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The impact of credit scoring on consumer lending

Liran Einav*

Mark Jenkins**

and

Jonathan Levin*

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.

1. Introduction

■ Over the last two decades, consumer lending has become increasingly sophisticated as lenders have moved from traditional interview-based underwriting to a reliance on data-driven models to assess and price credit risk. This article presents a snapshot of this transition. We describe the magnitude and channels by which the adoption of credit scoring affected loan originations, repayment and defaults, and profitability at a large auto finance company. Although the study, by design, is focused on a single company, and its experience surely has idiosyncrasies, we suspect that many of our findings may be illustrative of similar transitions at other companies, which taken together have revolutionized markets for consumer credit.

As late as the early 1990s, most lenders were still using a single "house rate" and relied on interview procedures to screen borrowers (Johnson, 1992). As data storage and computing costs

*Stanford University and NBER; leinav@stanford.edu, jdlevin@stanford.edu.
**University of Pennsylvania; mjenk@wharton.upenn.edu.
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fell, and underwriting technology improved, lenders increasingly began to use estimates of default risk to price individual loans. Today, automated credit scoring has become a standard input into the pricing of mortgages, auto loans, and unsecured credit. Using data from the Survey of Consumer Finances, Edelberg (2006) documents the extent of this transformation. She finds that as a result the correlation between loan pricing and estimated and realized default risk has sharply increased. Grodzicki (2012) documents a similar pattern in the credit card industry and ties it specifically to lenders' investments in information technology. Other articles provide related although more indirect evidence of these effects in the context of small business lending by banks (Frame, Srinivasan, and Woosley, 2001; Petersen and Rajan, 2002; Akhavein, Frame, and White, 2005).

These studies rely either on aggregated data or survey measures of realized loans that allow us to see how the correlation of interest rates and default risk has increased over time. However, whereas the near-universal adoption of credit scoring techniques indicates their value to lenders, there is relatively little specific evidence on *exactly* how the benefits are realized, the size of the effects, and their organizational impacts. By focusing more narrowly, we are able to complement existing studies by using detailed applicant- and loan-level data to identify the specific channels by which credit scoring impacts loan originations and outcomes, as well as the magnitude of these effects.

We begin in Section 2 by describing the setting of our case study. The data come from an auto finance company that specializes in the low-income, high-risk consumer market. The market 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 value from stratifying borrowers can be seen in the fact that the top third of borrowers in terms of predicted risk are about 20 percentage points more likely to default than the bottom third.

Until 2001, the company relied on uniform loan pricing and traditional interviews to screen borrowers. The company then contracted with an external credit scoring company that used credit bureau reports and historical data from the company to provide estimates of default risk that could be used to price loans. Starting in June 2001, the company shifted to a centralized risk-based pricing regime, in which new loan applicants were assigned a credit score, and the score determined the minimum down payment required for purchase and the set of cars for which financing would be available. Our empirical analysis in this article focuses on describing the *short-run* effects of this change, using applicant-level and loan-level data about loans originated a year before and a year after the date when credit scoring was implemented.

In Section 3, we present and calibrate a stylized two-period model, which helps guide our subsequent empirical approach. The model illustrates two distinct responses that result from being able to classify applicants as higher or lower risk. When faced with a high-risk applicant, the lender optimally increases the down payment and reduces the quality of the car, and thus the loan amount. Both effects lead to a fall in the probability of sale and a rise in the repayment rate. When faced with a lower-risk applicant, the lender optimally lowers the down payment and raises car quality, increasing the probability of sale and the amount of credit extended. In each case, the profit per loan and overall expected profit increase. These results motivate us to focus on the heterogeneous effect of credit scoring across applicant pools of different risks.

In Section 4, we present the empirical analysis. 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 these metrics, both on aggregate and for the stratified groups, before and after the advent of credit scoring. Finally, we translate the 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 find that the adoption of credit scoring, and the changes it enabled in lending increased profits by roughly 1,000 dollars per loan. The effect is substantial: at the time, the average loan principal was around 9,000 dollars. We also analyze an alternative measure of profitability, the profit (or "net revenue") per loan applicant. After the adoption of credit scoring, loan originations fell, but the profit per applicant still increased, from $751 to $1,070, or by roughly 42%.

Consistent with the theoretical model, we 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. High-risk applicants saw their required down payment increase by more than 25%, creating a higher hurdle to obtain financing. Close rates for this group fell notably, and also default rates, consistent with the idea that higher-risk borrowers were screened out by the higher down payment requirement. Translating this into dollar terms, we find that improved loan repayment was largely responsible for what we measure to be about a 1,200 dollar increase in profit per high-risk loan.

We estimate a similar increase in profitability for lower-risk loans, but the mechanism is different. Required down payments and close rates changed little for lower-risk applicants. Instead, consistent with the model, we observe that car quality and average loan sizes increased substantially. Default rates did not change much, and hence the larger loans had a substantial profit impact due to the high interest rates charged in this setting. For lower-risk loans, the increased "size" of each investment is largely responsible for the dollar increase in profit. Hence, the two channels through which credit scoring theoretically increases profitability in the model both appear to be operative and substantial in the data.

A useful feature of the episode we study is that most salient features of the lending environment, such as advertising, car pricing, sales force 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. At the same time, concerns about identification can be raised for any before-and-after study, and given that we compare outcomes before and after a single change in company policy, we cannot rule out definitively that there was some underlying confounding change in the environment. A variety of robustness checks, however, support the interpretation we have outlined. In particular, we show that the inclusion of controls for applicant quality and local economic conditions has little effect on any qualitative conclusions one might draw. Our conclusions about the effects of down payment requirements and loan sizes are also consistent with results in Adams, Einav, and Levin (2009) and Einav, Jenkins, and Levin (2012), which use data from the same lender but rely on more recent data and a different identification strategy that relies on sharp changes in pricing schedules for different groups of loan applicants.

