The Impact of Information Technology on Consumer Lending*

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Abstract

We study the adoption of automated credit scoring at a large auto finance company and the changes it enabled in lending practices. Credit scoring appears to have increased profits by roughly a thousand dollars per loan. We identify two distinct benefits of risk classification: the ability to screen high-risk borrowers and the ability to target more generous loans to lower-risk borrowers. We show that these had effects of similar magnitude. We also document that credit scoring compressed profitability across dealerships, and provide evidence consistent with the view that credit scoring may have substituted for varying qualities of local information.

KEYWORDS: Information technology, Credit scoring, Consumer lending.

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1 Introduction

Over the last thirty years information technology has revolutionized consumer lending. Automated credit scoring and underwriting have replaced traditional interview procedures to screen borrowers, and loan pricing has become increasingly sophisticated. This transformation has impacted virtually every consumer loan market, from mortgages to auto financing to unsecured lending such as credit cards. While the near universal adoption of these techniques indicates their value to lenders, there is relatively little specific evidence on exactly how benefits are realized, the size of the effects, and their organizational impacts.

We describe in this paper a natural case study of the changes in consumer lending. We analyze the implementation of automated credit scoring at an auto finance company. The company specializes in the low-income, high-risk consumer market — a market that is particularly well-suited for studying informational problems facing lenders. Default risk is high and recovery values are low, so profitability hinges on identifying better risks in the applicant pool (Adams, Einav and Levin, 2009; Einav, Jenkins and Levin, 2012). Loan applicants also vary substantially in their risk of default, and their characteristics and credit histories provide prospective information about this risk. The potential to stratify borrowers can be seen in the fact that the top third of borrowers in terms of predicted risk are more than forty percent more likely to default than the bottom third.

We find that the adoption of credit scoring, and the changes it enabled in lending, increased profits by roughly a thousand dollars per loan. The effect is substantial: at the time, the average loan principal was around nine thousand dollars.[1] We also identify two distinct channels through which better information improved loan profitability. First, credit scoring allowed the lender to set different down payment requirements for different applicants, creating a higher financing hurdle for severe default risks. Second, credit scoring allowed the lender to target more generous loans to low risks, increasing the quality of cars these consumers could purchase. We trace out these two channels — the screening out of marginal borrowers and the improved targeting of credit to inframarginal borrowers — and show that

[1] We also analyze an alternative metric of profitability, which is the profit (or "net revenue") per loan applicant. After the adoption of credit scoring, loan originations fell, but profit per applicant nevertheless increased from $751 to $1070, or roughly 42%.

together they explain the overall increase in profitability quite well.

The availability of detailed transaction-level data from before and after the adoption of scoring allows for a straightforward empirical approach. We first classify potential borrowers by assigning each loan applicant to a credit category using a rule that mirrors the lender's assignment following adoption. We then construct measures of profitability and related performance metrics — "close rates" on auto purchases, car choices, financing decisions, repayment behavior and recoveries — and compare how these metrics changed, both on aggregate and for the stratified groups, with the advent of credit scoring. Finally, we translate these changes into dollar terms by decomposing profits into separate components: the probability the applicant becomes a borrower, the size of the investment in each borrower, and the return in terms of loan payments actually made.

We observe very different changes in lending patterns to high and low risk applicants. Following the adoption of credit scoring, high risk applicants saw their required down payment increase by more than 25 percent, and the close rates for this group fell notably. Default rates for high risk borrowers also fell, consistent with the idea that higher risk borrowers were screened out by the higher down payment. When we translate these effects into dollar terms, we find that the improved loan repayment was largely responsible for what we measure to be about 1,200 dollar increase in profit per high-risk loan.

The increase in profitability on loans to low risk applicants is of similar size, but the mechanism is different. We find that required down payments and close rates changed little for low risk applicants. Instead, we observe a substantial increase in the average loan sizes and car quality. Even though default rates did not change much, we show that the larger loans had a substantial profit impact due to the high interest rates charged in the market. The increased "size" of each investment is largely responsible for the dollar increase in profit per low-risk loan. Both the changes we document in lending behavior are consistent with how firms theoretically should respond to the availability of better information about borrower risk. We elaborate on this point below by laying out a simple profit-maximizing model of lender behavior that captures the key features of the market we consider.

A useful feature of the episode we study is that most salient features of the lending environment, such as advertising, car pricing, salesperson incentives, and the composition of the applicant pool, remained stable during the periods before and after credit scoring was adopted. This makes for a relatively clean observational setting. While we cannot rule out every possible confounding change in the environment, particularly idiosyncratic shocks at specific dealerships, a variety of robustness checks support the general story we outlined. We show that the inclusion of controls for applicant quality and local economic conditions has little effect on any qualitative conclusions one might draw, and if anything slightly increases the estimated quantitative effects. Our analysis of the effects of down payment requirements and loan sizes is also consistent with results reported in Adams, Einav and Levin (2009) and Einav, Jenkins and Levin (2012). Those papers use more recent data from the same lender and exploit sharp changes in the pricing schedule to estimate the effects of alternative pricing on loan originations and subsequent loan performance.

The last part of the paper looks at the differential impact of credit scoring across dealerships in order to gauge its organizational implications. Research by Stein (2002) and others suggests that automated loan underwriting might involve a trade-off, with the increased use of "hard" information crowding out the production and use of "soft" information (see also Berger et al., 2004). This line of thinking indicates that credit scoring might reduce profitability differences across dealerships, particularly if in the absence of scoring dealers differ in their ability to tailor loan terms to buyers.[2] We show that prior to credit scoring, there was in fact dramatic variation across dealerships in profitability, related primarily to differences in default rates and the matching of cars to borrowers. The advent of credit scoring compressed this variation, as one might expect from the increased reliance on company-wide guidelines. In particular, while almost all dealerships became more profitable, the improvement was greater for dealerships that had higher default rates and less pronounced matching of cars to borrowers of different risks, the two dimensions that credit scoring tried to address.

This paper relates to a significant practitioner literature on credit scoring models. Much of this research focuses on statistical methods for predicting default (e.g. Hand and Henley, 1997; Straka, 2000). We focus on the complementary question of how credit scoring ultimately gets used. In this sense, the paper is closer to a smaller academic literature on the effect

[2] Bloom et al. (2011) provide an interesting analysis of the multiple possible effects on information technology adoption on organizations.

of information technology on lending. Much of this work has focused on bank practices in lending to small businesses (see, e.g. Frame, Srinivasan and Woosley, 2001; Petersen and Rajan, 2002; and Akhavein, Frame and White, 2005). Several of our own papers (Adams, Einav and Levin, 2009; Jenkins, 2009; and Einav, Jenkins and Levin, 2012) analyze the subprime auto market in more detail and use similar data, although they focus on different aspects of the market.

2 Data and Environment

2.1 The Lending Environment

The company we study specializes in making auto loans to consumers with low incomes or poor credit records. During the period we study, the company's average loan applicant had an annual household income of around 28,000 dollars. Almost a third of the applicants had no bank account, and only 14 percent owned their own home. A large majority of loan applicants had a FICO score below 600. Low FICO scores frequently reflect a history of loan delinquencies or defaults, which is consistent with the credit histories of the loan applicants in our data. Over the six months prior to their loan application, more than half of the company's applicants were delinquent on at least 25 percent of their debt. Such credit histories make it highly unlikely that the applicants could obtain a standard, "prime" auto loan, leading such applicants to seek other sources of credit. Indeed, the credit report for the average applicant recorded about nine credit inquiries.[3]

The lending process in the market operates as follows. Consumers fill out an application when they arrive at a dealership. They work with a sales representative and the dealership manager to select a vehicle and discuss financing terms. About forty percent of the loan applicants we observe purchase a car. The purchased cars typically are five to seven years old, with odometer readings in the 65,000 to 100,000 range. The average sale price is eight or nine thousand dollars, which represents a notable markup over the dealer cost (see Table I). Buyers are required to make a down payment, but usually finance about ninety percent

[3] A credit inquiry is recorded on one's credit report when he or she attempts – successfully or unsuccessfully – to obtain credit. Most inquiries stay on a credit report for up to two years.

of the purchase price. The financing terms are relatively standard across our sample. Buyers are expected to make regular payments at the dealership for a fixed term, typically around three years, and interest rates on the loans are high reflecting the risk of the borrower pool. Annual interest rates average close to thirty percent in our sample.

A central feature of the market is that consumers tend to be tightly cash-constrained. In earlier work, we used abrupt changes in the pricing schedule to estimate demand elasticities (Adams, Einav and Levin, 2009). A striking finding was that a loan applicant's probability of purchasing falls sharply when faced with a higher required down payment. We estimated that every hundred dollar increase in the minimum down payment reduces the purchase probability by two to three percentage points. Moreover, more than forty percent of buyers pay exactly the minimum amount down, and these "marginal" purchasers represent substantially worse default risks than buyers who pay more than the minimum down (Einav, Jenkins and Levin, 2012).

The role of the down payment in screening out marginal buyers is important for understanding the way in which risk-based pricing affects loan originations. In the period prior to the adoption of credit scoring, all buyers were required to make a down payment of at least 600 dollars. After credit scoring was put in place, minimum down payments were held constant or even modestly decreased for lower risk borrowers, but increased to as much as 1,500 dollars for high risks. As we will see, this increase helps explain why the fraction of applicants purchasing a car, and the subsequent default rate, fell in the period after credit scoring was adopted.

As can be seen in Table I, defaults during the repayment period are common and tend to occur relatively early in the repayment period. About 35 percent of loans default during the first year of repayment. Less than forty percent are repaid in full.[4] Following a default, the lender attempts to recover the car, and generally succeeds, but frictions in the recovery process result in a relatively low dollar value of recoveries after expenses are netted out (Jenkins, 2009). The average recovery in our sample was around 1,200 dollars, or around 25

[4] These are significantly higher default rates than those reported by Heitfield and Sabarwal (2004) in their study of securitized subprime auto loans, reflecting the relatively poor credit quality of the borrowers in our sample even compared to other subprime populations.

percent of the original dealer cost of the car prior to the transaction.[5]

The combination of early defaults and low recoveries means that transaction outcomes have a bimodal pattern. Early defaults tend to result in losses, whereas fully paid loans can be quite profitable. Figure 1 documents this pattern by showing the distribution of transaction-level returns. For each sale, we computed the present value of borrower payments — the down payment, loan payments and recovery in the event of default — discounted back to the date of sale. We use a ten percent discount rate, which seems to be in line with industry standards. Neither the calculation here nor similar calculations later in the paper are very sensitive to using a somewhat higher or lower number.[6] We then divided the present value of borrower payments by the dealer cost of the car, providing a highly accurate overall rate of return on each transaction. The striking bimodal distribution of returns presented in Figure 1 illustrates the benefits of being able to identify the more credit-worthy applicants from those who are relatively more likely to default.

2.2 Implementation of Credit Scoring

The lender we study adopted credit scoring in the end of June 2001.[7] Prior to this time, the company did not use the credit bureau histories of prospective borrowers. Employees at the dealership were responsible for eliciting information from applicants during the sales process and much of this information was not formally recorded. Prospective buyers were asked for basic information about their income, family and work status, scheduled debt payments and so forth, and as noted above all buyers were required to make at least a 600 dollar down payment. This traditional approach to lending was typical of the high-risk auto loan market at that time.

[5] This is for several reasons. In more than a quarter of defaults, for instance, it is hard to find the borrower, leading to a lengthy and costly recovery process. About a third of defaults are directly associated with a decrease in car value, such as mechanical breakdowns, car theft, and accidents (without maintaining appropriate insurance). See Jenkins (2009) for more details.

[6] Specifically, we ran all the analyses in the paper using discount rates of 5 and 15 percent, and the results hardly change.

[7] To the best of our knowledge (which relies on conversations with the company's executives), there was nothing particularly special about the timing of implementation. In fact, many executives associate the company's idea to adopt automated credit scoring with the hiring of a senior executive who had quantitative background (and affection) in the late 1990s. Devloping, testing, and implementing the idea has taken several years.

With the adoption of credit scoring, the company began to pull information from the major credit bureaus and use a proprietary algorithm to assess each applicant's risk profile. The scoring algorithm achieves impressive risk stratification. If we look at loans made in the first year after credit scoring began, borrowers in the top third of the applicant pool in terms of expected risk were 1.65 times as likely to repay a loan in full as borrowers in the bottom third (50.3 compared to 30.5 percent, respectively). A natural question is why the company uses its own scoring algorithm rather than a potentially cheaper metric available from the credit bureaus. Our understanding from discussions with experts is that a specialized scoring model may have particular value for niche markets such as this one. Standard credit models are designed to broadly assess the entire range of consumers, while those in our data are clustered at the low end of the credit spectrum. Lending to this part of the distribution requires separating consumers with transitory bad records from persistently bad risks, as opposed to simply identifying red flags in a consumer's history.[8]

The company uses the assigned credit score in several ways. As described above, a primary use of scoring is to establish a schedule for minimum down payments. Each applicant is required to pay at least some fixed dollar amount down; the amount depends on the applicant's credit score but not on the car being purchased. The credit scores are also used to match customers with appropriate cars. An applicant deemed a better risk is eligible to obtain financing for a larger range of vehicles, in particular newer, lower mileage cars that are more expensive. Applicants with better credit scores, however, do not qualify for any kind of automatic price discount. Finally, borrowers at a given dealership pay similar interest rates regardless of their credit score, as the rates are constrained by usury laws, and are clustered at, or close to, the relevant state interest rate cap.

