Credit markets: preliminaries

Theory of credit markets is very similar to theory of insurance markets:

- Adverse selection:
    - Insurance: high risk individuals value insurance more, so higher prices or greater coverage disproportionally attract bad risks.
    - Credit: high risk individuals are more willing to take loans, so higher interest rates or larger loans disproportionally attract bad risks.
- Moral hazard:
    - Insurance: more coverage implies less incentive to take precautions, higher risk.
    - Credit: larger loan implies less likely to be able to repay, so higher risk (due to behavioral or "mechanical" reasons; distinction not that important for many questions).
- Thus, most of the theoretical results from insurance carry over to credit, e.g.:
    - Positive correlation between (ex ante) loan size and (ex post) risk.
    - Adverse selection could make markets shrink.
    - Screening risk types is useful.

Important difference:

- Insurance: consumers pay today, get money tomorrow.
- Credit: consumers get money today, pay tomorrow.

Why is this difference important? Various forms of myopic behavior by consumers much more of an issue in credit markets:

- In insurance, myopic behavior implies no/less insurance. This is easy to fix (mandatory insurance), and the effect is somewhat limited due to the behavioral response (more careful behavior).
- In credit, myopic behavior implies over borrowing. This is harder to fix (unless eliminating the market), and the effect is exacerbated due to the behavioral response.

Thus, much more attention in credit markets to possible irrational behavior and various behavioral economics models. In insurance we are worried about adverse selection eliminating markets, here some may think it’s a good thing …

As in insurance, credit markets are attractive for empirical work for exactly the same reasons (rich data, well measured products and choice sets, lots of policy interest/relevance).

"Liquidity Constraints and Imperfect Information in Subprime Lending" by Adams, Einav, and Levin (*AER*, 2009)

- Very rich data from a large auto sales company.
- Show liquidity constraints and imperfect information in the same market, and a simple model that show why they may be connected.
- Try to separately quantify adverse selection and moral hazard (without a pure experiment …).
- Theory on the board (based on Jaffe and Russell, 1976).

Data and Environment

- Large auto sales company in the U.S.
- Purchases used cars at auction and resells (≈100 dealerships).
- Customers are low-income with poor credit histories:
  - Median household income $29,000.
  - More than half have FICO score below 500 (2nd percentile in U.S.).
  - One-third have no bank account.
- Data we use:
  - Applicants (N>>50,000) and sales (about a third of apps) from June 2001 until December 2004.
  - Loans tracked through April 2006.

Description of a typical transaction

Buyer arrives on lot and applies for credit.

- Credit grade determines car and financing offer.

Key offer terms are minimum down and car price.

