, 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 of 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.[13]

In a placebo test, we regress *Early Default* on *Days to Month End* for the sample of dealerships that sell only used cars. Since these dealerships only sell used cars, these dealerships do not qualify

[13] 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 that of our main specification.

for automotive manufacturers' incentives, and they typically employ piece-rate incentives to motivate their salespeople. If defaults are higher at month's end in the sample of used-car dealerships, then the manufacturers' incentives are likely to be correlated with an unobserved factor that is also related to defaults (i.e., an endogeneity concern with the 2SLS model). In Table 5, 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.

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

In this section, we examine whether customers who default on month-end new-car purchases are more financially constrained than other month-end new-car 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 should be higher for these customers. We measure the level of financial constraint by the ratio of monthly car payment 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 6. 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 this financially stretched 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-point 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), 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 do not default at a higher rate if their loans are signed at month's end (relative to on other days).

We repeat the tests using the top and bottom DTI quartiles as samples and report the results in Table 7. The results are similar to those in Table 6—new car buyers in the top DTI quartiles (i.e., those that are the most financially constrained) are more likely to default if they purchase their cars at month's end, while new-car customers in the bottom DTI quartile 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 month's end, financially constrained customers are the most likely to default.

4.6. 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 reliability. If a car breaks down frequently and becomes a liability, the borrower may need to replace it. Importantly, borrowers are responsible for loan repayment even if the car breaks down, is damaged, or is repossessed (i.e., the loans are full recourse). As a result, borrowers must sometimes contend with outstanding debt on a vehicle even after a replacement vehicle is purchased. To explore the characteristics of vehicles sold at the end of the month and their relationship to loan defaults, we use vehicle reliability scores (*Reliability* spans 0 to 100) from Consumer Reports (Consumer Reports, 2017) and regress *Reliability* on *Month End*, *New Car*, and their interaction term.

The results are reported in Table 8. 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 who purchase new cars at the end of the month are more or less 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. An 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. New cars typically depreciate 25%–35% in the first year after the sale (BlackBook, 2019). In contrast, two- to six-year-old vehicles typically depreciate in the 8%–15% range annually. We use the variable *GAP Dummy* to indicate whether a loan includes GAP insurance. We estimate a model similar to that of *Reliability* and report the results in Table 9. 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, relative to other new-car buyers.

Though descriptive in nature, these results on possible mechanisms underlying the default rates are largely consistent with the incentive structures that dealerships use to complete deals. There is little evidence to suggest that customers who are predisposed to buy less reliable vehicles or to forgo GAP insurance are also more likely to make their purchases at the end of the month. Taken together, these results suggest that when subprime borrowers purchase new cars at the end of the month, they make economic trade-offs that have long-term consequences. Specifically, these trade-offs increase the borrowers' likelihood of default through more rapid vehicle depreciation, and related exposure to vehicles with more mechanical problems. These findings are consistent with subprime borrowers being myopic in considering the higher likelihood of a loan default when they are influenced to purchase a new car.

4.7. 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 its full weight. 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).[14] 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 for the fixed effects described in earlier specifications. Table 10 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.[15] More generally, month-end incentives for sales representatives do appear to reduce transaction-level profitability. 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 11 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 correlate with the lender's profit margin.[16] 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, despite bidding for loans in a highly competitive market, appears to price the risks associated with deadline-based convex incentives and the resultant mismatching that occurs at month's end.

4.8. Robustness checks

In this section, we perform several robustness checks to alleviate concerns about our choice of measurement of default. First, we estimate Equations (1) and (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.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*

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

[15] Recall that the majority of new car dealership sales profits result from OEM dealer incentive programs.

[16] In unreported results, we examine the impact on lender profitability from (1) borrower payments prior to default, and (2) post-default cash flows from collections and the repossession and sale of the vehicle, and find the the month-end effect is not significant.

and *New Car* is also significant across all time horizons. These findings are consistent with our main finding (in Table 3) 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 2 and 3, the coefficient on *Adj. Month End* in Panel A is positive and significant, as is the coefficient on the interaction term in Panel B.

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.[17] 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, 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 defaults on month-end loans drives our results. There is no observable evidence that this is the case.

5. Discussion and Conclusion

Although much ink has been devoted to the agency conflicts that arise in mortgage lending, the connection between financial services and physical product sales remains underexplored in many 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 affects the outcomes of those loans.