2.3 Data

We focus our analysis on the pre-credit scoring period from January 2000 through December 2000, and the post-scoring period from July 2001 to June 2002. We drop the first half of

[8]Indeed, beyond the standard and generally used FICO score, the credit bureaus also sell lenders more specialized scores, associated with default risks in specific markets, such as mortgages or auto loans. Presumably the benefit from a proprietary and customized algorithm is higher when the product and/or the customer base is more unique.

2001, when the company adopted a simple income cut-off to set minimum down payments in anticipation of credit scoring.[9] Finally, we include applications and sales data only from dealerships for which we have complete data for both the pre- and post-scoring periods.[10]

We compare full year periods rather than shorter pre-and-post windows for two reasons. First, the market has strong seasonality patterns: business peaks from February to April when many prospective buyers receive income tax rebates that facilitate down payments (Adams, Einav and Levin, 2009), and there is a slowdown around the December holidays. Second, although we can point to a specific date in late June 2001 on which dealers were required to use applicant credit scores in lending decisions, the practical day-to-day adjustments required for a successful implementation started earlier and continued later, which makes it more interesting to analyze changes over a moderate time period than a very narrow window.[11]

On the other hand, one reason to focus on a single year rather than longer run effects of credit scoring is that we are able to consider a period where other features of the lending environment remained constant. During the period we study, the sales and financing process and the incentive structure for salespeople and dealership managers were stable.[12] We also have little reason to believe that the inflow of prospective buyers into dealerships was affected by the implementation of credit scoring. The company did not change its marketing and customers have little way of knowing the specific financing terms for which they qualify without visiting the dealership and filling out the loan application. This stability can be seen in Table I. Applicant characteristics are similar before and after credit scoring went into effect.

One qualification to this is that the number (but not the composition) of loan applicants

[9] We have looked at this period in some detail though we do not report the analysis. Perhaps not surprisingly, this intermediate approach led to intermediate outcomes.

[10] In Adams, Einav and Levin (2009) and Einav, Jenkins and Levin (2012), we used data from the post-scoring period, allowing us to expand the number of dealerships, applicants and borrowers in the post-period by roughly 50 percent relative to the (already large amount of) data we use here.

[11] We looked at time-series pictures around the implementation date, but between the seasonality and month-to-month variability it is hard to draw very sharp conclusions about the exact pace and timing of outcome changes.

[12] In fact, in late June 2002 the company significantly altered the incentive structure that governs loan origination. Thus, using data on loans originated after June 2002 would potentially confound the effects of credit scoring and incentives.

was somewhat lower in the year after credit scoring, only 88% of the number in the year before scoring.[13] We are not aware of notable changes in the competitive environment, but one possible explanation is broader macroeconomic changes. Economic growth was fairly strong through the first half of 2000, but then slowed until the fourth quarter of 2001. To account for this in our analysis, we use data on local unemployment rates and local housing prices as controls in our empirical specifications. We also focus our analysis on the screening of applicants, the characteristics of loans made to borrowers, and their subsequent performance rather than try to explain the flow of customers into dealerships.

Table I shows significant changes in these basic operating metrics between the pre-scoring and post-scoring periods. The fraction of applicants who became buyers (the "close rate") dropped by about 15 percent, the average quality of cars sold increased (for example, the average odometer read was 7,000 lower after credit scoring), transaction prices and down payments were significantly higher, defaults were lower and loan revenues substantially increased. Overall, the firm's profitability increased markedly over the period, both on a per-transaction and a per-applicant basis.

3 Credit Scoring and Lender Behavior

In this section, we present an empirically-motivated model to illustrate how a lender might use better credit scoring information to: (i) increase down payment requirements for high risk borrowers, (ii) increase car quality for low risk borrowers, and (iii) generate increased profits from both types of borrowers. To proceed, we first describe the model, then explain how we calibrate the model's parameters to match our data, and finally derive the implications for a profit-maximizing lender.

3.1 A Model of Subprime Borrowing

We consider a two-period model of borrowing and repayment. In the first period, the customer arrives at the dealership and is offered a car of value V at a price P, of which D must

[13] Note that to preserve the company's confidentiality, we do not report the exact number of loan applicants in Table I. Instead we report numbers of applicants and buyers as fractions of the number of loan applicants in 2000. For statistical inference purposes, these numbers are all quite large.

be paid as down payment while $P - D$ can be borrowed. The loan carries an interest rate R. If the customer decides to purchase, he chooses in the second period whether to repay the loan or default.

The customer's problem is to maximize utility across the two periods. Customers vary in their available cash in the two periods, which we denote by Y_1 and Y_2. If a customer doesn't purchase, he consumes his available cash each period and receives utility $\ln(Y_1) + \beta \ln(Y_2)$, where β is the between-period discount factor. If a customer does purchase, his first period utility is $V + \ln(Y_1 - D)$. In the second period, if he repays the loan obligation $L = R(P - D)$, his utility is $V + \ln(Y_2 - L)$. If he defaults, he loses the car and receives utility $\ln(Y_2)$.

We model customer heterogeneity by assuming that customers vary in their available cash, so that (Y_1, Y_2) are drawn from a joint normal distribution

$$\begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{1\theta} \\ \mu_{2\theta} \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}\right), \tag{1}$$

with $\rho \geq 0$. The parameter $\theta \in \{L, H\}$ indicates a consumer's risk type, with L denoting "low-risk" and H denoting "high risk." In particular, $\mu_{1L} \geq \mu_{1H}$ and $\mu_{2L} \geq \mu_{2H}$, so high-risk customers on average have less cash. Each customer knows his risk type, and learns Y_t before making his time t decision. The lender never observes a customer's cash position, but can obtain information about his risk type with effective credit scoring.

We adopt a simplified, but in our case fairly realistic, approach to modeling the lender's problem. We assume that the value of the car V is purely a function of its cost to the dealer, $V = \alpha C$. We also assume that the price P is determined by a fixed mark-up over cost, $P = C + M$, and that both the mark-up M and the interest rate R are given exogenously.[14] These assumptions allow us to focus on the lender's choice of car cost C (or equivalently, value V) and required down payment D, as the key decisions that affect profitability.

To solve the model, we start with the customer's problem and work backward from the

[14] In practice, the lender we study offered the majority of loans at the state interest rate cap, and in the time period we consider here, did not vary the mark-up across cars. Later it moved to a system where more costly cars had higher (dollar) markups. Another simpification in this model is that although many borrowers pay the minimum down payment chosen by the lender, borrowers can choose to pay more upfront and some do, although the amounts are never very large relative to the overall loan size.

second period. Having purchased, it is optimal to repay the loan if $V + \ln(Y_2 - L) \geq \ln(Y_2)$. Repayment is infeasible if $Y_2 < L$, but if the customer has sufficient funds, he will repay if

$$Y_2 \cdot \left(1 - e^{-V}\right) \geq L. \tag{2}$$

The customer's expected utility from purchase is:

$$U_P = V + \ln(Y_1 - D) + \beta \mathbb{E}_{Y_2|Y_1,\theta}[\max\{V + \ln(Y_2 - L), \ln(Y_2)\}] \tag{3}$$

The borrower purchases if this value is greater than $U_0 = \ln(Y_1) + \beta \mathbb{E}_{Y_2|Y_1,\theta}[\ln(Y_2)]$.

The purchasing decision also follows a threshold rule. If we subtract U_0 from U_P and re-arrange the terms, we see that it is optimal to purchase if

$$Y_1 \cdot \left(1 - e^{-V - \beta \Delta U_\theta(Y_1)}\right) \geq D, \tag{4}$$

where $\Delta U_\theta(Y_1) = \mathbb{E}_{Y_2|Y_1,\theta}[\max\{V + \ln(1 - L/Y_2), 0\}]$ is the customer's option value from being able to repay the loan and keep the car in the second period. The value of this option is higher for customers with higher Y_1 (because $\rho \geq 0$). So provided that the price is not prohibitive, individuals purchase in the first period if they have sufficient cash.

The lender's problem is to choose the required down payment D and the car cost C, given borrower behavior. Both choices involve trade-offs. A higher down payment can reduce the probability of sale by causing lower-income customers not to purchase, but raise the chance of repayment because of the smaller loan size and stronger cash position of those who do purchase. Offering more valuable cars raises the customer's benefits and costs in both periods, and a priori has an ambiguous effect on both purchasing and repayment. The interaction of the down payment and car quality also is not obvious. All else equal, a lender might be inclined to raise the required down payment for more expensive cars, unless the more expensive cars were being targeted at a better borrower population.

3.2 Fitting the Model to Data

To examine the effect of credit scoring in this model, we calibrate the model to match observed data on purchasing and repayment outcomes in the pre-scoring period. We first choose values for the parameters in the borrower's utility function: $\alpha = 0.2$ and $\beta = 0.9$. We then set prices to their approximate averages in the pre-scoring period: $D = \$600$, $C = \$5,500$, $M = \$2,500$, and $R = 1.4$. The latter approximates the total repayment amount per dollar borrowed on a loan with an interest rate of 29.9 percent and a 42 month term. Finally, we set $\rho = 0.5$ and calibrate the remaining distributional parameters μ_{1L}, μ_{1H}, μ_{2L}, μ_{2H}, σ_1, and σ_2 to match six observed moments in the data.

Table II shows our six matched moments and calibrated parameters. The moments include the probability of sale and probability of default for both types of borrowers at the prices noted above, the semi-elasticity of the close rate with respect to changes in the required down payment (3 percent per \$100), and the semi-elasticity of the default rate with respect to changes in loan size (1 percent per \$100). The latter two values are taken from Adams, Einav, and Levin (2009).

Figure 2 provides intuition for the model by plotting customers in the space of (Y_1, Y_2). Customers with low Y_1 do not purchase and, conditional on purchase, customers with low Y_2 default. Roughly, our calibration procedure matches the probability of purchase for each type of borrower by shifting the mean of each type's Y_1 distribution, and the probability of default by shifting the mean of Y_2. Low-risk types have a higher μ_1, corresponding to their observed higher probability of purchase, and a higher μ_2, corresponding to their lower probability of default. The figure shows the low risk distribution above and to the right of the high risk distribution. The effect of down payment on purchase probability is matched by shifting σ_1, and the effect of loan size on the default rate is matched by shifting σ_2. In both cases, conditional on matching the other moments, a higher variance corresponds to a lessened sensitivity.

The final step in the calibration is to choose parameters for the lender's profit function so that the optimal down payments and car costs match observed down payments and costs in the pre-period. The lender's expected profit from a type θ customer is:

$$\pi_\theta(C,D) = q_\theta(C,D)[D + z_\theta(C,D) - C], \tag{5}$$

where $q_\theta(C,D)$ is the probability that the customer purchases the car, and $z_\theta(C,D)$ is the expected value of loan payments conditional on purchase. To match the data, we write $z_\theta(D,C) = p_\theta L + (1-p_\theta)(\kappa L + \omega C) - \psi$, where p_θ is the probability of repayment by a type θ borrower, κ is a parameter intended to capture the fraction of payments typically made prior to a default, ω is the fraction of the original car cost recovered if there is a default, and ψ is the fixed cost of administering a loan. We set $\kappa = 0.37$ based on Adams, Einav, and Levin (2009). We then choose $\omega = 0.35$ and $\psi = \$1,800$ so that the pre-scoring D and (average) C are profit maximizing, assuming the lender cannot distinguish between types.

3.3 Credit Scoring and Pricing

We assume that credit scoring allows the lender to separately identify low and high risk borrowers, i.e. to observe θ. With no knowledge of types, the lender chooses C and D to maximize profits over the population of applicants, that is:

$$\max_{D,C} \sum_{\theta\in\{L,H\}} \pi_\theta(C,D)\cdot w_\theta = \sum_{\theta\in\{L,H\}} q_\theta(C,D)[D + z_\theta(c,D) - C]\cdot w_\theta, \tag{6}$$

where w_θ is the fraction of type θ customers in the applicant pool. With credit scoring, the lender chooses (C_L, D_L) and (C_H, D_H) to separately maximize $\pi_L(C,D)$ and $\pi_H(C,D)$.