The last section examines 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., 2005). 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.[1] 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 companywide guidelines. Although almost all dealerships became more profitable, the relative 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.

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

2. Data and environment

□ **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, which would put him at around the 33rd percentile in the United States (Current Population Survey, 2001). Almost a third of the applicants had no bank account, and only 14% owned their own home. A large majority of loan applicants had a FICO score below 600, which is the 35th percentile in the U.S. population and would not qualify for a prime mortgage. 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% of their debt. This type of credit history makes it highly unlikely the applicants in our data could obtain a standard "prime" auto loan.

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 40% 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 mile range. The average sale price is 8,000 or 9,000 dollars, which represents a notable markup over the dealer cost (see Table 1). Buyers are required to make a down payment but usually finance about 90% 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 are high, reflecting the risk of the borrower pool. Annual interest rates average close to 30% in our sample.

A central feature of the market is that consumers tend to be tightly cash constrained. In earlier work, we use abrupt changes in the pricing schedule to estimate demand elasticities (Adams, Einav, and Levin, 2009). A striking finding was that every hundred dollar increase in the minimum down payment reduces the purchase probability of an applicant by two to three percentage points. Moreover, more than 40% 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 how 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 1, defaults during the repayment period are common and tend to occur relatively early in the repayment period. About 35% of loans default during the first year of repayment. Less than 40% are repaid in full.[2] 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, 2010). The average recovery in our sample was around 1,200 dollars, or around 25% of the original dealer cost of the car prior to the transaction.[3]

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

[2] 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.

[3] 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 (2010) for more details.

TABLE 1 Summary Statistics

	January–December 2000				July 2001–June 2002			
	Mean	Standard Deviation	5%	95%	Mean	Standard Deviation	5%	95%
Applicant characteristics		$N = 1.00$				$N = 0.88$		
Applicant demographics								
Monthly income	2,214	973	1,204	4,000	2,256	975	1,238	4,000
Residual monthly income	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			
Transaction characteristics		$N = 0.43$				$N = 0.32$		
Buyer characteristics								
Monthly income	2,319	973	1,300	4,088	2,410	984	1,360	4,286
Residual monthly income	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 (miles)	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 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 (all sales)	691	951	0	2,530	923	1,216	0	3,224
Recovery (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

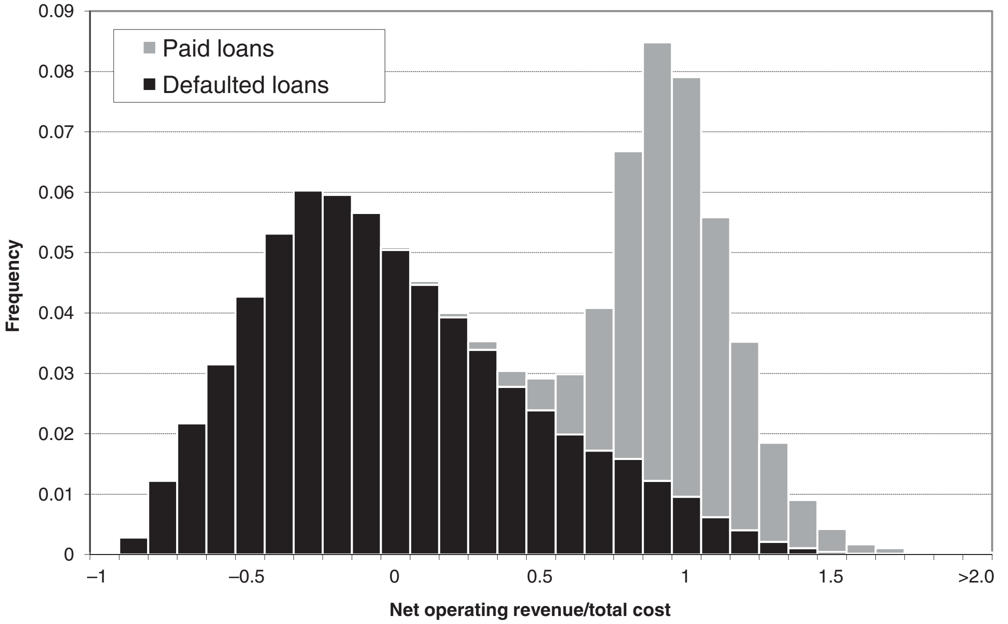
Note: Residual monthly income = Residual monthly income after debt payments. To preserve confidentiality of the company that provided the data, the number of observations is normalized by the number of applicant in year 2000, N ($N >> 10{,}000$). Loan payments, recovery amount, gross operating revenue are in present value (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.

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 10% discount rate, which seems to be in line with industry standards. Neither the calculation here nor similar calculations later in the article are very sensitive to using a somewhat higher or lower number.[4] We then divided the present value of borrower payments by the dealer cost of the car, providing an 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 creditworthy applicants from those who are relatively more likely to default.

[4] Specifically, we ran all the analyses using discount rates of 5% and 15%, and the results hardly change.

FIGURE 1

DISTRIBUTION OF PER-LOAN RATE OF RETURN



Note: Net operating profits = down payment + PV of loan payments + PV of recoveries − total cost. The histogram uses all observations used in the subsequent analysis, pooling the preperiod and postperiod (see Table 1).

□ **Implementation of credit scoring.** The lender we study adopted credit scoring toward the end of June 2001.[5] 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.

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%, respectively).