[17] 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, our use of this data is limited to the comparison of customer characteristics across days of the month.

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. The new-car buyers at month's end are markedly more likely to purchase less reliable vehicles. And more financially constrained buyers are more likely to default on an end-of-the-month new car purchase.

The customers we examine 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 between new and used vehicles but are unlikely to fully comprehend the financial implications or associated risks of the loan contracts. While naive borrowers suffer the consequences of loan default, we find little evidence that the lenders or dealers are harmed. These results contrast with Larkin (2014), who shows that sophisticated buyers collude with salespeople to get better deals. The interaction between convex deadline based incentives and buyer sophistication is a fruitful area for future research.

Additional research on how manufacturers' incentives create negative externalities for borrowers in the $1.3 trillion auto loan market is merited. Our data does not address the welfare implications of buying a new car at month's end. We do not consider whether customers are truly worse off with the increased default risk, or whether the risk is outweighed by the joys of new-car ownership. However, our data does strongly suggest that many consumers may substantially damage their credit through undisciplined borrowing behavior (Charles et al., 2008; Morton et al., 2003). This lending outcome is particularly troubling, given the known differences in vehicle prices and interest rates across customer race—an inequality that applies more broadly in consumer and entrepreneurial credit (Chatterji and Seamans, 2012). We also note that the manufacturers who generate increased customer defaults through their convex dealer incentive design may suffer unexpected long-term costs from them, even if they do not underwrite the loans. Subprime borrowers who default on loans or even file for bankruptcy are unlikely to be approved for future new car loans; nor are they likely to return to the brand that ruined their credit. In this way, manufacturers may cannibalize their pool of *future* customers to increase their current sales volume.

We note that our study's implications extend beyond the design of vertical contracts. Deadline-based convex incentives are ubiquitous in firms that offer discontinuous rewards associated with quarterly profitability targets and meeting analyst estimates (Degeorge et al., 1999; Roychowdhury, 2006).[18] While achieving discrete performance targets rewards executives, convex incentives have implications for not only the firm but also stakeholders such as employees, investors, suppliers, and vendors. If managers ignore the spillover costs to third parties, they overestimate the net benefits associated with the deadline-based incentives.

[18] Similar evidence exists on the reward for beating the inclusion threshold for equity indexes (Shleifer, 1986; Chang et al., 2015).