Changes in C and D have multiple effects: on the probability of purchase, the resulting distribution of borrower incomes and the probability of repayment, and on profits directly, holding fixed the applicant's behavior. This makes it hard to obtain general comparative statics predictions about the effects of credit scoring, but with the calibrated model we obtain clear results. From the pre-scoring baseline of $D = 700$ and $C = 5,000$, the lender optimally uses credit scoring to raise the down payment for high risks to $D_H = 900$, lower the car quality for high risks to $C_H = 4,600$, and conversely to lower the down payment for low risks and raise their car quality.

Figure 3 illustrates the optimal choice of down payment and car cost for the three relevant cases: low risk customers, high risk customers, and unidentified customers (who are low risk with probability w_L and high risk with probability w_H). When the lender lowers the down payment and raises car quality for the low risks, their probability of sale increases, their repayment rate decreases, and the profit per loan and expected profit increase. For high risk customers, the increase in down payment and reduction in car quality leads to a fall in the probability of sale and a rise in the repayment rate. Again, both the profit per loan and expected profit increase. We will see below that these same effects and results are observed in our data.

4 Empirical Strategy

4.1 Constructing Matched Applicant Pools

The adoption of credit scoring allowed the company to make systematically different offers to loan applicants with different risk profiles. Our analysis therefore compares the experiences of different types of loan applicants in the periods before and after scoring was adopted. For the period subsequent to adoption, we observe the credit score assigned by the company and the relevant information on which it was based, although not the exact algorithm. For the period prior to adoption, the lender collected less detailed data; we observe basic financial and demographic information for each applicant rather than a complete credit history.

To obtain comparable risk groups in the two periods, we construct a risk measure that classifies applicants into low, medium and high risk using variables that are in the data for both periods, and then use this risk classification for *both* periods. To do this, we model each applicant's risk as a function of his or her household income and debt-to-income ratio. We assign each applicant to a cell based on the decile of his or her household income and debt-to-income ratio. We then assign each cell a risk category in a way that minimizes the distance in the post-scoring period between our assignment and the company's, subject to the constraint that our classification be monotone in both household credit variables. The appendix provides details on the procedure.[15]

[15] We also experimented with several other classification schemes and obtained nearly identical results for

Table III provides summary statistics for each risk category in the periods before and after the credit scoring. Low and medium risk applicants were much more likely to become buyers than high risk applicants, and this difference increased in the post-scoring period. Low risk buyers also tended to purchase more expensive cars in both periods. This difference also increased in the later period. Finally, despite taking larger loans, the lower risk applicants have lower default rates.

One point to emphasize is that our risk classification is imperfect. Ideally, we would have access to full credit histories for all applicants and construct risk groups by applying the company's algorithm retrospectively to the pre-scoring applicants. Relative to this approach, our construction may classify as low risk some applicants that the company treated as high risk, and vice versa. As a result when we look at the *differential* effect of credit scoring on low and high risk applicants, our estimates may underestimate the impact of credit scoring. As we will see, however, the differential effects we observe are quite large even with our current classification scheme.

4.2 Measuring the Effect

We measure the effect of credit scoring by estimating the change in different outcome variables between the pre-period (January-December 2000) and the post-period (July 2001 - June 2002).

The results we report rely on regressions of the following form:

$$y_i = \alpha_{R(i)} + \beta_{R(i)} D_i + X_i \gamma + \varepsilon_i, \tag{7}$$

where i is an individual, y_i is an outcome variable of interest, $R(i)$ is the individual's risk category (low, medium, or high), D_i is a dummy variable equal to one if the individual appeared at the dealership following the advent of credit scoring (that is, in the post-period), and X_i is a set of controls.

the analysis that follows.

From this model, we can define:

$$y_{pre,r} = \mathbb{E}[y_i|D_i = 0, R(i) = r] = \alpha_r + \mathbb{E}[X_i|D_i = 0, R(i) = r]\gamma, \quad (8)$$

$$y_{post,r} = \mathbb{E}[y_i|D_i = 1, R(i) = r] = \alpha_r + \beta_r + \mathbb{E}[X_i|D_i = 1, R(i) = r]\gamma, \quad (9)$$

so that $y_{pre,r}$ is the expected outcome for an applicant of risk type r with average characteristics in the pre-period, and $y_{post,r}$ is the equivalent quantity for the post-period.

Their difference, $\Delta y_r = y_{post,r} - y_{pre,r}$, is:

$$\Delta y_r = \beta_r + (\mathbb{E}[X_i|D_i = 1, R(i) = r] - \mathbb{E}[X_i|D_i = 0, R(i) = r])\gamma. \quad (10)$$

That is, the change in outcomes for risk group r can be decomposed into the estimated coefficient β_r, which we interpret as the effect of credit scoring, and the effect of changes in observable covariates within the risk group.

If both the pool of applicants and broader economic conditions were identical before and after the policy change, the second component of Δy_r will be zero, and β_r will reflect the same differences between the average outcomes for group r across the time periods observed in our earlier summary statistics. To the extent that the applicant pool and economic conditions changed, Δy_r will differ from β_r. Below we report estimates of β_r for regressions that gradually add more controls, allowing us to see the contribution of observable shifts in applicant characteristics and economic conditions. We discussed above that changes in the applicant pool were limited; this is reflected below in the fact that controlling for the composition of the applicant pool has little effect on our estimates of β_r. The estimates we report do suggest that economic conditions may have led to modest decreases in loan performance during the post-period, so that the effects of credit scoring may be a bit understated in the raw numbers.

One limitation to our observational data approach is that we cannot rule out some unobserved change in the lending environment that might have contributed to, or even independently generated, the effects we document below. We believe the latter is highly unlikely. The inclusion of observed controls does not attenuate the estimated effects, and the set of confounding events required to generate all the predicted effects we observe would need to be quite special. It is possible that there was some broad ongoing trend in the attitude of borrowers that we do not account for. If so, one might expect it to have had a fairly uniform effect on the risk groups we construct. In this case, the differences (across risk categories) between the β_r's that we emphasize below will still be informative about the impact of credit scoring. Many of the other unaccounted for changes that naturally come to mind (a large layoff, or the opening of a local competitor) would likely to have had a targeted effect at certain dealerships. The inclusion of dealership dummies accounts for these possibilities to some extent, and we also will see in Section 6 that essentially *all* dealerships experienced similar qualitative changes between the two period, something we might not expect if there were important local, risk-group specific, unobserved trends.

4.3 Profitability and Other Outcomes of Interest

To assess the effect of credit scoring, it is useful to identify several measures of profitability. In the short run, it seems natural to take the flow of applicants as given, and to view the firm's objective as maximizing per-applicant profits.

We can write the operating profits from applicant i as

$$\Pi_i = Sale_i \cdot [DP_i + LP_i + REC_i - C_i] \,. \tag{11}$$

Here $Sale_i$ is an indicator variable equal to 1 if i buys a car, DP_i is the down payment, C_i is the cost of the car offered to i, LP_i is the present value of loan payments and REC_i is the present values of recoveries in the event of default (or zero if the loan is fully repaid).[16] In our data, LP_i depends primarily on the transaction price (which after subtracting the down payment, determines the loan principal), and whether and when default occurs. More generally, it depends on the loan length and the interest rate, but as these did not change much with credit scoring, we do not discuss them separately.

In the longer run, and particularly in obtaining external financing, one may be more interested in the rate of return on capital. Restricting attention to buyers rather than

[16] As mentioned earlier, we use an annual interest rate of 10 percent to value the stream of payments and recoveries, and also experimented (in unreported regressions) with rates of 5 and 15 percent and verified that this assumed rate doesn't drive any of the results.

applicants, we can define the return on sale i as:

$$\Pi_i/C_i = DP_i/C_i + LP_i/C_i + REC_i/C_i - 1. \tag{12}$$

Below, we report regressions where the outcomes of interest are per-applicant profit and its components, regressions where the sample is restricted to buyers and the relevant outcomes are per-sale profit and its components, and regressions where the sample is buyers but the dependent variables are rate of return and its components. As we will see, the approaches yield similar insights, but a comparison is useful to facilitate interpretation.

5 Empirical Results

We report our regression results in Table IV. In the first panel (Table IV(a)), the unit of observation is an applicant, and we measure profit and its components in dollar terms. In the second panel, the unit of observation is a buyer, and we look at changes in profit per buyer measured in dollar terms. The third panel is also at the buyer level, with the dependent variables being rates of return.

Each panel has a similar structure. For each outcome of interest, we report in the left-most column its grade-specific average before credit scoring, while the remaining columns report estimates of the effect of credit scoring, β_r. Column (1) presents these estimates with no additional controls (essentially replicating the summary statistics of Table III). In column (2), we add dealership and calendar month fixed effects, and the household total (monthly) income, residual income, and debt-to-income ratio of each applicant or buyer. In column (3), we also include measures of local economic conditions (at the MSA in which the dealership is located) at the time of sale and over the initial twelve months of the loan.[17] The first set of covariates is intended to control for compositional changes in the applicant or buyer pool within a given credit category. The economic indicators are intended to account for

[17] Specifically, we construct eight variables to capture local economic conditions. Six are related to local unemployment rates: the average level, the average change, and the standard deviation of (monthly) local unemployment rates in the previous six months and in the subsequent 12 months. The last two are the annual change in the (quarterly) local housing price index for the previous 6 months and subsequent 12 months.

macroeconomic changes that might impact close rates or borrower repayment.

5.1 The Effect of Credit-Scoring on Profitability

All of our specifications show a very strong effect of credit scoring on profitability. We estimate that profits per transaction increased by over 1,000 dollars for each risk category, with the rate of return on capital increasing by 15-20 percent depending on the exact specification (Tables IV(b) and IV(c)). At a per-applicant level, we find that profits increased by almost 600 dollars for lower risk applicants and by 546 dollars for medium risk applicants. We find a slight decrease in profitability per applicant for high risks, reflecting the fact that the close rate declined substantially for this group and we calculate transactions in this category to have been profitable prior to the advent of credit scoring.

This last conclusion depends somewhat on how we account for the fixed costs associated with selling, handling, and collection activities associated with each loan. The company estimates these costs at around 1,000 dollars. If we were to include this as a cost for every transaction, high risk sales would have been only marginally profitable prior to credit scoring, and we would conclude that profits per applicant increased by 105 dollars per applicant for the highest risk category.[18] This adjustment also makes the rate of return effects even more dramatic, implying more than a doubling.

5.2 How did Profits Increase?

To understand the source of the profitability gains, it is useful to look at the separate components of profit. Here we focus discussion mainly on the estimates in the first column of Tables IV(a) and IV(b). What we want to emphasize is the very different channels through which profits increased for the better and worse risk groups.

The conventional story of credit scoring is apparent for high risks. Before credit scoring almost one in four applicants in our high-risk category became a buyer; with credit scoring

[18] This adjustment has little impact on the change in profitability from low and medium risk applicants because close rates for these groups hardly changed. Specifically, with the adjustment we estimate the effect on profits for low and medium risks to be 598 and 566 dollars per applicant, respectively (compared to 595 and 546 reported earlier).

this was cut by more than half (Table IV(a)). A likely cause of this change was the required down payment, which increased from 600 dollars prior to scoring to more than 1,000 dollars for the highest risk applicants. As noted above, increases in the down payment requirement have a remarkably large impact on purchasing decisions, and also lead to a better selection — that is, buyers who are just able to come up with the minimum down payment turn out to be substantially worse risks than buyers for whom this constraint is not binding (Einav, Jenkins and Levin, 2012). The results in Table IV(b) are consistent with this selection effect. Default rates for buyers in the highest risk category fell from 70 to 62 percent, leading to about a 1,000 dollar increase in repayments.

Credit scoring had a very different effect on the lower risk applicants. For applicants with better risk scores, the company did not raise the minimum down payment requirement, and indeed close rates remained virtually the same (Table IV(a)). Nevertheless profitability increased dramatically. Here the biggest factor appears to have been that lower risk applicants were allowed to take larger loans, leading them to purchase better cars, and leading the company to raise its markups on these cars. The incentive for the company to do this can be seen clearly in Table IV(c). Prior to credit scoring, the transaction rate of return was significantly higher for lower risk buyers than for higher risk buyers (38 percent vs. 26-29 percent). With the ability to identify these buyers, it was possible to extend them more credit. Table IV(b) shows the significant increase in car cost for the lowest risk buyers (431 dollars), an even greater increase – due to increased markups – in the price of these cars (1,125 dollars), and also the increase relative to buyers in higher risk categories.