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,

[5] 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. Developing, testing, and implementing the idea has taken several years.

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.

A natural question is why the company uses its own scoring algorithm rather than a potentially cheaper metric available from the credit bureaus. One view 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, whereas 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.[6]

□ **Data.** We focus our analysis on the precredit scoring period from January 2000 through December 2000, and the postscoring period from July 2001 to June 2002. We drop the first half of 2001, when the company adopted a simple income cutoff to set minimum down payments in anticipation of credit scoring.[7] Finally, we include applications and sales data only from dealerships for which we have complete data for both the pre- and postscoring periods.[8]

We compare full-year periods rather than shorter pre- and postwindows 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 rather than a very narrow window.[9]

On the other hand, one reason to focus on a single year rather than longer run effects 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.[10] 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 1. Applicant characteristics are similar before and after credit scoring went into effect. This stability is a feature of our focus on the relatively short run effect of credit scoring. The advent of credit scoring may affect the population of applicants over longer periods, perhaps through reputation or word of mouth.

A qualification is that the number (but not the composition) of loan applicants was somewhat lower in the year after credit scoring, only 88% of the number in the year before scoring.[11] We are not aware of notable changes in the competitive environment, but a possible explanation is

[6] 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, as the credit product is less standard and/or the customer base is less representative of the general population.

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

[8] In Adams, Einav, and Levin (2009) and Einav, Jenkins, and Levin (2012), we use data from the postscoring period, allowing us to expand the number of dealerships, applicants, and borrowers in the postperiod by roughly 50% relative to the (already large amount of) data we use here.

[9] 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.

[10] 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.

[11] Note that to preserve the company's confidentiality, we do not report the exact number of loan applicants in Table 1. 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.

the broader macroeconomy. Economic growth was fairly strong through the first half of 2000 but 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 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 1 shows significant changes in these basic operating metrics between the prescoring and postscoring periods. The fraction of applicants who became buyers (the "close rate") dropped by about 15%, the average quality of cars sold increased (e.g., the average odometer read was 7,000 miles 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 that helps in guiding and interpreting our empirical results. The model illustrates how a lender might use better credit scoring information to increase down payment requirements for higher-risk borrowers and at the same time increase car quality for lower-risk borrowers, and how each of these channels can generate increased profits. The theoretical analysis motivates our empirical strategy, in which we examine the effect of credit scoring separately for higher- and lower-risk borrowers, and focus on different mechanisms for each group.

□ **A model of subprime borrowing.** The model is a simplified version of the one we develop in Einav, Jenkins, and Levin (2012). 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 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 does not 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 censored joint normal distribution, where

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

with $\rho \geq 0$, and $Y_t = \max(Y_t^*, \varepsilon)$ for $t = 1, 2$.[12] 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 modelling 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 markup over cost, $P = C + M$,

[12] We assume ε is a small positive number, specifically $\varepsilon = 0.02$, although the exact choice is not particularly important. As will be clear, in the model customers with low enough amount of cash will not buy the loan in period 1 and will default in period 2, making the distribution of cash at the lower end of the support inconsequential for the customer's optimal decision and for the firm's profits.

and that both the markup M and the interest rate R are given exogenously.[13] 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 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

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

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 rearrange the terms, we see that it is optimal to purchase if

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

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.

□ **Fitting the model to data.** To examine the effect of credit scoring, we calibrate the model to match observed data on purchasing and repayment outcomes in the prescoring 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 prescoring 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% 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 2 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 semielasticity of the close rate with respect to changes in the required down payment (3% per \$100), and the semielasticity of the default rate with respect to changes in loan size (1% 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

[13] 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 markup across cars. Later it moved to a system where more costly cars had higher (dollar) markups. Another simplification in this model is that although many borrowers pay the minimum down payment chosen by the lender, borrowers can choose to pay more up front and some do, although the amounts are never very large relative to the overall loan size.

TABLE 2 Model Calibration

	Actual Value	Model Value	Calibrated Parameter	Calibrated Value
Demand Moment				
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 minimum 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 minimum down without scoring	\$600	\$700	ω	0.35
Optimal car cost without scoring	\$5,500	\$5,000	ψ	1,800

Note: 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_{1L} are the mean repayement 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, 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 the mean of σ_2. In both cases, conditional on matching the prescoring period. The last two rows show two parameters of the lender's profit function: the fraction of the original car cost recovered in the event of default (ω) and the fixed cost of administering a loan (ψ). These parameters are calibrated by matching the lender's observed pricing decisions in the prescoring period.

borrower by shifting the mean of each type's Y_1 distribution, and the probability of default by shifting the mean of Y_2. Lower-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 lower-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 preperiod. 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 prescoring D and (average) C are profit maximizing, assuming the lender cannot distinguish between types.