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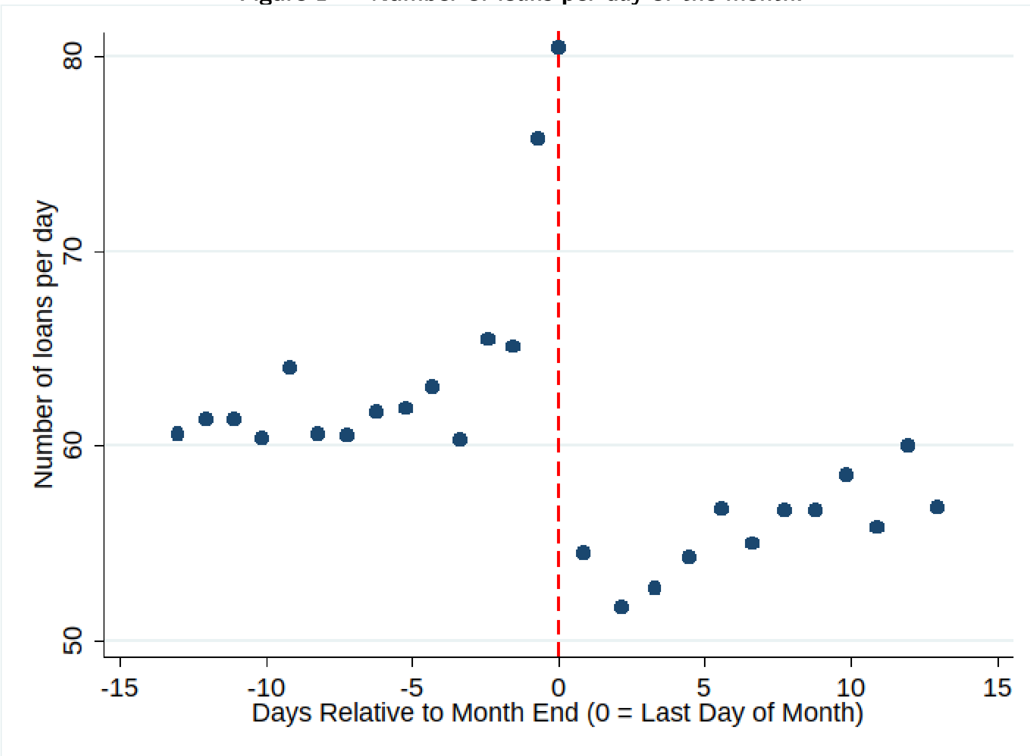
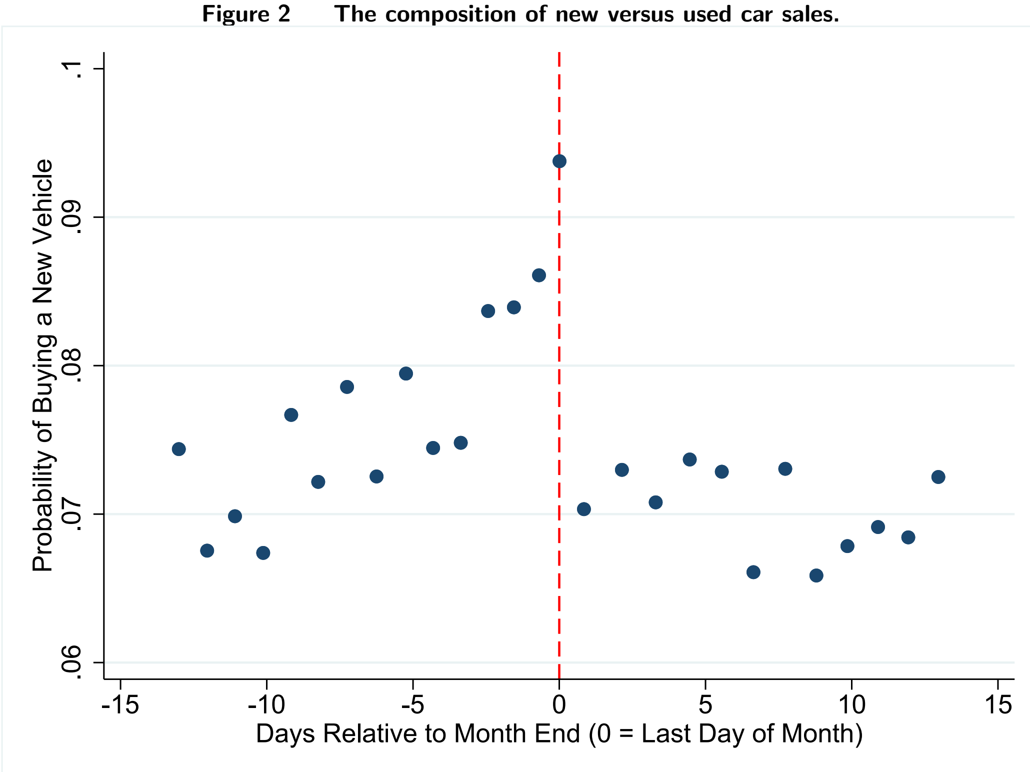
Figure 1 Number of loans per day of the month.