To see how these different effects aggregate into an overall change in profit per-buyer, consider the high risk buyers first. Their down payments increased by 309 dollars, and loan payments by 1,021, from which we need to subtract a modest 184 dollar increase in car costs. Incorporating a small increase in recoveries leads to the 1,205 increase in profit per buyer reported in Table IV(b). For the low risk buyers, car costs and car prices increased much more, by 431 dollars and 1,125 dollars respectively, and also loan sizes because the increase in down payments (of 234 dollars) did not increase enough to offset it. The increase in profitability of 1,059 can be therefore attributed almost entirely to the larger stream of loan payments received on the larger loans, almost 1,000 per buyer, plus a 306 increase in recoveries reflecting the initially higher quality of the cars.

5.3 Potential Confounding Factors

The preceding discussion focused on the first column of Tables IV(a)-(c), in which we make no attempt to control for compositional or macroeconomic changes that might impact our results. Column (2) adds dealer and calendar month fixed effects, as well as individual characteristics. As we describe below, dealership performance varies substantially, and we have already mentioned the seasonality effects in the data. Nevertheless, the inclusion of these variables has virtually no effect on our estimates. This basically reflects the fact that within each of our credit categories, the composition of applicants and buyers did not change very much during the evaluation period, neither across dealers, nor across months, nor in terms of individual characteristics.[19]

Column (3) of Tables IV(a)-(c) reports on specifications where we control for local (MSA-level) economic indicators related to unemployment and housing prices (see footnote 17). Repayment in the subprime market can be quite sensitive to employment shocks (Jenkins, 2009), and unemployment rates were somewhat higher during the post-scoring period. This suggests that our estimates of how much credit scoring increased profitability might be attenuated by adverse macroeconomic changes. Indeed when we control for these macroeconomic factors — interacting these controls with the risk category to allow for different risk groups to be affected differentially — we find somewhat larger effects at the per-buyer level (Table IV(b)) and on a rate of return basis (Table IV(c)). We estimate an increase in profit per buyer of 1,430 dollars for low risks and 1,277 for high risks when we include the full set of controls, compared to 1,059 and 1,205 in the baseline specification. There are corresponding changes in the estimates of the profit components, but nothing in the results leads us to revisit the qualitative interpretations above.

[19] The results do not change noticeably if we leave out the individual characteristics (household income and debt-to-income ratio), or if we add additional characteristics (that we have only for buyers) such as the number of dependents or the time that the buyer has been living in his current address.

6 Differential Effects across Dealerships

In this final part of the paper, we investigate the effect of the implementation of company-wide credit scoring on specific dealerships. We start by documenting the heterogeneity across dealerships prior to credit scoring, and highlighting two specific differences between more and less profitable dealerships. We then measure the effect of credit scoring at each dealership and document that while credit scoring improved performance at virtually all dealerships, the effect was bigger at poorly performing dealerships, leading to a compression in performance across dealerships.

6.1 Dealerships Heterogeneity

Table V presents summary statistics for "high" and "low" performing dealerships. To construct the table, we rank dealerships by their profit per applicant in the pre-credit scoring period. Table V(a) shows statistics for the top third of dealerships, and Table V(b) for the bottom third.

Dealerships in the top third were dramatically more profitable than dealerships in the bottom third, earning about 1,000 dollars more per sale. The difference does not appear to be driven by the composition of the applicant pools, which are similar on observables. We make this point more rigorously below in the context of a regression model for profitability that includes dealership fixed effects along with controls for applicant quality. Absent observable differences in the applicant pool, what may then generate the heterogeneity in profitability? Possibilities include: (i) better selection (on unobservables) of borrowers out of the applicant pool; (ii) better sorting of borrowers to cars; and (iii) better extraction of profits from otherwise identical transactions, e.g. due to better collection or recoveries.

A closer inspection of Table V indicates that, indeed, top performing dealerships had a sharper wedge between the cars sold to high and low risk borrowers. While all dealerships sold, on average, more expensive cars to lower risk borrowers, the difference is notably greater for top performing dealerships, consistent with these dealerships being better at assessing borrowers prior to credit scoring. Specifically, the two groups of dealerships sold similar cars to low risk applicants, but the more profitable dealerships sold cheaper cars (by roughly

200 dollars) to medium and high risk borrowers. The more profitable dealerships also had significantly lower default rates, particularly for medium and high risk borrowers. The difference in repayment rates suggests that higher performing dealerships were either more effective in their collection efforts or that their borrowers were more inclined to repay for reasons that we cannot account for even with the rich individual-level borrower characteristics in our data.

Motivated by these observations, we can now link back to the model of Section 3 and consider two dimensions along which dealership may vary. One is the ability to convert sales to profits, via the function $z^d_\theta(C, D)$, which is now allowed to vary with dealership d. For example, better collection efforts could be captured by more profitable dealerships having a higher value of p_θ and/or κ. This dimension of heterogeneity is unlikely to be significantly affected by the implementation of credit scoring. The second dimension on which dealerships may vary is their ability — prior to the availability of centralized credit scoring information — to use "soft information" to identify differences in repayment risk of potential borrowers. Suppose for instance that prior to credit scoring dealerships were able to observe an imperfect (binary) signal of borrower quality, and that at dealership d, a perceived low risk borrower was in fact low risk with probability $w^d_L = \lambda^d + (1 - \lambda^d)w_L$. With this parameterization, a value of $\lambda^d = 0$ implies that the dealership has no soft information, while $\lambda^d = 1$ implies that the dealership could replicate the later credit scoring. The calibrated model implies that dealerships with a higher λ^d can match cars to borrowers more effectively, leading to a greater wedge in the cars they assign to low risk versus high-risk borrowers. We therefore interpret this wedge as a proxy for dealership information. (We also note that even for a dealership with $\lambda^d = 1$, the advent of credit scoring would have a positive effect because company headquarters went from mandating a uniform down payment requirement to setting differentiated down payment requirements.)

The rest of this section presents evidence on the differential impact of credit scoring across dealerships. This investigation links somewhat to an interesting hypothesis in the organizational economics literature that the adoption of "hard information" technologies such as quantitative risk assessment may crowd out the use of "soft information" obtained at the dealership level (Stein, 2002), and may reduce profitability differences across dealerships. In our specific setting, the first statement is true almost by design, as after the implementation of credit scoring dealerships had to follow not only company-wide policies regarding minimum down requirement but also regarding the matching of cars to potential borrowers, where they previously had more discretion. Nevertheless, to the extent that dealerships varied in other dimensions, such as their ability to encourage repayment, profitability need not converge.

6.2 Specification and Results

To measure how the adoption of credit scoring affected individual dealerships, we adapt our earlier regression model to allow the effect of credit scoring to vary across dealerships:

$$y_i = \alpha_{d(i)} + \beta_{d(i)} D_t + \delta_{R(i)} + X_i \eta + \upsilon_i. \tag{13}$$

As before, i is an individual, y_i an outcome variable of interest, $d(i)$ is the dealership involved in the transaction, $R(i)$ is the individual's risk category (low, medium, or high), D_i is a dummy variable which takes the value of 1 in the post-scoring period, and X_i is a set of other controls. We separate the credit category dummies from the rest of the controls because we vary the set of Xs but always control for credit category. In this specification, the coefficient α_d represents the dealership effect prior to credit scoring, while the coefficient β_d represents the dealership-specific effect of credit scoring. The sum $\alpha_d + \beta_d$ is the dealership effect after credit scoring.

For our main analysis, the outcome of interest is the dollar profit per applicant (analyses of the other metrics of profits used in Table IV reveal an almost identical pattern). We estimate the regression without controls and then with a full set of controls (as in column (3) of Table IV). Using either specification, the dealership effects are less dispersed after credit scoring. Without controls, the coefficient of variation of the estimated α_d's is 0.304, while the coefficient of variation of the post-scoring dealership effects, the $\alpha_d + \beta_d$'s, is 0.237. Dispersion drops by 22 percent. With a full set of controls, we find a similarly sharp reduction. The coefficient of variation of dealership effects falls from 0.232 to 0.165 (29 percent).

Figure 4 presents a graphical illustration of the estimates. It plots the cross-sectional distribution of dealership profitability before and after the implementation of credit scoring. In particular, define $\overline{\alpha}$ and $\overline{\beta}$ be the average of (respectively) the α_d's and the β_d's, so that $\alpha_d / \ \overline{\alpha}$ is the (normalized) profitability of dealership d prior to credit scoring, and $(\alpha_d + \beta_d) / \left(\overline{\alpha} + \overline{\beta}\right)$ is the (normalized) profitability after credit scoring. Figure 4 plots the distribution of $\alpha_d / \overline{\alpha}$ and $(\alpha_d + \beta_d) / \left(\overline{\alpha} + \overline{\beta}\right)$, first using the estimates without controls (top panel) and then the estimates with the full set of controls (bottom panel). Both plots show that after credit scoring, dealership profitability had a tighter distribution.

In Figure 5 we present evidence that the homogenization of profits across dealerships appears to be associated with the implementation of credit scoring rather than reflecting some unobserved time trend. Motivated by the patterns in Table V, we sort dealerships based on two pre-scoring performance measures that plausibly capture dealership differences in the use of "soft information" prior to credit scoring: the wedge between the cars assigned to low risk and high risk borrowers, and the default rate. The top panel of Figure 5 shows that the heterogeneity in both metrics was reduced after credit scoring. The vast majority of the dealerships increased the spread of car values assigned to low risk and high risk borrowers, and dealerships that originally had a lower spread had a greater increase. Similarly, default rates declined at the vast majority of dealerships, and the decline was greater at dealerships with higher default rates prior to credit scoring. The bottom panel of Figure 5 shows that these effects were associated with profit increases. As the figure makes clear, almost all dealerships experienced an increase in profitability, but dealerships with the smallest spread in car values for low and high risk borrowers, and with the highest default rates, experienced the greatest increases in profits.

7 Conclusions

In this paper, we reported detailed results on the adoption of automated credit scoring and the changes it enabled in lending at a large auto finance company. A primary conclusion is that the adoption of new credit scoring technology led to a large increase in profitability. Lending to the highest risk applicants contracted due to more stringent down payment requirements, and lending to lower risk borrowers expanded driven by more generous financing for higher quality, and more expensive, cars. We find that these effects were remarkably consistent across dealerships, and that the impact of credit scoring helped to compress large performance differences across dealerships.

Several aspects of our analysis may be interesting to follow up in other contexts. Much of the academic and practitioner literature emphasizes how better information about customers enables more efficient screening of marginal borrowers; our work highlights how improved information technology also allows better customization of contract terms to inframarginal borrowers. A related point is that in our setting the relevant margins of adjustment following the advent of credit scoring was not the interest rate, but rather the down payment and maximum loan sizes — i.e. the amount of leverage borrowers were allowed to take on. It has become increasingly clear that this leverage aspect of consumer borrowing, particularly in regards to the subprime market, deserves much more attention than it has generally received.

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Appendix: Matching Algorithm

We describe the process we followed to construct the matched applicant pool. Recall that the main challenge arises because the company did not credit score applicants in the pre-period, and, moreover, did not collect all the individual characteristics which are used as inputs for the (proprietary) credit scoring algorithm. Therefore, to construct our matched applicant pools, we need to construct our own credit scoring algorithm, which relies on the individual characteristics that are observed both before and after credit scoring, income and debt-to-income ratio. To do so, we assume that applicants can be of one of three risk categories – high, medium, or low – and use the actual risk classification from the post-period as a guide.

Formally, the problem we try to solve is to find a function $f : \mathbb{R}^2_+ \rightarrow \{high, medium, low\}$, which maps applicants' income and debt-to-income ratio into one of the three risk categories. A naive approach (which turns out to do reasonably well) is to use the post credit scoring period, and in particular the high/medium/low risk category each applicant in the post period is classified to (by the company), and run an ordered probit regression of this classification on income and debt-to-income. Since the goal is to predict well, we allow for flexible functional form by generating ten decile dummies for income and debt-to-income, and fully interacting them. Given the estimation results, we then compute the predicted values for the predicted latent variable, order them over the 100 cells, and assign a risk category to each cell accordingly, in order to match the overall distribution of high, medium, and low risk categories in the post-period data (which are 29, 46, and 25 percent, respectively). We then assign each applicant in the pre-period data a credit category based on his or her income and debt-to-income cell. The top panel of Table A.I presents the results. It shows that the risk category is close to monotone in both income and debt-to-income ratio. That higher-income applicants are generally lower risk is intuitive. It turns out that, in our data, higher debt is also associated with lower risk. Presumably, for this population higher debt is associated with the extension of credit by other lenders, which serves to indicate creditworthy behavior, and this underlying correlation dominates any likely effect of debt burden on default risk.