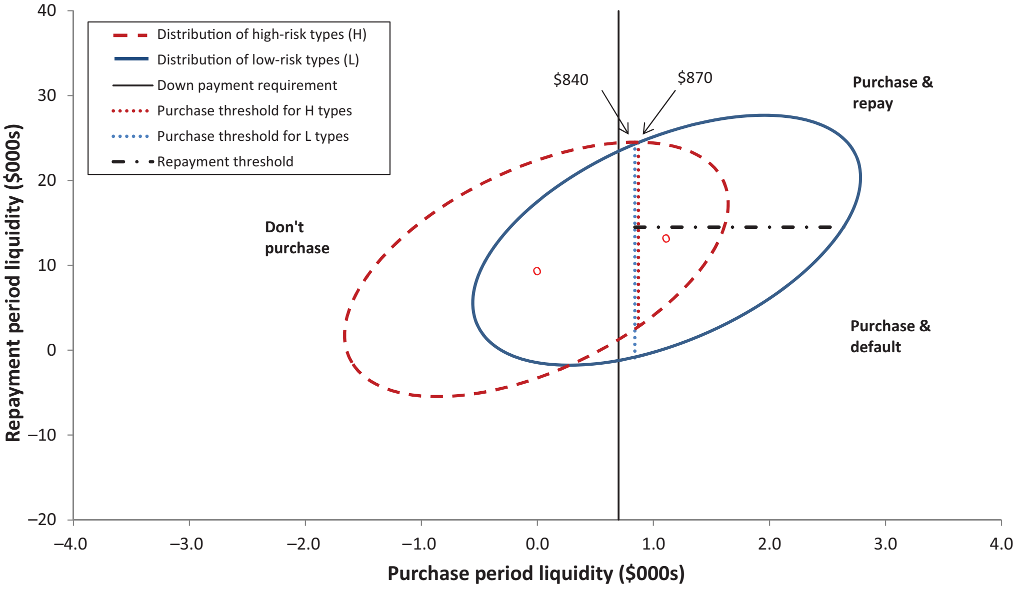
□ **Credit scoring and pricing.** We assume that credit scoring allows the lender to separately identify low- and high-risk borrowers, that is, to observe θ. With no knowledge of types, the lender chooses C and D to maximize profits over the population of applicants, that is,

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

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 $\pi_H(C, D)$.

FIGURE 2

ILLUSTRATION OF CALIBRATED MODEL



Note: 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 isodensity 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, because 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, because full repayment requires that repayment liquidity exceeds the repayment amount. Thresholds for purchase and repayment are shown with dashes.

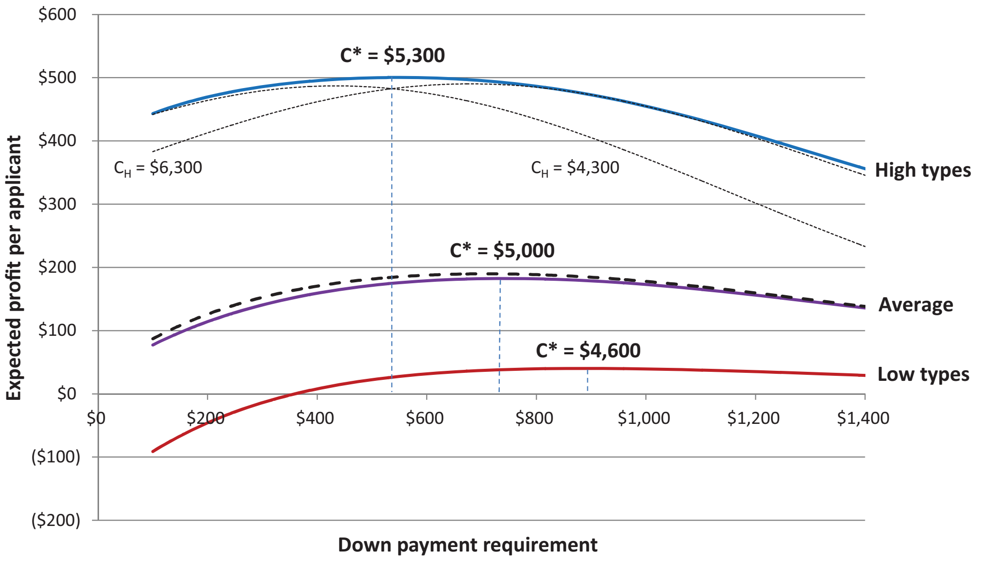
Changes in C and D have multiple effects: on the probability of purchase, the resulting distribution of borrower incomes and the probability of repayment, and on profits directly, holding fixed the applicant's behavior. This makes it hard to obtain general comparative statics predictions about the effects of credit scoring, but with the calibrated model we obtain clear results. From the prescoring 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 lower the down payment for lower 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 lower 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 lead 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.

These theoretical predictions guide our empirical analysis, which examines the effect of credit scoring on higher-and lower-risk applicants separately. Specifically, the model predicts that for high-risk applicants, credit scoring can raise profits by allowing better screening of marginal applicants. In contrast, for lower-risk applicants, credit scoring can raise profits by allowing them

FIGURE 3

OPTIMAL DOWN PAYMENTS BY TYPE



Note: 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 high-risk applicants.

to borrow more. As we will see in the next section, these same mechanisms are observed in our data.

4. Empirical strategy

□ **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 postscoring 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.[14]

[14] We also experimented with several other classification schemes and obtained similar results.

TABLE 3 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						
Monthly income	3,528	2,130	1,557	3,620	2,152	1,646
Residual monthly income	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
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						
Monthly income	3,424	2,042	1,453	3,459	2,032	1,387
Residual monthly income	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 miles	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 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

Note: See notes to Table 1 for sample size and variable definitions.

Table 3 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 postscoring period. Lower-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 prescoring applicants. Relative to this approach, our construction may classify as lower risk some applicants who 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.

□ **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 postperiod), and X_i is a set of controls.

From this model, we can define

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

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

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 postperiod.

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

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

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.

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_rs 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 periods, something we might not expect if there were important local, risk-group specific, unobserved trends.

□ **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).[15] 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 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, 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 4. In Table 4a, we measure profit and its components in dollar terms. In Table 4b, the dependent variables are normalized by the car cost, so they represent rates of return. Each panel has a similar structure. For each outcome of interest, we report in the leftmost column its grade-specific average before credit scoring, and 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 3). 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 12 months of the loan.[16] 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 local changes that might impact close rates or borrower repayment.