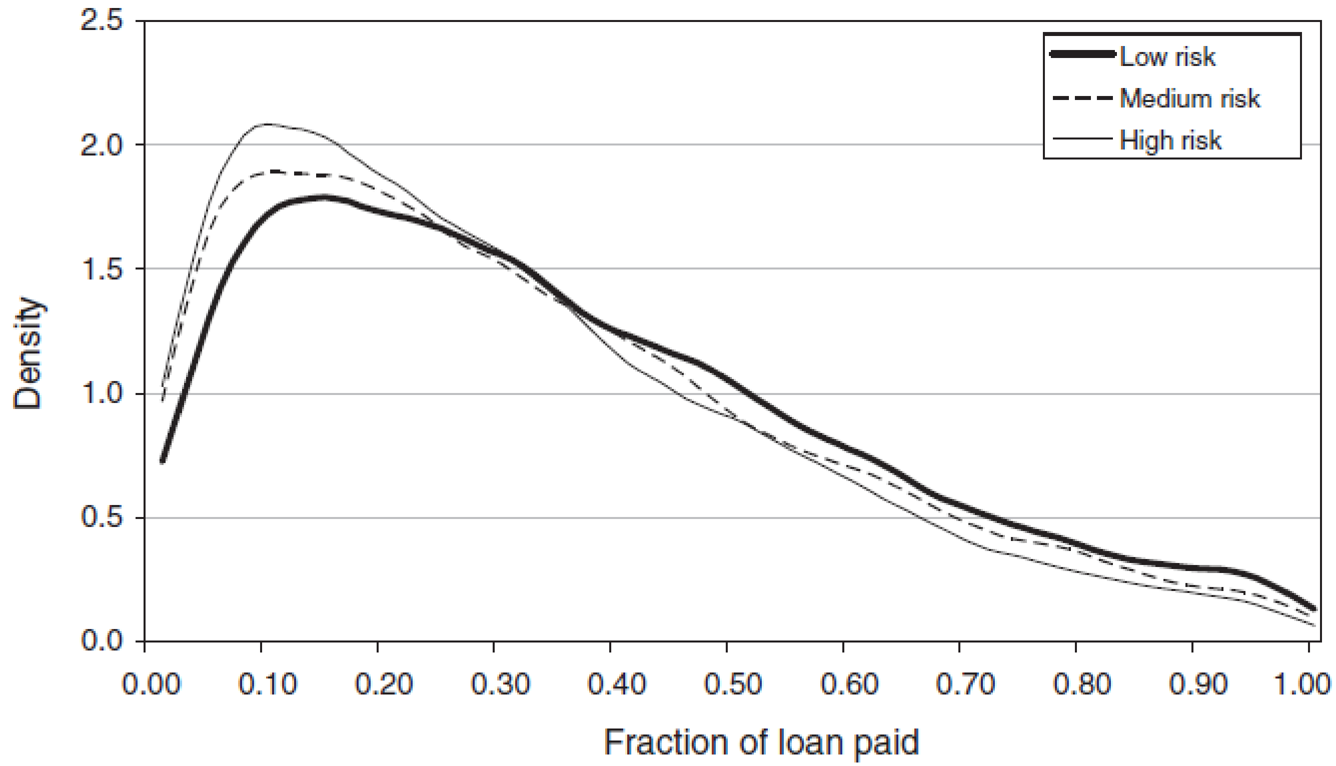
- Minimum down payment ($400-1,500) depends on grade (but not on car).
- Sales prices are negotiated: $9,000-12,000, with car costs of $5,000-7,000.