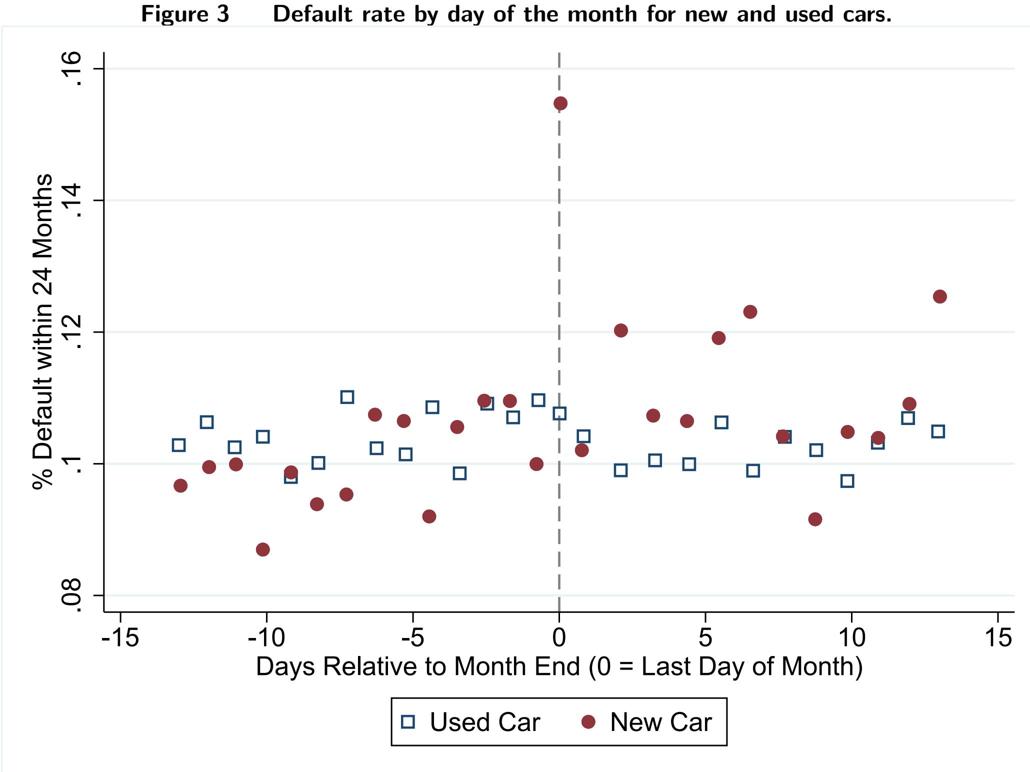
This figure is a binned scatter plot of the number of loans that are signed on the same day each month versus a variable that indicates the number of days relative to the end of the month. The vertical dashed line represents the last day of month.

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 1 Summary statistics.

	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

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.

Table 2 **Car sales on the last day of the month and loan default.**

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

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.

Table 3 **New car sales on the last day of the month and loan default.**

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

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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include 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.

Table 4 Manufacturer's cash rebates for new cars and loan default.

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

This table reports estimates from the 2SLS 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.

Table 5 Dealership incentives and loan default.

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

This table reports estimates from the 2SLS 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 the 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.

Table 6 Loan default on new cars sold at month end for top and bottom PTI quartile.

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

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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include 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.

Table 7 Loan default on new cars sold at month end for top and bottom DTI quartile.

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

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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include 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.

Table 8 Vehicle reliability rating on different days of the month.

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

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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include Luxury Indicator, Ln(Mileage), 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 9 GAP insurance on different days of the month.

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

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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include Luxury Indicator, Ln(Mileage), 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 10 Dealer profitability of loans signed on the last day of the month.

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

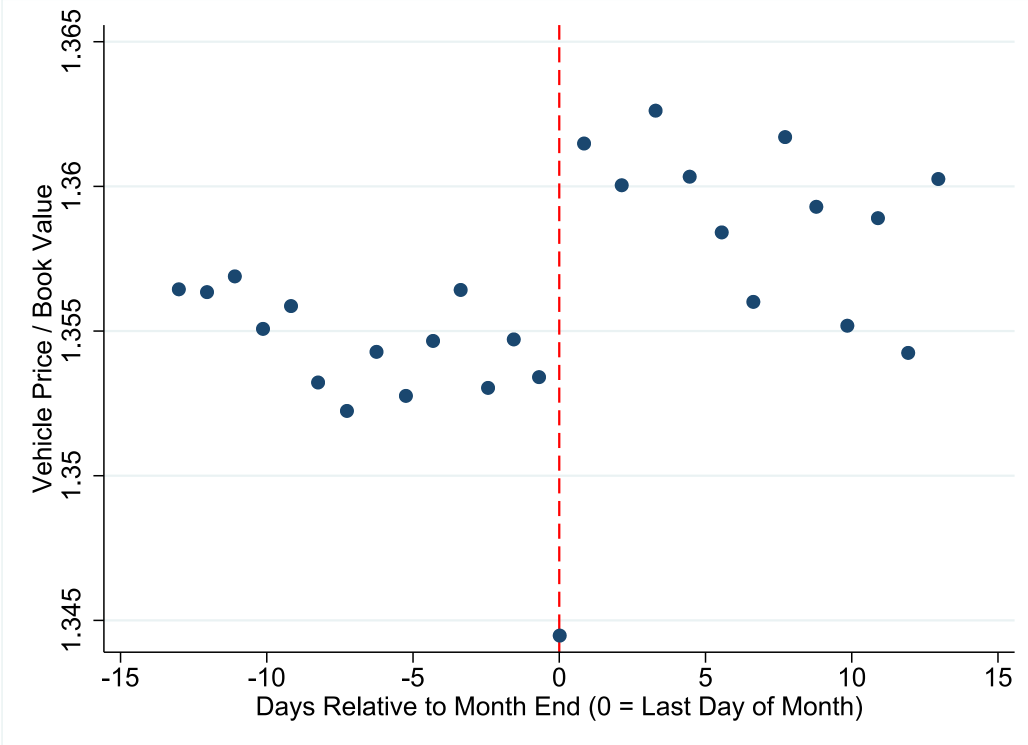
This table reports estimates from regressions of dealer profit margin on whether the loan is signed on the last day of the month and whether the vehicle is new. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *Dealer Profit Margin* is the profit margin 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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include 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.