□ **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% depending on the exact specification. 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

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

[16] Specifically, we construct 10 variables to capture local economic conditions. Six are related to local unemployment rates: the average level, average change, and standard deviation of (monthly) local unemployment rates in the previous 6 months and subsequent 12 months. The last four variables are the annual changes in the (quarterly) local housing price index and rental price index for the previous 6 months and subsequent 12 months. All these local economic condition variables are measured as deviations from the sample mean of that variable in each month. This is because the effect of a national trend in any variable cannot be separately identified from the effect of credit scoring, which is what we seek to measure.

TABLE 4a The Effect of Credit Scoring (Levels)

			(1)		(2)		(3)	
		Preperiod Average	Estimated Change	Standard Error	Estimated Change	Standard Error	Estimated Change	Standard Error
Sample: all applicants								
Close rate (%)	Low risk	57.3	−0.4	(1.2)	0.7	(1.2)	0.5	(0.4)
	Med. risk	54.5	−2.0	(1.3)	−2.0	(1.1)	−1.9	(0.3)
	High risk	23.5	−11.6	(1.0)	−10.8	(0.9)	−10.8	(0.3)
Profit ($US)	Low risk	1,300	595	(36)	618	(33)	608	(25)
	Med. risk	882	546	(36)	541	(34)	535	(19)
	High risk	313	−11	(22)	−7	(18)	−12	(19)
Sample: all buyers								
Price ($US)	Low risk	8,703	1,125	(56)	1,107	(52)	1,100	(13)
	Med. risk	8,391	911	(52)	900	(48)	892	(10)
	High risk	7,851	653	(61)	621	(54)	620	(20)
Default (%)	Low risk	61.9	−2.5	(0.9)	−2.8	(0.9)	−2.8	(0.7)
	Med. risk	68.4	−4.5	(0.7)	−4.4	(0.6)	−4.3	(0.5)
	High risk	70.4	−8.0	(0.9)	−7.2	(1.1)	−6.9	(1.0)
Down payment ($US)	Low risk	762	234	(16)	229	(15)	232	(6)
	Med. risk	725	269	(13)	261	(12)	262	(5)
	High risk	746	309	(20)	307	(18)	302	(9)
Loan payments ($US)	Low risk	6,912	952	(70)	969	(71)	946	(57)
	Med. risk	5,979	934	(47)	909	(43)	884	(43)
	High risk	5,319	1,021	(101)	890	(108)	837	(83)
Recovery ($US)	Low risk	710	306	(23)	297	(22)	292	(15)
	Med. risk	709	217	(23)	217	(21)	210	(11)
	High risk	620	59	(25)	76	(22)	77	(21)
Gross ($US)	Low risk	8,400	1,490	(67)	1,493	(68)	1,467	(50)
	Med. risk	7,424	1,421	(43)	1,388	(40)	1,356	(38)
	High risk	6,695	1,389	(92)	1,272	(101)	1,215	(73)
Cost ($US)	Low risk	6,134	431	(37)	416	(36)	407	(13)
	Med. risk	5,807	319	(39)	301	(34)	289	(10)
	High risk	5,364	184	(49)	150	(41)	150	(19)
Profit ($US)	Low risk	2,267	1,059	(60)	1,077	(59)	1,061	(49)
	Med. risk	1,617	1,102	(48)	1,087	(43)	1,067	(37)
	High risk	1,331	1,205	(87)	1,122	(89)	1,065	(71)
Sample: defaulters only								
Recovery (per default)	Low risk	1,146	564	(26)	557	(26)	545	(19)
	Med. risk	1,036	413	(26)	409	(24)	393	(14)
	High risk	881	207	(31)	214	(26)	206	(27)
Controls								
Dealer fixed effects					Yes		Yes	
Calendar month dummies					Yes		Yes	
Applicant characteristics					Yes		Yes	
Local indicators∗ risk category							Yes	

Note: All regressions are based on equation (7), where D is postperiod dummy and y is in 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) are in parentheses.

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

TABLE 4b The Effect of Credit Scoring (Rates of return)

			(1)		(2)		(3)	
		Preperiod Average	Estimated Change	Standard Error	Estimated Change	Standard Error	Estimated Change	Standard Error
Sample: all buyers								
Down payment/cost (%)	Low risk	12.5	2.9	(0.3)	2.8	(0.2)	2.9	(0.1)
	Med. risk	12.6	3.9	(0.2)	3.9	(0.2)	3.9	(0.1)
	High risk	14.0	5.6	(0.4)	5.6	(0.4)	5.5	(0.1)
Loan payments/cost (%)	Low risk	113.8	7.4	(1.1)	8.0	(1.0)	7.7	(0.9)
	Med. risk	104.1	10.2	(1.1)	10.1	(0.9)	9.9	(0.7)
	High risk	100.3	15.8	(1.9)	14.4	(1.8)	13.4	(1.4)
Recovery/cost (%)	Low risk	11.5	3.8	(0.3)	3.7	(0.3)	3.6	(0.2)
	Med. risk	12.1	2.8	(0.3)	2.8	(0.3)	2.8	(0.2)
	High risk	11.4	0.6	(0.4)	0.9	(0.4)	1.0	(0.3)
Gross/cost (%)	Low risk	138.1	14.0	(1.0)	14.4	(0.9)	14.2	(0.8)
	Med. risk	129.0	16.9	(0.9)	16.8	(0.8)	16.5	(0.6)
	High risk	125.9	21.9	(1.7)	20.9	(1.6)	19.8	(1.2)
Profit/cost (%)	Low risk	38.1	14.0	(1.0)	14.4	(0.9)	14.2	(0.8)
	Med. risk	29.0	16.9	(0.9)	16.8	(0.8)	16.5	(0.6)
	High risk	25.9	21.9	(1.7)	20.9	(1.6)	19.8	(1.2)
Sample: defaulters only								
Recovery/cost (%)	Low risk	18.6	7.1	(0.4)	7.1	(0.4)	7.0	(0.3)
	Med. risk	17.7	5.6	(0.3)	5.6	(0.3)	5.4	(0.2)
	High risk	16.3	3.1	(0.5)	3.2	(0.4)	3.2	(0.4)
Controls								
Dealer fixed effects					Yes		Yes	
Calendar month dummies					Yes		Yes	
Applicant characteristics					Yes		Yes	
Local indicators∗ risk category							Yes	