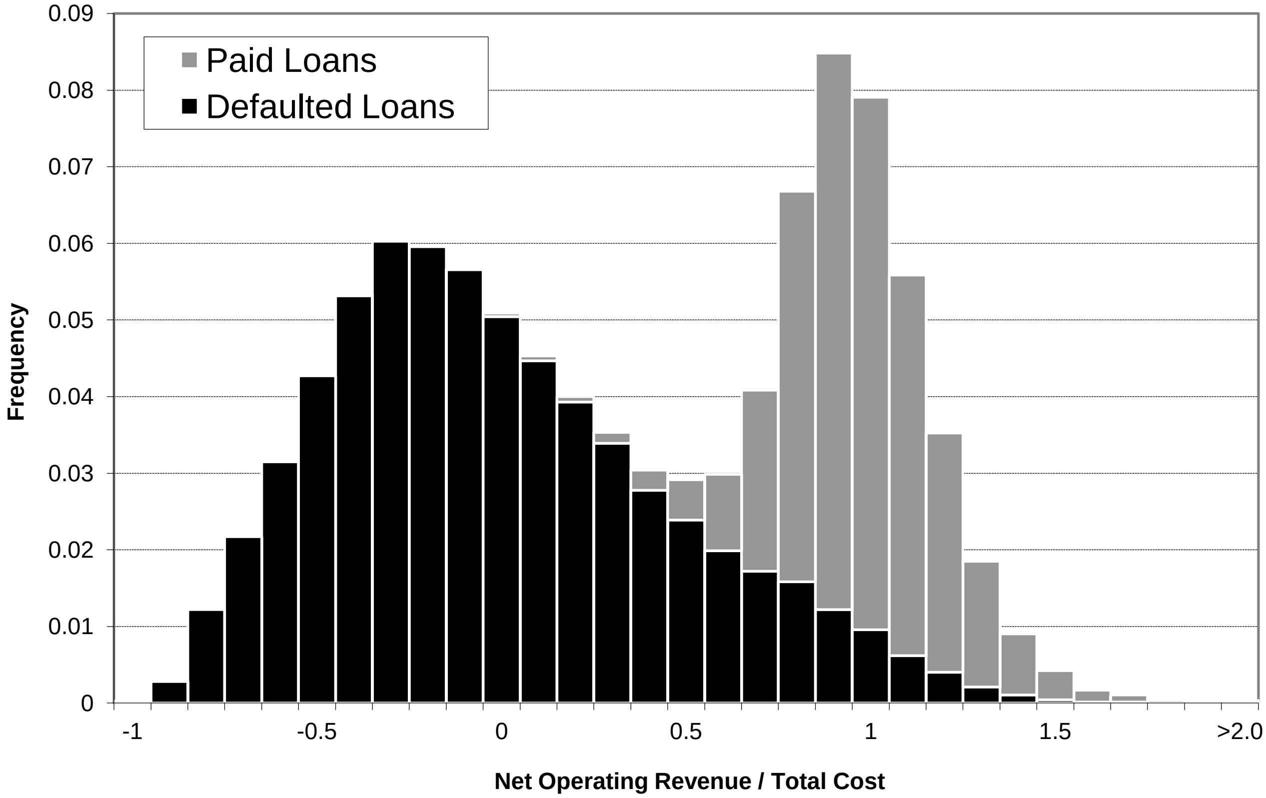
Our actual risk categorization is a small modification of the above described procedure. Motivated by the few cases of non-monotonicities in the top panel of Table A.I – which are likely driven by sampling errors – we reran this prediction model, under the restriction that $f(\cdot)$ is (weakly) monotone in both income and debt-to-income ratio, again characterizing each individual by the interaction of his income and debt-to-income decile dummy variables. Among the set of monotone mappings, we seek a mapping that meets two objectives: it matches the individuals' actual credit score, and it accurately predicts the fraction in the population of each risk category (as classified by the company in the post-period). Let $s_i \in \{H, M, L\}$ be applicant i's actual credit category and $f(x_i) \in \{H, M, L\}$ be individual i's predicted credit category. We then parametrize a loss function over prediction models, so that the optimal prediction model $f(\cdot)$ (within the set of monotone models) minimizes

$$\sigma_1 \sum_i I\left(s_i \neq f(x_i)\right) + \sigma_2 \sum_i \left(I\left(s_i = L, f(x_i) = H\right) + I\left(s_i = H, f(x_i) = L\right)\right) + \\ +\omega \sum_{j \in \{H,M,L\}} \left| \sum_i I\left(f(x_i) = j\right) - \sum_i I\left(s_i = j\right) \right|, \tag{14}$$

where ω, σ_1, and σ_2 are non-negative parameters. That is, the first component in the loss function penalizes for wrong predictions, the second component increases the penalty for "really bad" predictions (predicting high risk although actual score is low risk, and vice versa), and the third component penalizes against deviation from the overall mix of high, medium, and low risks in the population.

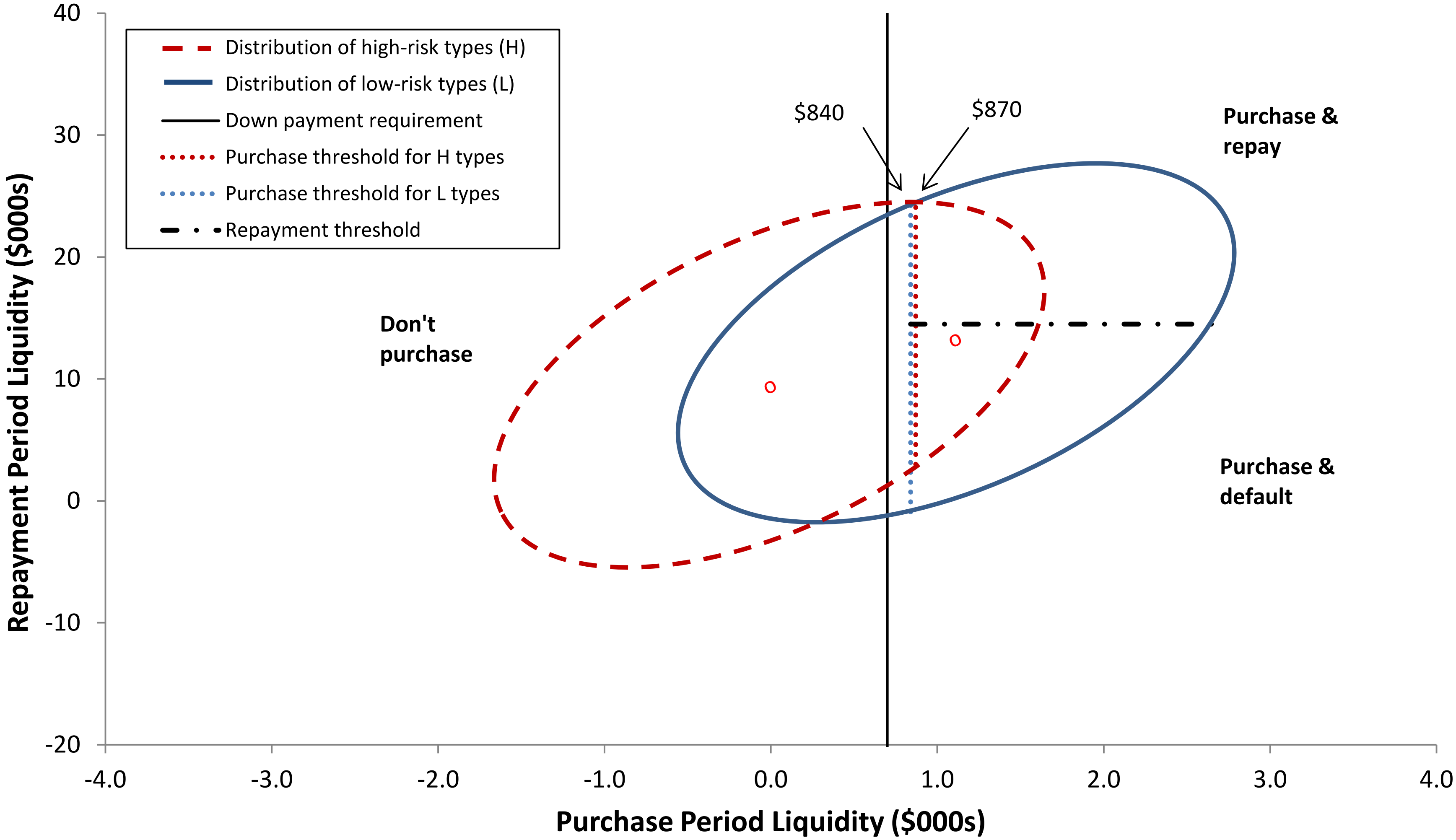
We solve this constrained optimization problem numerically, by searching over the entire set of monotone functions. Based on many different trials, it seems that the prediction model is largely insensitive to the exact values of the weights σ_1, σ_2, and ω. The results presented in the paper use weights of $\sigma_1 = 1$, $\sigma_2 = 3$, and $\omega = 8$. The bottom panel of Table A.I reports its predictions. As one can see, it is similar to the results obtained from the ordered probit model (top panel), but it imposes monotonicity, and is slightly different for some marginal cells.

Figure 1: Distribution of Per-Loan Rate of Return



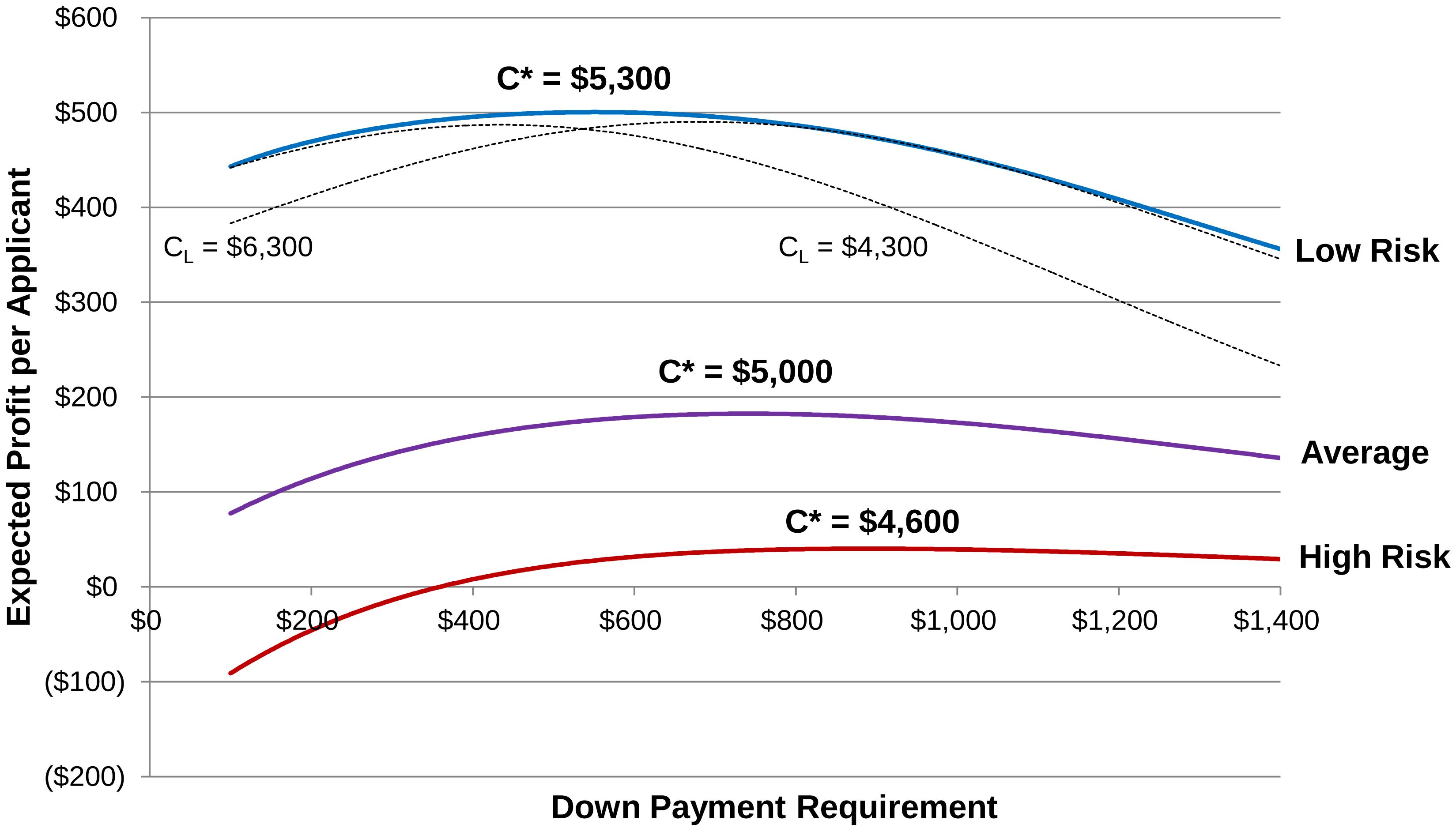
Notes: Net opertaing profits = down payment + PV of loan payments + PV of recoveries - total cost. The histogram uses all observations used in the subsequent analysis, pooling the pre-period and post-period (see Table I).