- Loans tend to be 3-4 years, most at state APR caps (25-30%).
- Unlike regular market, car selection is not a major issue.

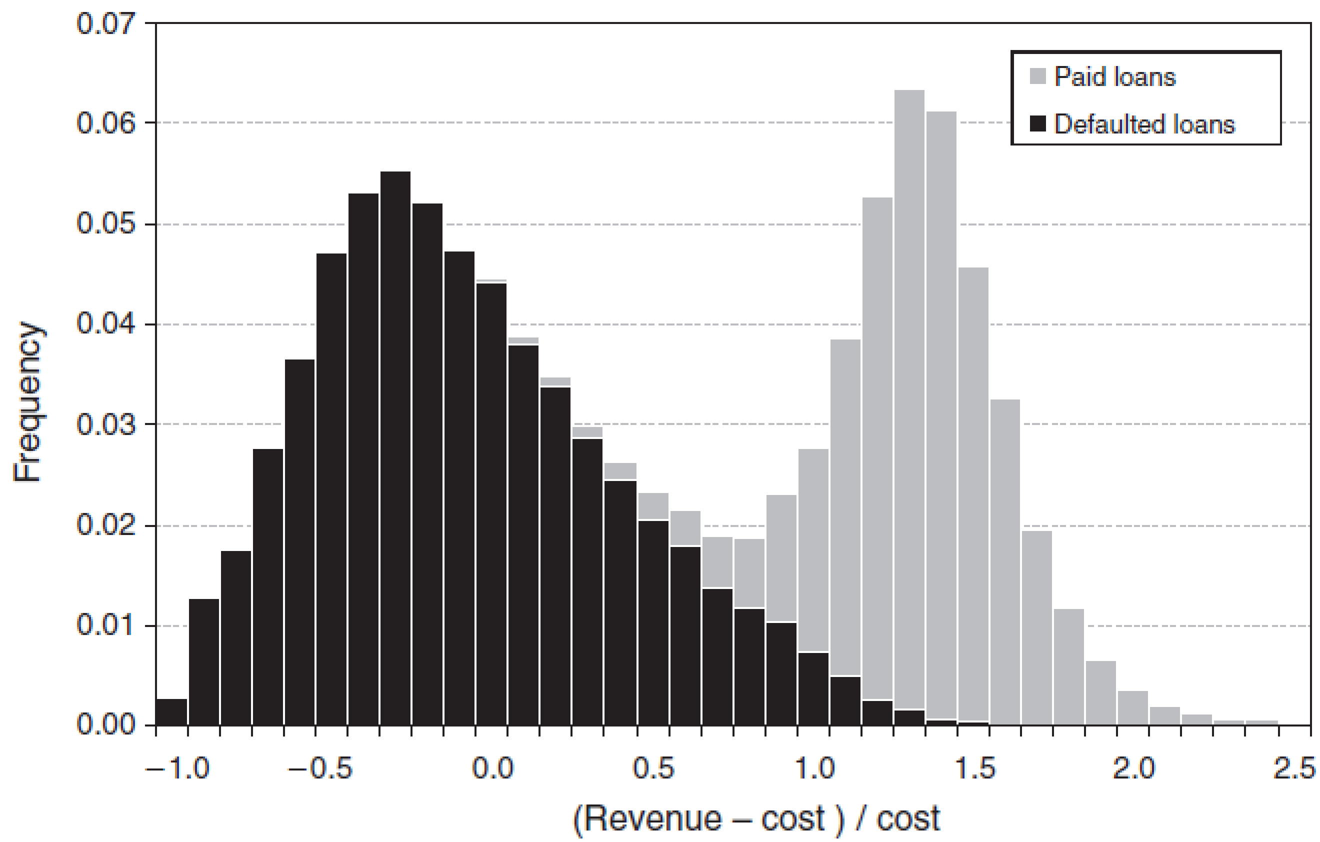
Buyers finance heavily and default often:

- Typical down payment is less than $1,000, with loans of $9,000-12,000.
- Majority of loans, more than 60%, end in (early) default.

TABLE 1—SUMMARY STATISTICS

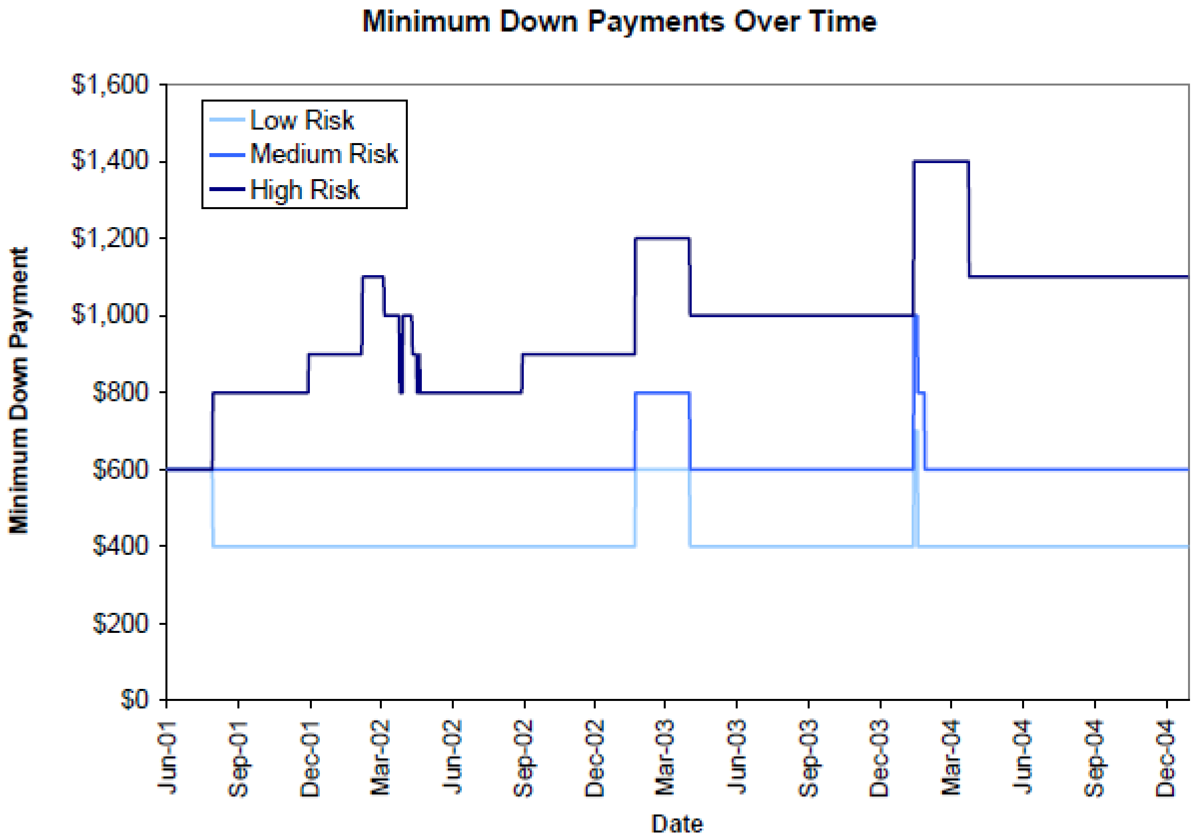
	Number of observations[a]	Mean	Standard deviation	Fifth percentile	Ninety-fifth percentile
Applicant characteristics					
Age	N	32.8	10.7	19	53
Monthly income	N	2,414	1,074	1,299	4,500
House owner	N	0.15	—	—	—
Lives with parents	N	0.18	—	—	—
Bank account	N	0.72	—	—	—
Risk category					
Low	N	0.27	—	—	—
Medium	N	0.45	—	—	—
High	N	0.29	—	—	—
Car purchased	N	0.34	—	—	—
Buyer characteristics					
Age	$0.34N$	34.7	10.8	20	55
Monthly income	$0.34N$	2,557	1,089	1,385	4,677
House owner	$0.34N$	0.17	—	—	—
Lives with parents	$0.34N$	0.16	—	—	—
Bank account	$0.34N$	0.76	—	—	—
Risk category					
Low	$0.34N$	0.35	—	—	—
Medium	$0.34N$	0.47	—	—	—
High	$0.34N$	0.17	—	—	—
Car characteristics					
Acquisition cost	$0.34N$	5,213	1,358	3,205	7,240
Total cost	$0.34N$	6,096	1,372	4,096	8,213
Car age (years)	$0.34N$	4.3	1.9	2	8
Odometer	$0.34N$	68,776	22,091	31,184	102,300
Lot age (days)	$0.34N$	33	44	1	122
Car price	$0.34N$	10,777	1,797	8,095	13,595
Transaction characteristics					
Minimum down payment (applicants)	N	750	335	400	1,400
Minimum down payment (buyers)	$0.34N$	648	276	400	1,200
Interest rate (APR)	$0.34N$	26.2	4.4	17.7	29.9
Loan term (months)	$0.34N$	40.5	3.7	35	45
Down payment	$0.34N$	963	602	400	2,000
Loan amount	$0.34N$	10,740	1,802	7,982	13,560
Monthly payment	$0.34N$	395	49	314	471
Default (uncensored observations only)	$0.13N$	0.61	—	—	—
Recovery amount (uncensored defaults)	$0.08N$	1,382	1,386	0	3,784