Note: All regressions are based on equation (7), where *D* is postperiod dummy and *y* is in 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) are in parentheses.

conclude that profits per applicant increased by 105 dollars per applicant for the highest-risk category.[17] This adjustment also makes the rate of return effects even more dramatic, implying more than a doubling.

□ **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 Table 4. What we want to emphasize is the very different channels through which profits increased for the better and worse risk groups.

The story is apparent for high risks. Before credit scoring, almost one in four applicants in our high-risk category became a buyer; with credit scoring, this was cut by half. 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 4a are consistent with this selection effect. Default

[17] 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).

rates for buyers in the highest-risk category fell from 70% to 62%, 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. 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 4b. Prior to credit scoring, the transaction rate of return was significantly higher for lower-risk buyers than for higher-risk buyers (38% vs. 26%–29%). With the ability to identify these buyers, it was possible to extend them more credit. Table 4a shows the significant increase in car cost for the lower-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 4a. For the lower-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 dollors can therefore be attributed almost entirely to the larger stream of loan payments received on the larger loans, almost 1,000 dollars per buyer, plus a 306 dollar increase in recoveries reflecting the initially higher quality of the cars.

□ **Potential confounding factors.** The preceding discussion focused on the first column of Tables 4a and 4b, 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.[18]

Column (3) of Tables 4a and 4b reports on specifications where we control for local (MSA-level) economic indicators related to unemployment and housing and rental prices (see footnote 16). The results remain qualitatively similar. We estimate an increase in profit per buyer of 1,061 dollars for lower risks and 1,065 dollars for high risks when we include the full set of controls, compared to 1,059 and 1,205 dollars in the baseline specification. The changes in the estimates of the profit components are also small, with nothing in the results leading us to revisit the qualitative interpretations above.

6. Differential effects across dealerships

■ In this final part of the article, 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 although credit scoring improved performance at virtually all dealerships, the

[18] 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 at his current address.

effect was bigger at poorly performing dealerships, leading to a compression in performance across dealerships.

□ **Dealership heterogeneity.** Table 5 presents summary statistics for "high" and "low" -performing dealerships. To construct the table, we rank dealerships by their profit per applicant in the precredit scoring period. Table 5a shows statistics for the top third of dealerships, and Table 5b for the bottom third.

Dealerships in the top third were dramatically more profitable than dealerships in the bottom third, earning about 600–800 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, such as due to better collection or recoveries.

A closer inspection of Table 5 indicates that, indeed, top-performing dealerships had a greater difference between the cars sold to high- and lower-risk borrowers. Although 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 lower-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 $z_\theta^d(C, D)$, 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 lower-risk borrower was in fact lower risk with probability $w_L^d = \lambda^d + (1 - \lambda^d)w_L$. With this parameterization, a value of $\lambda^d = 0$ implies that the dealership has no soft information, whereas $\lambda^d = 1$ 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 difference between the cars they assign to lower-risk and high-risk borrowers. We therefore interpret this difference 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 companywide policies regarding minimum down payment requirement but also

TABLE 5a Summary Statistics for High-Preperiod-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									
Monthly income	3,569	3,696	127	2,142	2,158	16	1,536	1,644	108
Residual monthly income	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
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									
Monthly income	3,466	3,551	86	2,073	2,047	−26	1,447	1,392	−54
Residual monthly income	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 miles	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 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

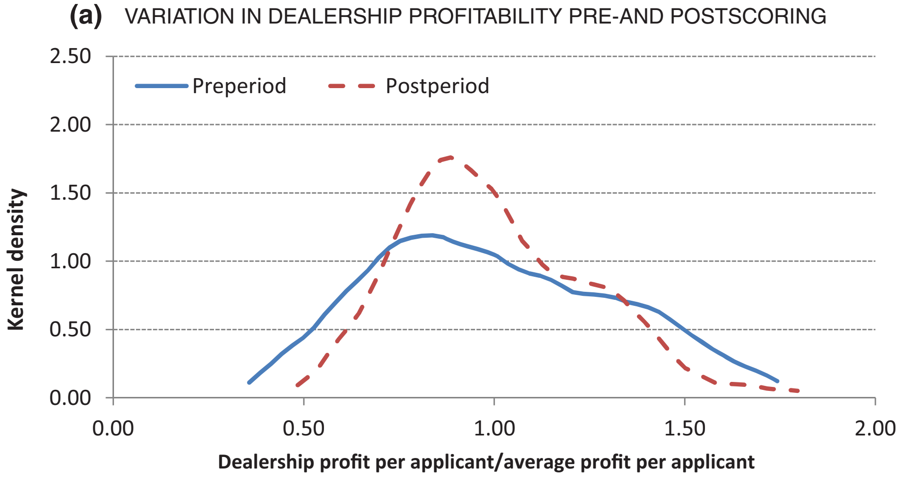
Note: Includes dealers in top third by preperiod net operating revenue per applicant. See notes to Table 1 for sample size and variable definations.