Table 11 Lender profitability of loans signed on the last day of the month.

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

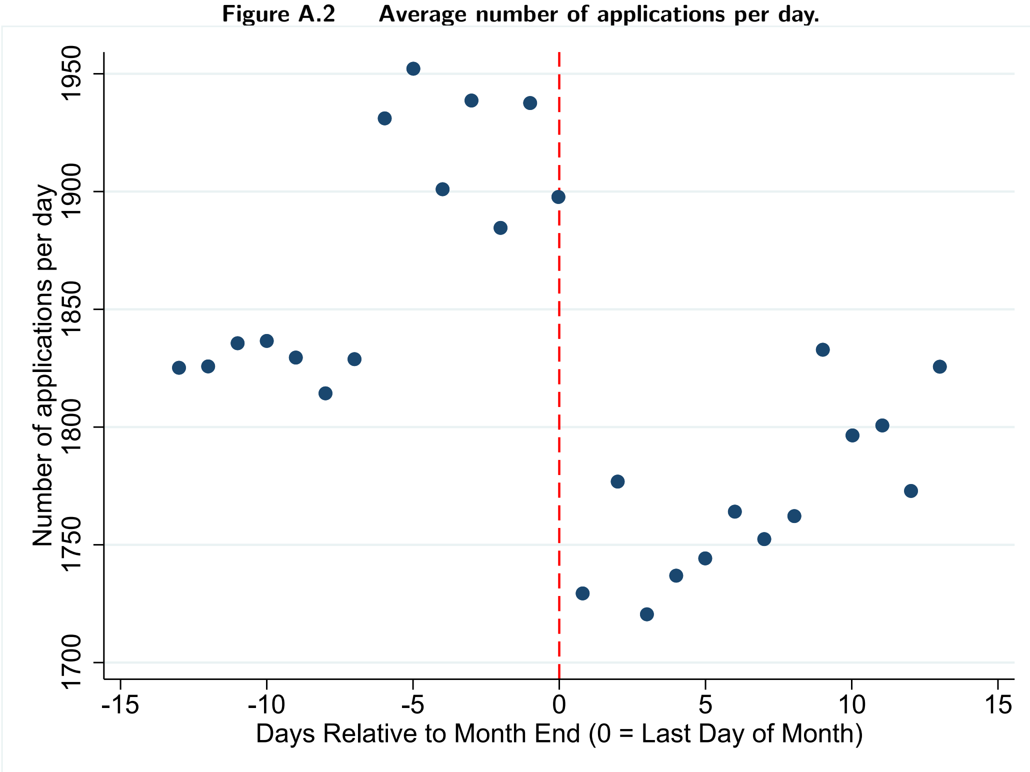
This table reports estimates from regressions of lender profit margin on whether the loan is signed on the last day of the month and whether the vehicle is new. The sample is restricted to loans originated in dealerships that sell both new *and* used vehicles. *Lender Profit Margin* is the ratio of the 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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include 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.

Figure A.1 Vehicle price-to-value ratio by day of the month.