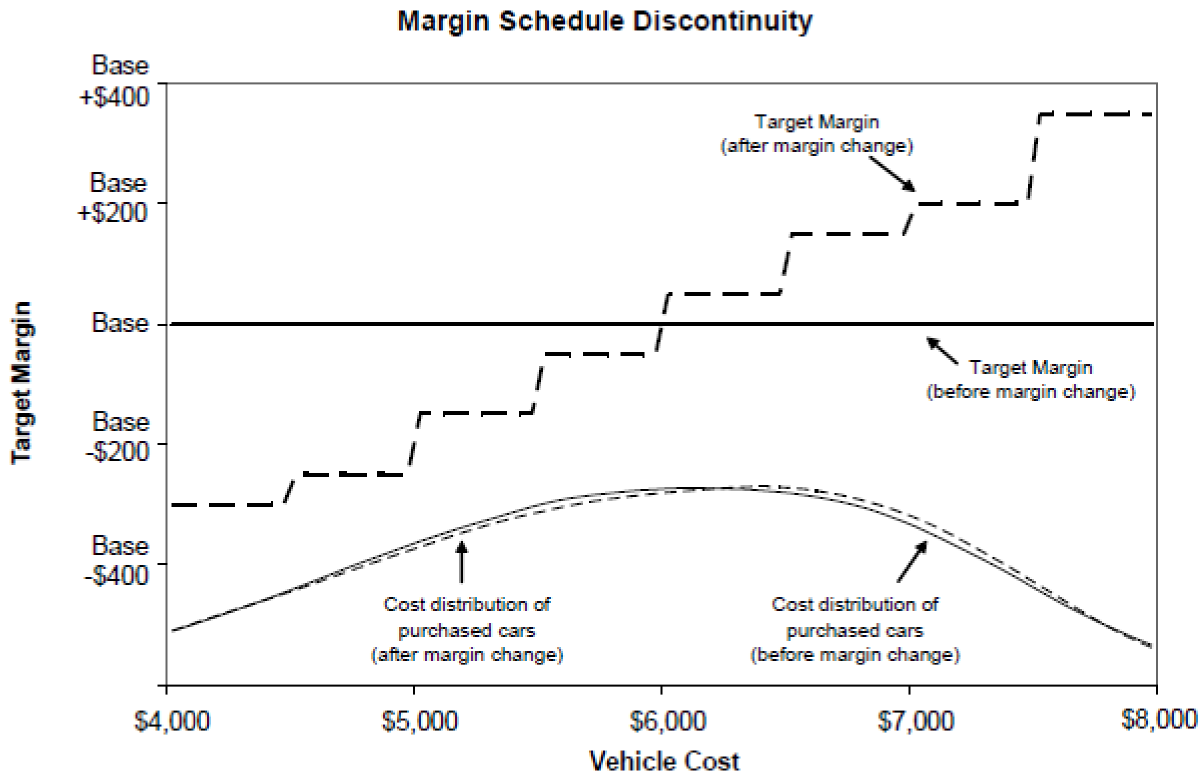

Low risk
Medium risk
High risk
Density
2.5
2.0
1.5
1.0
0.5
0.0
0.00
0.10
0.20
0.30
0.40
0.50
0.60
0.70
0.80
0.90
1.00
Fraction of loan paid


0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Frequency
Paid loans
Defaulted loans
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
(Revenue – cost) / cost

Identification

- Two key variables throughout: minimum down payment and car price.
- Minimum down payment:
  - More than 20 discrete changes, of $100-500 for a subset of grades:
    * Regression discontinuity (RD) identification around the changes.
    * "Differences-in-differences" identification across grades.
  - Also observe the finer credit score, and use RD given the discontinuous minimum down payment schedule across grades.
- Car price:
  - Sale price likely endogenous, so instrument with "list price."
  - List price is a function of total cost (which is a regressor everywhere) and margin. Use variation in margin schedule:
    * RD around two major changes in margin schedule during obs. period.
    * RD in car cost: margins change in discrete jumps as a function of costs.
  - RD in credit score, controlling for grade, also useful.


Minimum Down Payments Over Time
Low Risk
Medium Risk
High Risk
$1,600
$1,400
$1,200
$1,000
$800
$600
$400
$200
$0
Minimum Down Payment
Jun-01
Sep-01
Dec-01
Mar-02
Jun-02
Sep-02
Dec-02
Mar-03
Jun-03
Sep-03
Dec-03
Mar-04
Jun-04
Sep-04
Dec-04
Date



Margin Schedule Discontinuity
Base +$400
Base +$200
Base
Base -$200
Base -$400
Target Margin
Target Margin (after margin change)
Target Margin (before margin change)
Cost distribution of purchased cars (after margin change)
Cost distribution of purchased cars (before margin change)
$4,000
$5,000
$6,000
$7,000
$8,000
Vehicle Cost