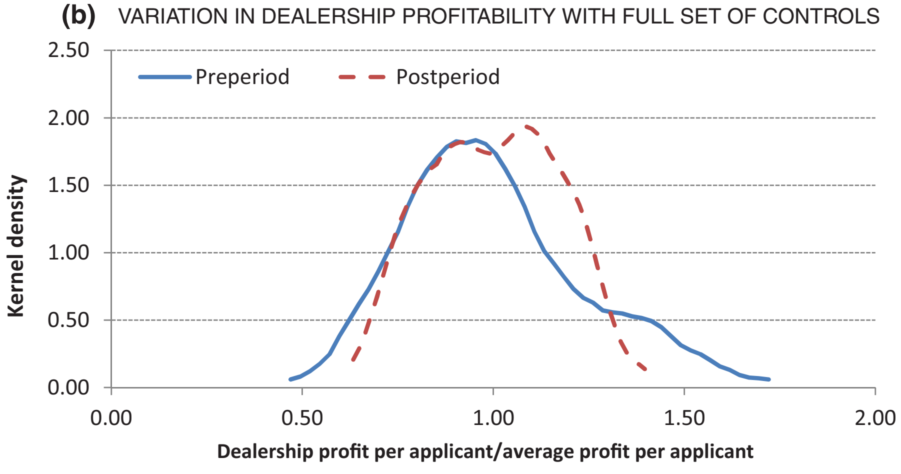
TABLE 5b Summary Statistics for Low-Preperiod-Profit Dealers

	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									
Monthly income	3,492	3,588	96	2,135	2,149	15	1,564	1,653	89
Residual monthly income	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
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									
Monthly income	3,390	3,400	10	2,005	2,017	12	1,469	1,388	−81
Residual monthly income	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 miles	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 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

Note: Includes dealers in bottom third by preperiod net operating revenue per applicant. See notes to Table 1 for sample size and variable definitions.

FIGURE 4





Note: Each of the graphs presents estimates from a regression of the form of equation (13), with profit per applicant as the dependent variable. The preperiod graph plots a kernel density of the estimated alpha divided by the mean alpha across dealerships, and the postperiod graph plots a kernel density of the estimated alpha+beta, also divided by the mean across dealerships. Panel (a) uses no other controls (except credit grade fixed effects), and Panel (b) uses a full set of controls (as in column (3) of Table 4).

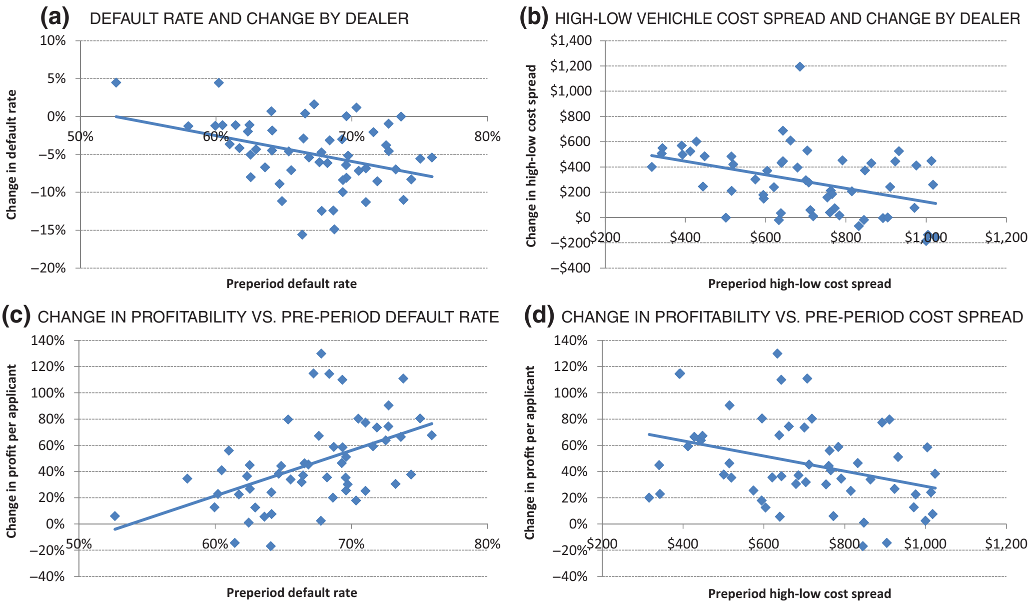
regarding the matching of cars to potential borrowers, where they previously had more discretion. Nevertheless, to the extent that dealerships varied in other dimensions, such as their ability to encourage repayment, profitability need not converge.

□ **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 that takes the value of 1 in the postscoring 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

FIGURE 5



Note: Each point on the charts represents a dealership. The x axes on the upper and lower panels show two measures of preperiod dealership performance: 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 1 for definition) from loans originated in each period, divided by total applications in each period. In all panels, change is postperiod minus preperiod.

always control for credit category. In this specification, the coefficient α_d represents the dealership effect prior to credit scoring, whereas 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 4 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 4). Using either specification, the dealership effects are less dispersed after credit scoring. Without controls, the coefficient of variation of the estimated α_ds is 0.304, and the coefficient of variation of the postscoring dealership effects, the $\alpha_d + \beta_d$s, is 0.237. Dispersion drops by 22%. 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%).