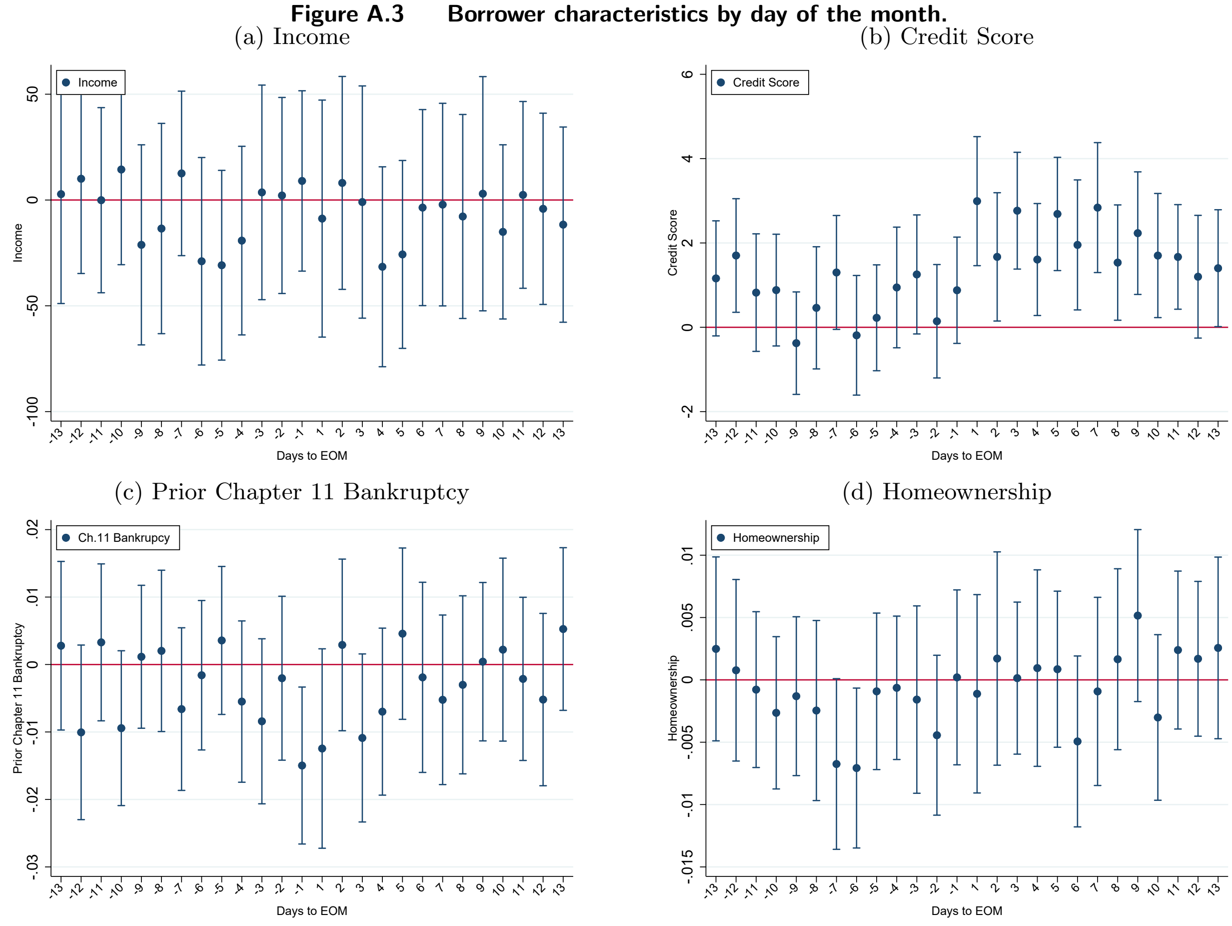
This figure is a binned scatter plot of the vehicle price to book value ratio of loans that are signed on the same day each month versus a variable that indicates the number of days relative to the end of the month. To construct the binned scatter plot, we first regressed y- and x-axis variables on a 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.

Figure A.3 Borrower characteristics by day of the month.



Each graph in this figure plots day-of-the-month coefficients from the regression of a borrower characteristic on day-of-the-month indicators (the last day of the month is omitted), year-month fixed effects, and dealer fixed effects. The confidence intervals are at the 95%level.

Table A.1 Customer profiles.

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
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
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 Indicator	218219	0.066	0.25	11237	0.068	0.25	0.0020	0.41

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.2 Application profiles.

	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
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.3 Car sales on the last day of the month and different default horizons.

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

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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include 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.

Table A.4 Car sales on the last day of the month and loan default, with different end-of-month definition.

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

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 include APR, Loan-to-Value, Ln(Loan Amount), Ln(Discount), Ln(Terms), and Ln(Down Payment). Vehicle Characteristics include 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.