Figure 2: Illustration of Calibrated Model



Notes: This figure illustrates the model presented in Section 3. The figure shows a two-dimensional space of applicant characteristics. The x-axis represents the applicant's cash in hand at the time of purchase. The y-axis represents the applicant's cash generated in the repayment period. Negative values can be viewed as truncated at zero. Each ellipse is an iso-density curve from the bivariate normal distribution of applicants of each type, as determined by the model calibration. The calibration assumes that the means of Y1 and Y2 differ for the two types, but the covariance matrices of Y1 and Y2 for both types are the same. This assumption can be relaxed without changing the qualitative implications of the model. Based on the calibration, low risk applicants have a higher mean liquidity at purchase and a higher mean repayment liquidity. The former implies that low risk applicants are more likely to purchase, since a necessary condition for purchase is that cash on hand is greater than the minimum down payment. The latter implies that, conditional on purchase, they are less likely to default, since full repayment requires that repayment liquidity exceeds the repayment amount. Thresholds for purchase and repayment are shown with dashed lines.

Figure 3: Optimal Down Payments by Type



Notes: This chart shows the relationship between expected profits per applicant and down payment requirements under different credit scoring regimes. Each curve plots expected profit per applicant as a function of the minimum down payment, conditional on a fixed vehicle cost, as computed using the calibrated model described in Section 3. The vehicle cost for each curve is chosen to maximize the expected profit per applicant. The three curves represent optimal pricing for low risk applicants (top curve), high risk applicants (bottom curve), and a weighted average of the two types (middle curve). The figure shows that the optimal down payment is increasing in the borrower risk level. The small dashed lines show expected profits per applicant as a function of vehicle cost, conditional on a fixed down payment, for low risk borrowers. These curves illustrate how the optimal vehicle cost is determined. Similar curves can be drawn for the high risk applicants.

Figure 4(a): Variation in Dealership Profitability Pre- and Post-Scoring

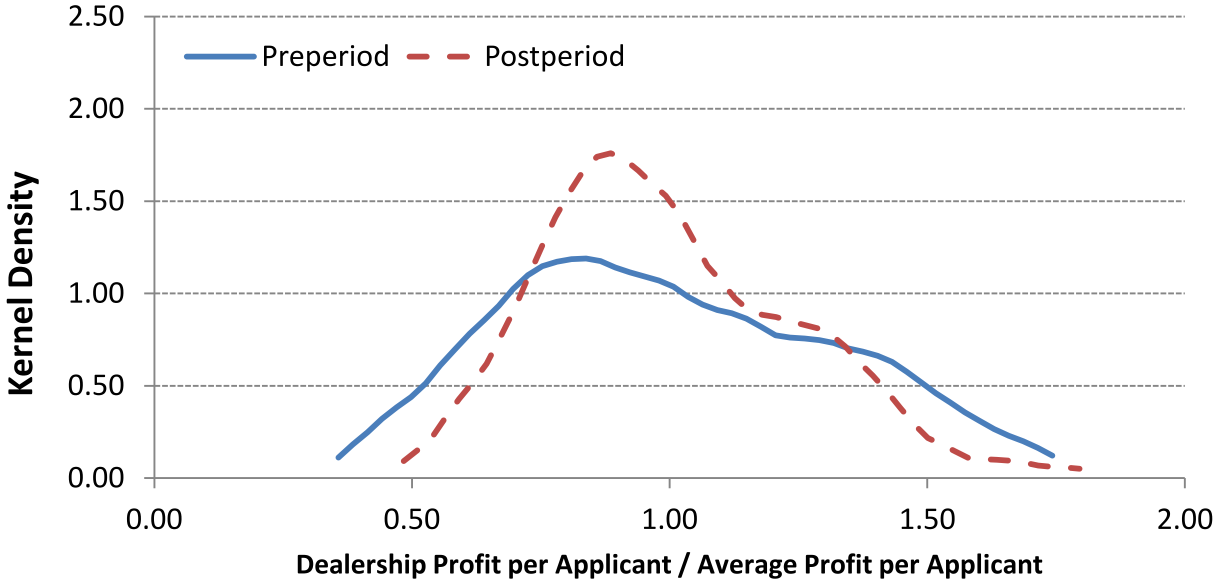
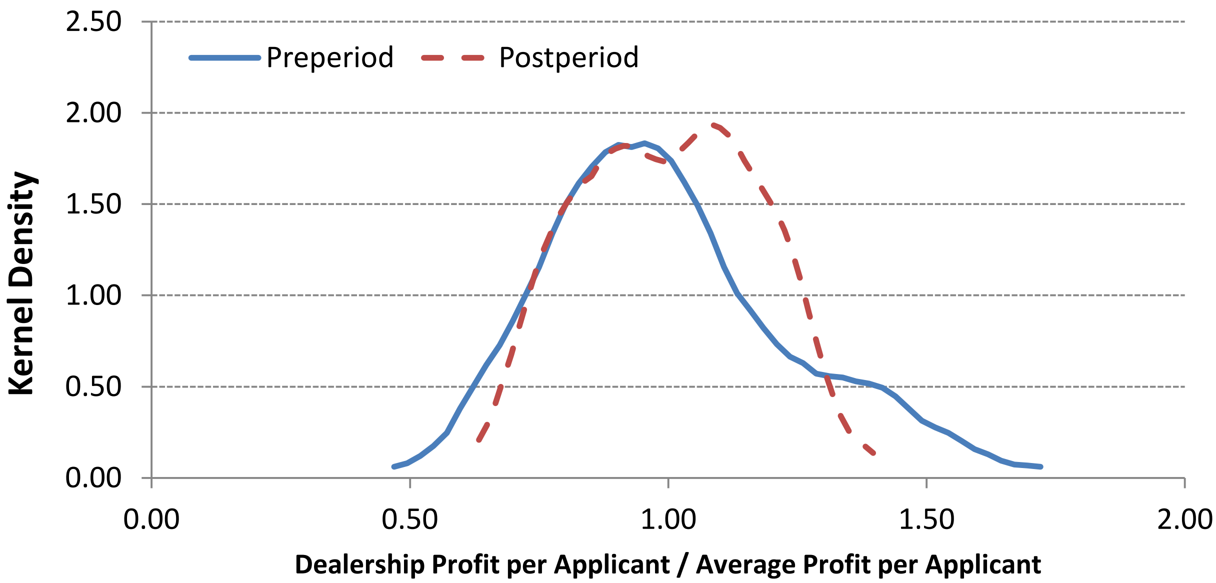
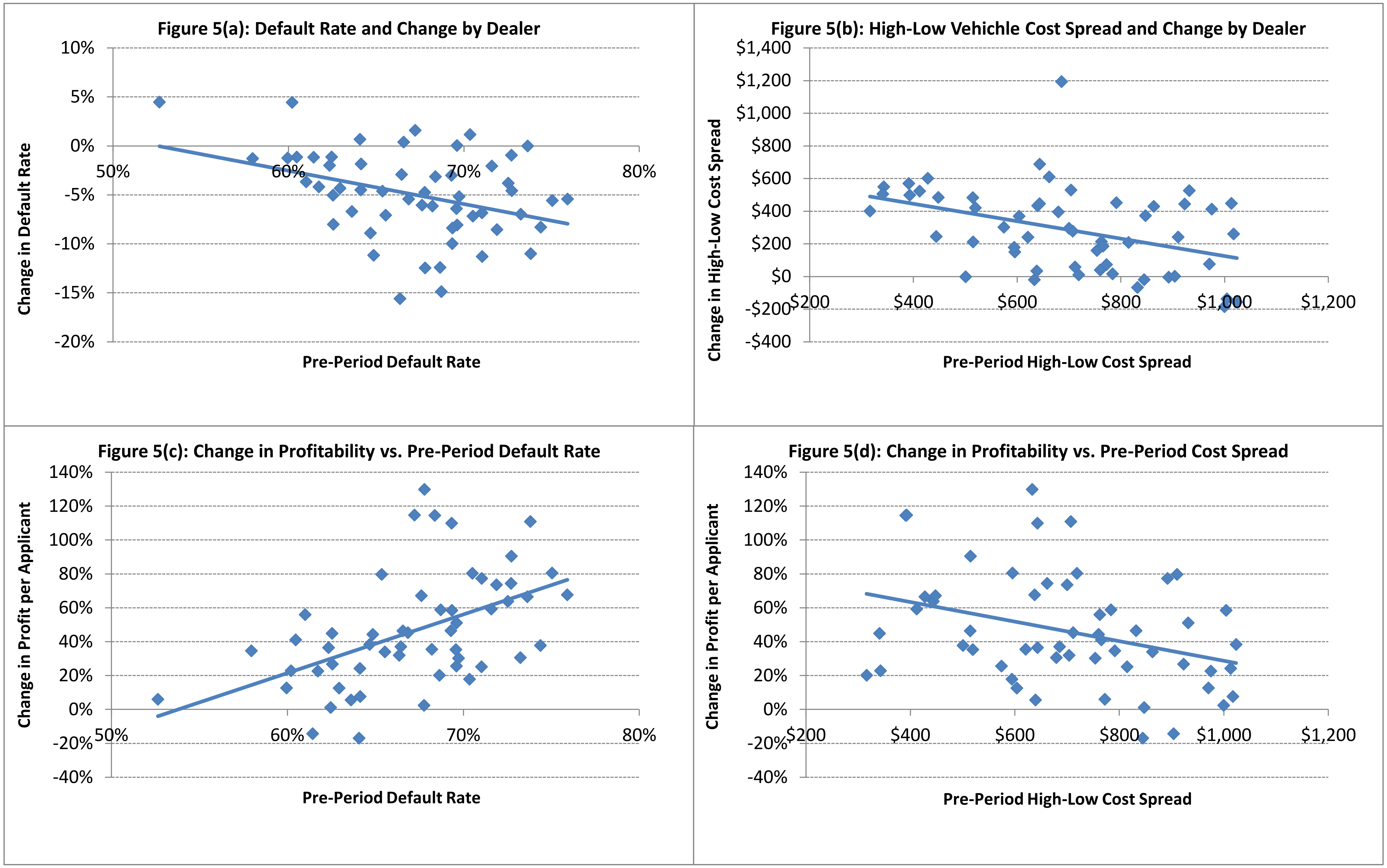


Figure 4(b): Variation in Dealership Profitability with full set of controls



Notes: Each of the graph presents estimates from a regression of the form of equation (13) in the paper, with profit per applicant as the dependent variable. The pre-period graph plots a kernel density of the estimated alpha divided by the mean alpha across dealerships, and the post-period graph plots a kernel density of the estimated alpha+beta, also divided by the mean across dealerships. The top panel uses no other controls (except credit grade fixed effects), while the bottom panel uses a full set of controls (as in column (3) of Table IV).



Notes: Each point on the charts represents a dealership. The x-axes on the upper and lower panels show two measures of pre-period dealership perfomrance: the default rate and the high-low vehicle cost spread. The default rate for each dealership in a period is calculated as total defaults on loans originated in the period divided by total originations in the period. The high-low vehicle cost spread for each dealership in a period is calculated as the average vehicle cost for low risk borrowers minus the average vehicle cost for high risk borrowers originated in the period. Profit per applicant is calculated as total dealership net revenue (see Table I for definition) from loans originated in each period, divided by total applications in each period. In all panels, change is post-period minus pre-period.