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 $\overline{\beta}$ to be the average of (respectively) the α_ds and the β_ds, so that $\alpha_d/\,\overline{\alpha}$ is the (normalized) profitability of dealership d prior to credit scoring, and $(\alpha_d + \beta_d)/(\overline{\alpha} + \overline{\beta})$ is the (normalized) profitability after credit scoring. Figure 4 plots the distribution of $\alpha_d/\overline{\alpha}$ and $(\alpha_d + \beta_d/(\overline{\alpha} + \overline{\beta}))$, first using the estimates without controls (Panel (a)) and then the estimates with the full set of controls (Panel (b)). 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 5, we sort dealerships based on two prescoring performance measures that plausibly capture dealership differences in the use of soft information prior to credit scoring: the difference between the cars assigned to lower-risk and high-risk borrowers, and the default rate. Panels (a) and (b) show 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 lower-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. Panels (c) and (d) show 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 article, we report detailed results on the adoption of automated credit scoring and the changes it enabled in lending at a large auto finance company. The adoption of 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 credit scoring also allows better customization of contract terms to inframarginal borrowers. A related point is that in our setting the relevant margin of adjustment following the advent of credit scoring was not the interest rate but rather the down payment and maximum loan size, that is, the amount of leverage borrowers were allowed to take on. It has become increasingly clear that this leverage aspect of consumer borrowing, particularly in regard to the subprime market, deserves much more attention than it has generally received.

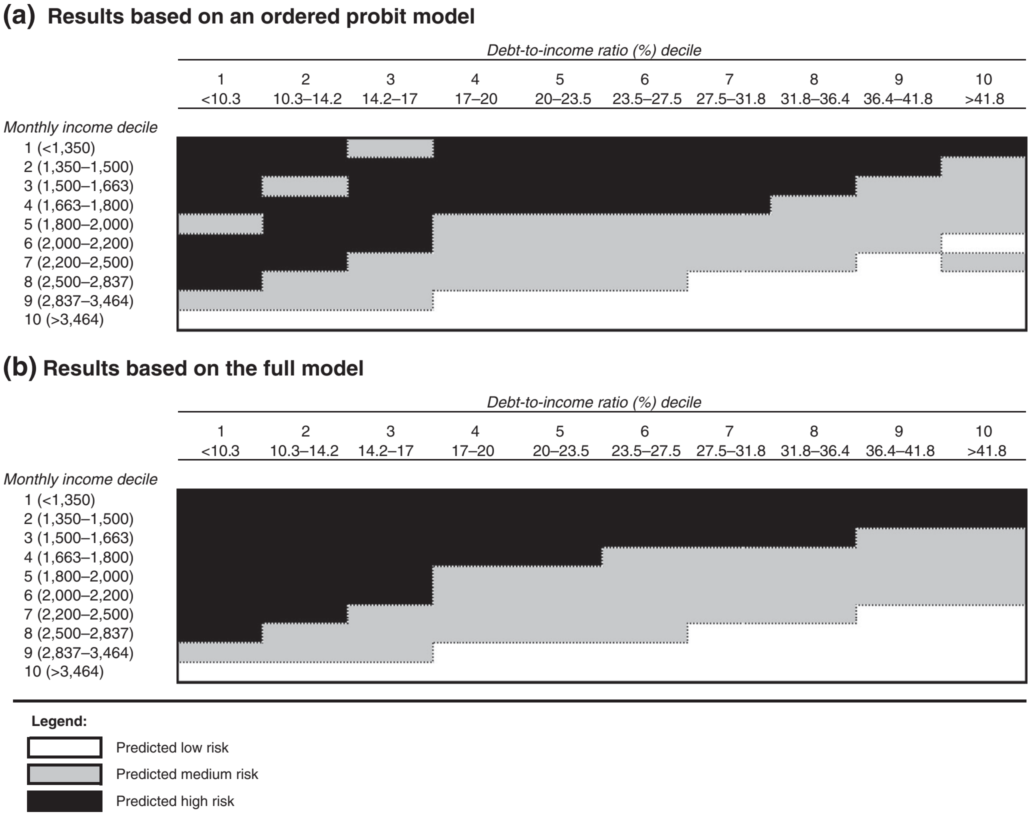
Appendix

In this appendix we provide more details about the construction of the matched applicant pool. Recall that the main challenge arises because the company did not credit score applicants in the preperiod and, moreover, did not collect all the individual characteristics that 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 $f : \mathbb{R}^2_+ \to \{high, medium, low\}$, 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 postcredit scoring period, and in particular the high-/medium-/low-risk category each applicant in the postperiod is classified as (by the company), and run an ordered probit regression of this classification on income and debt-to-income. Because the goal is to predict well, we allow for flexible functional form by generating 10 decile dummies for income and debt-to-income ratio 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 postperiod data (which are 29%, 46%, and 25%, respectively). We then assign each applicant in the preperiod data a credit category based on his or her income and debt-to-income cell. Table A1(a) 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 nonmonotonicities in Table A1(a) 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 individual's actual credit score, and it accurately

TABLE A1 Results from risk prediction model



predicts the fraction in the population of each risk category (as classified by the company in the postperiod). 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 parameterize a loss function over prediction models, so that the optimal prediction model $f(\cdot)$ (within the set of monotone models) minimizes

$$\sigma_1 \sum_i I(s_i \neq f(x_i)) + \sigma_2 \sum_i (I(s_i = L, f(x_i) = H) + I(s_i = H, f(x_i) = L))$$
$$+\,\omega \sum_{j \in \{H,M,L\}} \left| \sum_i I(f(x_i) = j) - \sum_i I(s_i = j) \right|, \tag{A1}$$

where ω, σ_1, and σ_2 are nonnegative 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 article use weights of $\sigma_1 = 1$, $\sigma_2 = 3$, and $\omega = 8$. Table A1b reports its predictions. As one can see, it is similar to the results obtained from the ordered probit model (table A1a), but it imposes monotonicity and is slightly different for some marginal cells.

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