Evidence of liquidity constraints I: drivers of demand

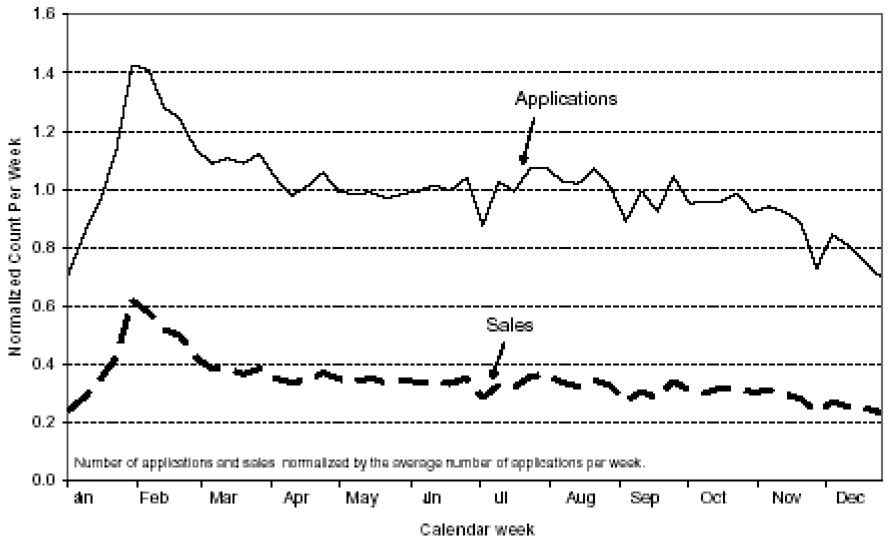
- Probit model of purchase decision for applicants.
- Look at sensitivity of demand to immediate and deferred payments, i.e. minimum down payment and car price.
- Without liquidity constraints, total payment is what matters:
  - E[PV of Payments]=Down+φ(Price-Down)
  - Calculate assuming rational expectation of default.
  - With 5-50% annual discount rate, $100 increase in down is the same as $30-108 increase in price.

- Demand very sensitive to minimum down: $100↑ ⇒ demand 9%↓.
- $900 price increase (≈ $50/month) would generate same effect.
- Implied annual discount rate: 427%.

TABLE 2—PURCHASING ESTIMATES

	Probit estimates of individual-level purchasing (Dep. var. = sale indicator)				Cell-level estimates (Dep. var. = log(sales))	
	dF/dx (1)	*dF/dx* (2)[a]	*dF/dx* (3)[b]	*dF/dx* (4)[c]	Coef. (5)[d]	Coef. (6)[e]
Offer variables						
Negotiated price ($100s)	−0.0002 (0.0002)	−0.0010 (0.0011)	−0.0022 (0.0007)	−0.0032 (0.0006)	−0.0061 (0.0016)	−0.0102 (0.0063)
Minimum down ($100s)	−0.0301 (0.0006)	−0.0299 (0.0006)	−0.0298 (0.0006)	−0.0303 (0.0006)	−0.0895 (0.0039)	−0.0889 (0.0039)
Maximum interest rate (APR)	−0.0010 (0.0004)	−0.0013 (0.0006)	−0.0016 (0.0005)	0.0003 (0.0006)	−0.0033 (0.0033)	−0.0049 (0.0041)
Term (months)	−0.0008 (0.0004)	−0.0002 (0.0008)	0.0006 (0.0006)	0.0025 (0.0006)	−0.0001 (0.0025)	0.0021 (0.0044)
Car characteristics						
Car cost ($100s)	0.0005 (0.0002)	0.0014 (0.0012)	0.0025 (0.0007)	0.0034 (0.0006)	0.0071 (0.0018)	0.0113 (0.0067)
Premium (cost > $7,500)	0.0040 (0.0032)	0.0038 (0.0035)	0.0036 (0.0034)	0.0006 (0.0035)	0.0990 (0.0376)	0.0966 (0.0379)
Car age (years)	0.0008 (0.0007)	0.0008 (0.0006)	0.0008 (0.0006)	−0.0001 (0.0006)	0.0086 (0.0067)	0.0088 (0.0066)
Odometer (10,000s)	−0.0008 (0.0004)	−0.0008 (0.0004)	−0.0008 (0.0004)	−0.0008 (0.0004)	−0.0139 (0.0042)	−0.0144 (0.0041)
Lot age (months)	−0.0019 (0.0007)	−0.0034 (0.0022)	−0.0055 (0.0015)	−0.0071 (0.0010)	−0.0232 (0.0068)	−0.0308 (0.0133)
Individual characteristics						
Income ($1,000s/month)	0.0245 (0.0008)	0.0250 (0.0010)	0.0258 (0.0008)	0.0284 (0.0009)	0.0983 (0.0060)	0.1014 (0.0075)
Age	0.0084 (0.0003)	0.0084 (0.0003)	0.0085 (0.0003)	0.0082 (0.0003)	0.0732 (0.0053)	0.0747 (0.0056)
Age squared	−0.0001 (3.7E−06)	−0.0001 (3.7E−06)	−0.0001 (3.8E−06)	−0.0001 (3.8E−06)	−0.0008 (6.7E−05)	−0.0008 (7.2E−05)
Bank account	0.0271 (0.0014)	0.0270 (0.0014)	0.0269 (0.0014)	0.0281 (0.0014)	−0.0010 (0.0296)	−0.0019 (0.0296)
House owner	−0.0320 (0.0018)	−0.0321 (0.0018)	−0.0321 (0.0018)	−0.0408 (0.0016)	−0.0171 (0.0367)	−0.0192 (0.0367)
Lives with parents	0.0091 (0.0021)	0.0090 (0.0021)	0.0089 (0.0021)	0.0097 (0.0021)	0.0391 (0.0387)	0.0339 (0.0379)
Credit category fixed effects[e]						
Representative low risk	0.0269 (0.0070)	0.0264 (0.0070)	0.0256 (0.0070)	0.0239 (0.0070)	0.1333 (0.0517)	0.1304 (0.0519)
Representative medium risk	0.0394 (0.0063)	0.0397 (0.0063)	0.0402 (0.0063)	0.0381 (0.0064)	0.2974 (0.0434)	0.2975 (0.0435)
Representative high risk	0.0043 (0.0050)	0.0045 (0.0050)	0.0048 (0.0050)	0.0038 (0.0051)	0.0489 (0.0494)	0.0524 (0.0493)
Month fixed effects[e]						
February (tax season)	0.1603 (0.0044)	0.1594 (0.0047)	0.1581 (0.0045)	0.1592 (0.0044)	0.5900 (0.0190)	0.5862 (0.0199)
Other fixed effects	Year, month, city, credit category	Year, month, city, credit category	Year, month, city, credit category	Year, month, credit category	Year, month, city, credit category	Year, month, city, credit category
Instrument for price	—	List price	Cost bucket dummies	State dummies	—	List price