Table I: Summary Statistics

	January – December 2000				July 2001 – June 2002			
	Mean	Std. Dev.	5%	95%	Mean	Std. Dev.	5%	95%
Applicant characteristics								
Applicant demographics	*N = 1.00*				*N=0.88*			
Monthy income	2,214	973	1,204	4,000	2,256	975	1,238	4,000
Residual monthly income after debt payments	1,715	985	748	3,525	1,843	1,024	824	3,750
Debt-to-income ratio	0.26	0.16	0.03	0.48	0.25	0.12	0.10	0.45
Car purchased	0.43				0.37			
Local economic indicators								
Local unemployment rate: prior 6 months	0.036	0.009	0.021	0.051	0.050	0.009	0.034	0.063
Local unemployment rate: following 12 months	0.037	0.008	0.022	0.049	0.056	0.007	0.041	0.066
Local housing price change: prior 2 quarters vs. year earlier	0.063	0.016	0.035	0.085	0.078	0.023	0.038	0.114
Local housing price change: following 4 quarters vs. year earlier	0.072	0.017	0.045	0.098	0.077	0.033	0.037	0.140
Transaction characteristics								
Buyer characteristics	*N = 0.43*				*N=0.32*			
Monthy income	2,319	973	1,300	4,088	2,410	984	1,360	4,286
Residual monthly income after debt payments	1,723	1,079	753	3,800	1,859	1,122	790	4,018
Debt-to-income ratio	0.32	0.13	0.15	0.49	0.32	0.10	0.16	0.47
Car characteristics								
Car cost	4,954	863	3,571	6,346	5,273	1,015	3,717	6,944
Car age (years)	6.4	1.8	4	9	5.5	1.7	3	9
Odometer	88,668	17,822	57,746	113,856	81,810	18,048	50,242	108,381
Inventory age (days)	68	62	13	178	72	63	13	184
Lot age (days)	40	57	1	145	43	58	1	152
Purchase Characteristics								
Sale price	8,370	930	6,907	9,795	9,368	1,297	7,307	11,495
Down payment	740	451	200	1,500	1,003	502	600	1,900
Loan term (months)	34.1	3.0	30.0	37.0	36.6	3.9	32.0	42.0
APR	0.288	0.019	0.259	0.299	0.284	0.026	0.219	0.299
Monthly equivalent payment	362	65	298	421	374	42	306	442
Loan performance								
Outcomes								
Default	0.67				0.62			
Fraction of payments made	0.57	0.37	0.05	1.00	0.59	0.37	0.06	1.00
Loan payments excluding down payment	6,113	3,916	653	11,837	7,146	4,441	766	13,636
Recovery amount (all sales)	691	951	0	2,530	923	1,216	0	3,224
Recovery amount (all defaults)	1,032	999	1	2,848	1,483	1,243	73	3,665
Components of Profits								
Gross operating revenue	7,557	3,530	2,284	12,706	9,084	3,901	3,013	14,744
Total cost	5,810	965	4,301	7,378	6,193	1,099	4,518	8,012
Net operating revenue	1,746	3,401	-3,434	6,144	2,891	3,727	-3,005	7,620

Notes: To preserve confidentiality of the company that provided the data, the number of observations is normalized by the number of applicants in year 2000, N (N >> 10,000). Loan payments, recovery amount, gross operating revenue, and net operating revenue are PV. Total cost includes car cost, taxes and fees, and shortfalls when value of trade-in does not cover down payment. Net operating revenue equals gross operating revenue minus total cost.

Table II: Model Calibration

Demand Moment	Actual Value	Model Value	Calibrated Parameter	Calibrated Value
Probability of purchase - high risk applicants	23%	24%	μ_{1H}	$0
Probability of purchase - low risk applicants	57%	58%	μ_{1L}	$1,100
Probability of default - high risk borrowers	70%	70%	μ_{2H}	$9,500
Probability of default - low risk borrowers	50%	50%	μ_{2L}	$13,500
Change in close rate per $100 change in min. down	3%	4%	σ_1	$1,200
Change in default rate per $100 change in loan size	1%	1%	σ_2	$8,000
Optimal Prices				
Optimal min. down without scoring	$600	$700	κ	0.350
Optimal car cost without scoring	$5,500	$5,000	ψ	$1,800

Notes: This table shows calibrated moments and parameters for the model presented in Section 3. The first six rows show the parameters of two bivariate normal distributions of applicant characteristics, one for high risk types and one for low risk types. The parameters μ_{1H} and μ_{1L} are the mean purchase period liquidities (Y1) for high risk types and low risk types, respectively; μ_{2H} and μ_{2L} are the mean repayment period liquidities (Y2) for high risk types and low risk types, respectively; and σ_1 and σ_2 are the variances of Y1 of Y2, respectively, for both risk types. As described in Section 3.2, the calibration roughly matches the probability of purchase for each type of borrower by shifting the mean of each type's Y1 distribution, and the probability of default by shifting the mean of Y2. The effect of down payment on purchase probability is matched by shifting σ_1, and the effect of loan size on the default rate is matched by shifting σ_2. In both cases, conditional on matching the other moments, a higher variance corresponds to a lessened sensitivity. Actual moment values are calculated using data from the pre-scoring period. The last two rows show two parameters of the lender's profit function: the fraction of loan payments made in the event of default (κ) and the fixed cost of administering a loan (ψ). These parameters are calibrated by matching the lender's observed pricing decisions in the pre-scoring period.

Table III: Summary Statistics by Applicants' Predicted Credit Grade

	January – December 2000			July 2001 – June 2002		
	Low Risk	**Medium Risk**	**High Risk**	**Low Risk**	**Medium Risk**	**High Risk**
Applicant characteristics						
Number of applicants*	*N=0.22*	*N=0.40*	*N=0.38*	*N=0.18*	*N=0.34*	*N = 0.35*
Applicant demographics						
Monthy income	3,528	2,130	1,557	3,620	2,152	1,646
Residual monthly income after debt payments	2,776	1,569	1,270	2,915	1,639	1,483
Debt-to-income ratio	0.26	0.30	0.22	0.24	0.29	0.20
Car purchased	0.57	0.55	0.23	0.57	0.53	0.12
Local economic indicators						
Local unemployment rate: prior 6 months	0.0370	0.0358	0.0357	0.0506	0.0496	0.0494
Local unemployment rate: following 12 months	0.0382	0.0372	0.0372	0.0567	0.0561	0.0560
Local housing price change: prior 2 quarters vs. year earlier	0.0646	0.0630	0.0608	0.0797	0.0779	0.0763
Local housing price change: following 4 quarters vs. year earlier	0.0744	0.0726	0.0703	0.0798	0.0765	0.0749
Transaction characteristics						
Number of buyers*	*N=0.12*	*N=0.22*	*N=0.09*	*N=0.10*	*N=0.18*	*N=0.04*
Buyer characteristics						
Monthy income	3,424	2,042	1,453	3,459	2,032	1,387
Residual monthly income after debt payments	2,670	1,461	1,042	2,718	1,479	1,318
Debt-to-income ratio	0.28	0.33	0.34	0.27	0.34	0.37
Car characteristics						
Car cost	5,235	4,949	4,569	5,602	5,212	4,707
Car age (years)	6.3	6.4	6.7	5.4	5.6	5.8
Odometer	89,593	88,735	87,198	81,924	81,823	81,471
Inventory age (days)	63	67	75	64	74	84
Lot age (days)	35	40	47	36	45	55
Purchase Characteristics						
Sale price	8,703	8,391	7,851	9,828	9,302	8,504
Down payment	762	725	746	996	995	1,055
Loan term (months)	34.2	34.1	34.1	37.1	36.5	36.0
APR	0.288	0.287	0.288	0.283	0.284	0.285
Monthly equivalent payment	380	363	334	391	372	339
Loan performance						
Outcomes						
Default	0.62	0.68	0.70	0.59	0.64	0.62
Fraction of payments made	0.63	0.56	0.54	0.62	0.58	0.59
Loan payments excluding down payment	6,912	5,979	5,319	7,864	6,914	6,340
Recovery amount (all sales)	710	709	620	1,016	926	679
Recovery amount (all defaults)	1,146	1,036	881	1,710	1,449	1,088
Components of Profits						
Gross operating revenue	8,400	7,424	6,695	9,890	8,845	8,085
Total cost	6,134	5,807	5,364	6,565	6,126	5,548
Net operating revenue	2,267	1,617	1,331	3,325	2,719	2,536

Notes: See notes to Table I for sample size and variable definitions.

Table IV(a): The Effect of Credit Scoring (Applicant level analysis)

		Pre-period Average	(1) Est. Change	(1) Std. Err.	(2) Est. Change	(2) Std. Err.	(3) Est. Change	(3) Std. Err.
Sample: All applicants								
Close rate (pct.)	Low risk	57.3	-0.4	(1.2)	0.7	(1.2)	-5.8	(4.2)
	Med. risk	54.5	-2.0	(1.3)	-2.0	(1.1)	-7.1	(3.6)
	High risk	23.5	-11.6	(1.0)	-10.8	(0.9)	-23.5	(3.4)
Price ($US)	Low risk	4,990	608	(122)	703	(119)	197	(383)
	Med. risk	4,577	309	(119)	317	(106)	-156	(315)
	High risk	1,844	-832	(75)	-764	(75)	-1,726	(294)
Default (pct.)	Low risk	35.5	-1.7	(1.0)	-0.9	(1.0)	-8.7	(3.8)
	Med. risk	37.3	-3.8	(1.0)	-3.7	(0.9)	-10.1	(3.0)
	High risk	16.5	-9.1	(0.7)	-8.4	(0.7)	-17.8	(2.9)
Down payment ($US)	Low risk	437	130	(11)	139	(10)	162	(37)
	Med. risk	396	127	(11)	125	(9)	144	(33)
	High risk	175	-50	(7)	-44	(7)	-76	(30)
Loan payments ($US)	Low risk	3,963	517	(83)	584	(76)	487	(249)
	Med. risk	3,261	370	(84)	365	(74)	267	(197)
	High risk	1,249	-495	(55)	-467	(49)	-1,177	(187)
Recovery ($US)	Low risk	407	172	(19)	181	(19)	173	(58)
	Med. risk	387	100	(17)	103	(16)	64	(49)
	High risk	146	-65	(7)	-53	(7)	-104	(49)
Gross ($US)	Low risk	4,817	817	(102)	902	(95)	803	(313)
	Med. risk	4,050	596	(103)	593	(91)	459	(258)
	High risk	1,572	-610	(66)	-565	(60)	-1,370	(238)
Cost ($US)	Low risk	3,517	223	(80)	283	(77)	-47	(249)
	Med. risk	3,168	50	(80)	52	(70)	-279	(212)
	High risk	1,260	-600	(51)	-558	(49)	-1,220	(202)
Profit ($US)	Low risk	1,300	595	(36)	618	(33)	851	(121)
	Med. risk	882	546	(36)	541	(34)	738	(90)
	High risk	313	-11	(22)	-7	(18)	-150	(83)
Controls								
Dealer fixed effects					yes		yes	
Calendar month dummies					yes		yes	
Applicant characteristics					yes		yes	
Local indicators * risk category							yes	

All regressions are based on equation (7), where D is a post-period dummy and y is on the left column. Only the estimated beta coefficients are reported. Individual characteristics include monthly income, debt-to-income ratio, and residual monthly income. Standard errors (clustered by dealer) in parentheses.

Table IV(b): The Effect of Credit Scoring (Buyer level analysis)

			(1)		(2)		(3)	
		Pre-period Average	Est. Change	Std. Err.	Est. Change	Std. Err.	Est. Change	Std. Err.
Sample: All buyers								
Price ($US)	Low risk	8,703	1,125	(56)	1,107	(52)	1,068	(108)
	Med. risk	8,391	911	(52)	900	(48)	697	(104)
	High risk	7,851	653	(61)	621	(54)	175	(148)
Default (pct.)	Low risk	61.9	-2.5	(0.9)	-2.8	(0.9)	-7.3	(3.4)
	Med. risk	68.4	-4.5	(0.7)	-4.4	(0.6)	-8.8	(2.6)
	High risk	70.4	-8.0	(0.9)	-7.2	(1.1)	-10.9	(3.4)
Down payment ($US)	Low risk	762	234	(16)	229	(15)	351	(48)
	Med. risk	725	269	(13)	261	(12)	362	(48)
	High risk	746	309	(20)	307	(18)	394	(53)
Loan payments ($US)	Low risk	6,912	952	(70)	969	(71)	1,277	(288)
	Med. risk	5,979	934	(47)	909	(43)	1,128	(218)
	High risk	5,319	1,021	(101)	890	(108)	826	(295)
Recovery ($US)	Low risk	710	306	(23)	297	(22)	348	(80)
	Med. risk	709	217	(23)	217	(21)	205	(69)
	High risk	620	59	(25)	76	(22)	1	(86)
Gross ($US)	Low risk	8,400	1,490	(67)	1,493	(68)	1,939	(268)
	Med. risk	7,424	1,421	(43)	1,388	(40)	1,659	(209)
	High risk	6,695	1,389	(92)	1,272	(101)	1,192	(286)
Cost ($US)	Low risk	6,134	431	(37)	416	(36)	509	(84)
	Med. risk	5,807	319	(39)	301	(34)	290	(82)
	High risk	5,364	184	(49)	150	(41)	-84	(114)
Profit ($US)	Low risk	2,267	1,059	(60)	1,077	(59)	1,430	(248)
	Med. risk	1,617	1,102	(48)	1,087	(43)	1,369	(200)
	High risk	1,331	1,205	(87)	1,122	(89)	1,277	(258)
Sample: Defaulters only								
Recovery (per default)	Low risk	1,146	564	(26)	557	(26)	787	(102)
	Med. risk	1,036	413	(26)	409	(24)	514	(81)
	High risk	881	207	(31)	214	(26)	213	(105)
Controls								
Dealer fixed effects					yes		yes	
Calendar month dummies					yes		yes	
Applicant characteristics					yes		yes	
Local indicators * risk category							yes	

All regressions are based on equation (7), where D is a post-period dummy and y is on the left column. Only the estimated beta coefficients are reported. Individual characteristics include monthly income, debt-to-income ratio, and residual monthly income. Standard errors (clustered by dealer) in parentheses.