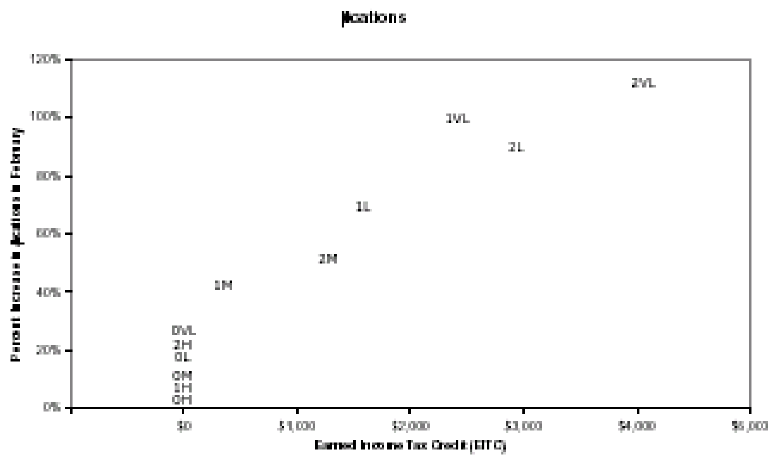
Evidence of liquidity constraints II: seasonality



- Demand spikes dramatically during "tax season."
  - Spike occurs despite higher minimum down payments.
  - Spike occurs in cash sales but not in trade-ins.

Evidence of liquidity constraints II: EITC

- Tax rebates can be large, up to $4,500 due to EITC.
- Create 12 categories of consumers based on EITC schedule (function of income and dependents). Look at % spike by category.



Identifying causes of liquidity constraints

- Why would poor consumers be liquidity constrained?
  - See graphs below
- Want to test for moral hazard and/or adverse selection problems in the loan market that might give rise to market failure
- How to test? Moral hazard and adverse selection both imply a positive correlation between loan size and default.
  - Moral hazard: larger loan leads to higher default risk
  - Adverse selection: higher default risks take larger loans
- "Easy" to test for the joint effect, but harder to test/quantify these forces separately:
  - Must separate how default rates correlate with loan size "within person" (MH) and across people (MH+AS).
  - Ideal experiment:
    - Randomize loan size to measure MH.
    - Allow choice of loan size to measure MH+AS.