Table IV(c): The Effect of Credit Scoring (Buyer level analysis; Rate of return)

			(1)		(2)		(3)	
		Pre-period Average	Est. Change	Std. Err.	Est. Change	Std. Err.	Est. Change	Std. Err.
Sample: All buyers								
Down payment/cost (pct.)	Low risk	12.5	2.9	(0.3)	2.8	(0.2)	4.1	(0.8)
	Med. risk	12.6	3.9	(0.2)	3.9	(0.2)	5.2	(0.8)
	High risk	14.0	5.6	(0.4)	5.6	(0.4)	7.6	(1.0)
Loan payments/cost (pct.)	Low risk	113.8	7.4	(1.1)	8.0	(1.0)	10.8	(4.5)
	Med. risk	104.1	10.2	(1.1)	10.1	(0.9)	13.2	(3.7)
	High risk	100.3	15.8	(1.9)	14.4	(1.8)	16.5	(5.0)
Recovery/cost (pct.)	Low risk	11.5	3.8	(0.3)	3.7	(0.3)	4.0	(1.2)
	Med. risk	12.1	2.8	(0.3)	2.8	(0.3)	2.2	(1.0)
	High risk	11.4	0.6	(0.4)	0.9	(0.4)	-0.9	(1.3)
Gross/cost (pct.)	Low risk	138.1	14.0	(1.0)	14.4	(0.9)	18.4	(4.1)
	Med. risk	129.0	16.9	(0.9)	16.8	(0.8)	20.0	(3.5)
	High risk	125.9	21.9	(1.7)	20.9	(1.6)	22.9	(4.6)
Profit/cost (pct.)	Low risk	38.1	14.0	(1.0)	14.4	(0.9)	18.4	(4.1)
	Med. risk	29.0	16.9	(0.9)	16.8	(0.8)	20.0	(3.5)
	High risk	25.9	21.9	(1.7)	20.9	(1.6)	22.9	(4.6)
Sample: Defaulters only								
Recovery/cost (pct.)	Low risk	18.6	7.1	(0.4)	7.1	(0.4)	9.7	(1.4)
	Med. risk	17.7	5.6	(0.3)	5.6	(0.3)	6.4	(1.1)
	High risk	16.3	3.1	(0.5)	3.2	(0.4)	2.2	(1.5)
Controls								
Dealer fixed effects					yes		yes	
Calendar month dummies					yes		yes	
Applicant characteristics					yes		yes	
Local indicators * risk category							yes	

All regressions are based on equation (7), where D is a post-period dummy and y is on the left column. Only the estimated beta coefficients are reported. Individual characteristics include monthly income, debt-to-income ratio, and residual monthly income. Standard errors (clustered by dealer) in parentheses.

Table V(a): Summary Statistics for High Pre-period Profit Dealers

	Predicted Grade: Low Risk			Predicted Grade: Medium Risk			Predicted Grade: High Risk		
	Pre	**Post**	**Change**	**Pre**	**Post**	**Change**	**Pre**	**Post**	**Change**
Applicant characteristics									
Number of applicants*	*N=0.075*	*N=0.060*		*N=0.124*	*N=0.106*		*N=0.128*	*N=0.114*	
Applicant demographics									
Monthy income	3,569	3,696	127	2,142	2,158	16	1,536	1,644	108
Residual monthly income after debt payments	2,781	3,016	235	1,579	1,665	86	1,249	1,492	243
Debt-to-income ratio	0.27	0.24	-0.03	0.30	0.29	-0.01	0.23	0.20	-0.02
Car purchased	0.61	0.59	-0.02	0.60	0.58	-0.03	0.29	0.15	-0.14
Local economic indicators									
Local unemployment rate: prior 6 months	0.042	0.052	0.010	0.040	0.050	0.011	0.039	0.050	0.011
Local unemployment rate: following 12 months	0.042	0.057	0.015	0.040	0.056	0.016	0.039	0.055	0.017
Local housing price change: prior 2 quarters vs. year earlier	0.065	0.090	0.026	0.062	0.086	0.025	0.059	0.084	0.025
Local housing price change: following 4 quarters vs. year earlier	0.075	0.104	0.029	0.072	0.098	0.026	0.069	0.095	0.026
Transaction characteristics									
Number of buyers*	*N=0.046*	*N=0.035*		*N=0.075*	*N=0.062*		*N=0.038*	*N=0.017*	
Buyer characteristics									
Monthy income	3,466	3,551	86	2,073	2,047	-26	1,447	1,392	-54
Residual monthly income after debt payments	2,675	2,851	176	1,498	1,530	32	1,031	1,335	303
Debt-to-income ratio	0.29	0.27	-0.02	0.33	0.32	0.00	0.34	0.36	0.02
Car characteristics									
Car cost	5,219	5,585	366	4,848	5,190	342	4,438	4,583	145
Car age (years)	6.6	5.6	-1.0	6.8	5.7	-1.1	7.1	5.9	-1.1
Odometer	89,685	83,366	-6,319	88,713	82,663	-6,050	87,249	81,527	-5,721
Inventory age (days)	63	65	3	66	75	8	71	77	7
Lot age (days)	34	38	4	38	47	9	43	50	8
Purchase Characteristics									
Sale price	8,647	9,685	1,039	8,277	9,194	917	7,736	8,396	660
Down payment	743	970	227	686	976	291	700	1,008	308
Loan term (months)	34.1	37.9	3.7	33.7	37.2	3.5	33.5	36.5	3.0
APR	0.296	0.295	-0.001	0.296	0.294	-0.002	0.295	0.290	-0.005
Monthly equivalent payment	391	385	-6	369	367	-2	339	333	-6
Loan performance									
Outcomes									
Default	0.58	0.57	-0.01	0.63	0.61	-0.03	0.66	0.59	-0.07
Fraction of payments made	0.66	0.65	-0.02	0.61	0.61	0.00	0.59	0.62	0.04
Loan payments excluding down payment	7,307	8,182	876	6,445	7,297	852	5,698	6,630	932
Recovery amount (all sales)	604	916	312	576	831	256	509	589	80
Recovery amount (all defaults)	1,044	1,610	566	909	1,373	464	769	1,002	233
Components of Profits									
Gross operating revenue	8,671	10,083	1,412	7,720	9,114	1,394	6,924	8,243	1,320
Total cost	6,083	6,497	414	5,638	6,043	405	5,168	5,385	216
Net operating revenue	2,588	3,586	999	2,082	3,071	989	1,755	2,858	1,103

Notes: Includes dealers in top third by pre-period net operating revenue per applicant. See notes to Table I for sample size and variable definitions.

Table V(b): Summary Statistics for Low Pre-period Profit Dealers

	Predicted Grade: Low Risk			Predicted Grade: Medium Risk			Predicted Grade: High Risk		
	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change
Applicant characteristics									
Number of applicants*	*N=0.071*	*N=0.059*		*N=0.138*	*N=0.115*		*N=0.137*	*N=0.122*	
Applicant demographics									
Monthy income	3,492	3,588	96	2,135	2,149	15	1,564	1,653	89
Residual monthly income after debt payments	2,750	2,905	155	1,575	1,634	59	1,279	1,485	206
Debt-to-income ratio	0.25	0.24	-0.01	0.29	0.29	0.00	0.21	0.20	-0.02
Car purchased	0.51	0.55	0.03	0.46	0.48	0.01	0.17	0.09	-0.08
Local economic indicators									
Local unemployment rate: prior 6 months	0.034	0.052	0.018	0.034	0.052	0.018	0.034	0.051	0.017
Local unemployment rate: following 12 months	0.037	0.060	0.023	0.037	0.060	0.023	0.037	0.059	0.022
Local housing price change: prior 2 quarters vs. year earlier	0.065	0.071	0.007	0.064	0.072	0.008	0.063	0.071	0.009
Local housing price change: following 4 quarters vs. year earlier	0.074	0.062	-0.011	0.072	0.063	-0.009	0.071	0.062	-0.009
Transaction characteristics									
Number of buyers*	*N=0.036*	*N=0.032*		*N=0.064*	*N=0.055*		*N=0.023*	*N=0.011*	
Buyer characteristics									
Monthy income	3,390	3,400	10	2,005	2,017	12	1,469	1,388	-81
Residual monthly income after debt payments	2,626	2,683	57	1,398	1,453	55	1,049	1,374	325
Debt-to-income ratio	0.28	0.28	0.00	0.34	0.34	0.00	0.33	0.37	0.04
Car characteristics									
Car cost	5,204	5,598	394	4,992	5,193	201	4,662	4,815	152
Car age (years)	6.2	5.3	-0.8	6.1	5.6	-0.5	6.3	5.8	-0.5
Odometer	88,544	80,496	-8,048	87,440	81,367	-6,073	86,146	82,235	-3,911
Inventory age (days)	67	66	-1	71	78	7	81	97	17
Lot age (days)	38	36	-2	43	46	3	51	64	13
Purchase Characteristics									
Sale price	8,830	10,178	1,347	8,598	9,593	995	8,086	8,705	619
Down payment	769	1,001	232	745	1,004	259	795	1,056	262
Loan term (months)	34.6	36.9	2.4	34.7	36.4	1.7	35.1	35.8	0.7
APR	0.270	0.260	-0.010	0.270	0.264	-0.006	0.272	0.273	0.001
Monthly equivalent payment	368	393	25	356	375	19	327	344	17
Loan performance									
Outcomes									
Default	0.65	0.62	-0.03	0.73	0.67	-0.06	0.74	0.65	-0.10
Fraction of payments made	0.59	0.60	0.01	0.51	0.55	0.04	0.49	0.57	0.08
Loan payments excluding down payment	6,508	7,596	1,088	5,522	6,610	1,088	4,950	6,138	1,188
Recovery amount (all sales)	760	1,095	335	808	984	176	722	702	-20
Recovery amount (all defaults)	1,168	1,773	606	1,109	1,465	356	974	1,088	114
Components of Profits									
Gross operating revenue	8,057	9,708	1,651	7,086	8,609	1,522	6,472	7,901	1,429
Total cost	6,072	6,558	485	5,832	6,115	283	5,466	5,661	196
Net operating revenue	1,984	3,150	1,165	1,254	2,493	1,239	1,006	2,239	1,233

Notes: Includes dealers in bottom third by pre-period net operating revenue per applicant. See notes to Table I for sample size and variable definitions.

Table A.I: Results from risk prediction model

A. Results based on an orderd probit model

Monthly income Decile	*Debt-to-income ratio (pct.) Decile* 1 <10.3	2 10.3-14.2	3 14.2-17	4 17-20	5 20-23.5	6 23.5-27.5	7 27.5-31.8	8 31.8-36.4	9 36.4-41.8	10 >41.8
1 (<1,350)	High	High	Medium	High	High	High	High	High	High	High
2 (1,350-1,500)	High	High	High	High	High	High	High	High	High	Medium
3 (1,500-1,663)	High	Medium	High	High	High	High	High	High	Medium	Medium
4 (1,663-1,800)	High	High	High	High	High	High	High	Medium	Medium	Medium
5 (1,800-2,000)	Medium	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Medium
6 (2,000-2,200)	High	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Low
7 (2,200-2,500)	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Low	Medium
8 (2,500-2,837)	High	Medium	Medium	Medium	Medium	Medium	Low	Low	Low	Low
9 (2,837-3,464)	Medium	Medium	Medium	Low	Low	Low	Low	Low	Low	Low
10 (>3,464)	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low

B. Results based on the full model

Monthly income Decile	*Debt-to-income ratio (pct.) Decile* 1 <10.3	2 10.3-14.2	3 14.2-17	4 17-20	5 20-23.5	6 23.5-27.5	7 27.5-31.8	8 31.8-36.4	9 36.4-41.8	10 >41.8
1 (<1,350)	High	High	High	High	High	High	High	High	High	High
2 (1,350-1,500)	High	High	High	High	High	High	High	High	High	High
3 (1,500-1,663)	High	High	High	High	High	High	High	High	Medium	Medium
4 (1,663-1,800)	High	High	High	High	High	Medium	Medium	Medium	Medium	Medium
5 (1,800-2,000)	High	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Medium
6 (2,000-2,200)	High	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Medium
7 (2,200-2,500)	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Low	Low
8 (2,500-2,837)	High	Medium	Medium	Medium	Medium	Medium	Low	Low	Low	Low
9 (2,837-3,464)	Medium	Medium	Medium	Low	Low	Low	Low	Low	Low	Low
10 (>3,464)	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low

Legend:

- Predicted Low Risk
- Predicted Medium Risk
- Predicted High Risk