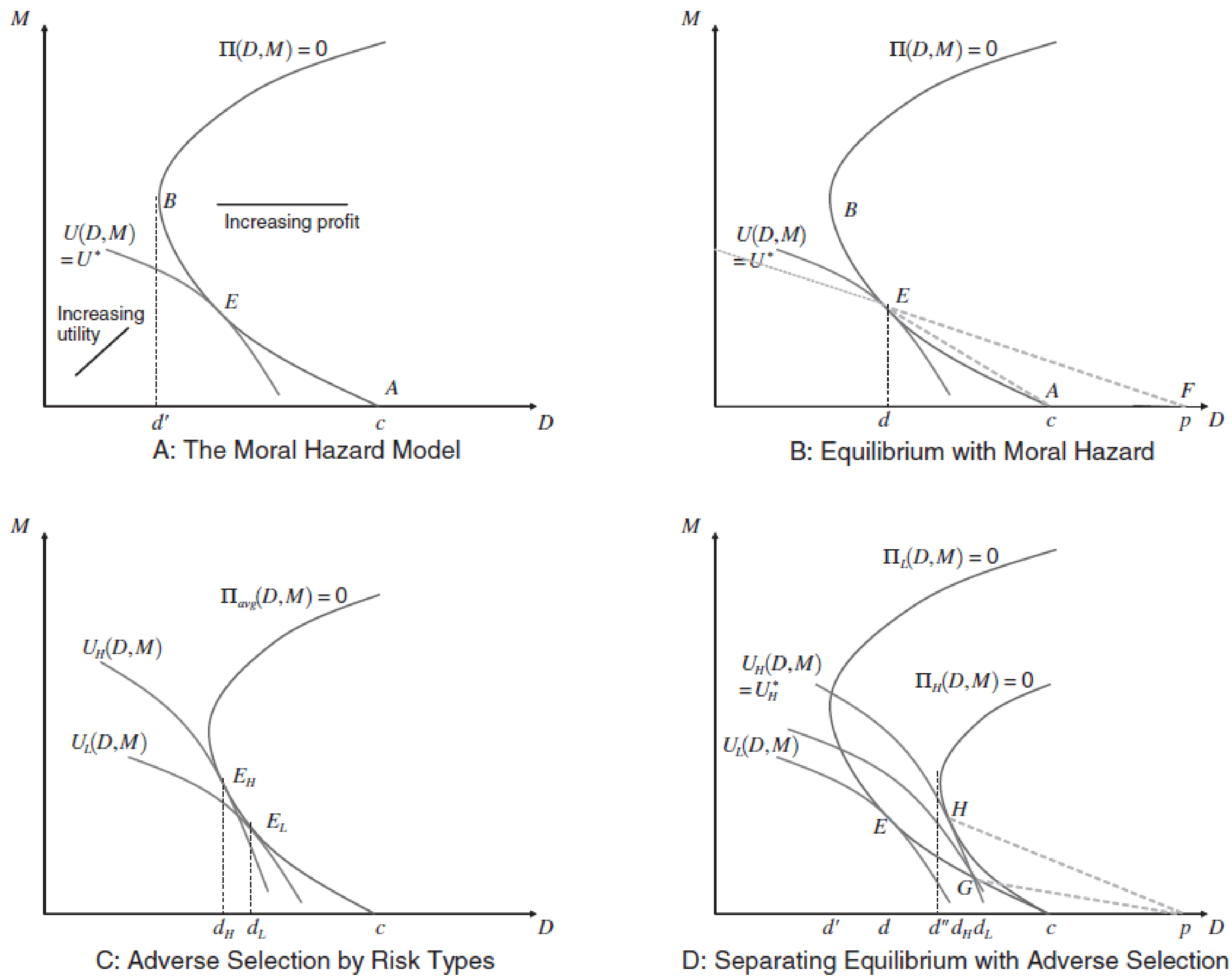


FIGURE 4. THEORY

Identifying moral hazard using a model of default

- Starting point: Cox hazard model of default:

$$h(t|x_i)=exp(x_i'\delta)h_0(t)$$

- Goal: identify (MH) effect of loan size $L=P-D$ on default.
- Problem: direct estimate will be confounded if there are unobservables that affect both default and down payment (i.e. coefficient will measure MH+AS, not MH)
- Solution: jointly model and estimate down payment (using tobit):

$$D_i = \begin{cases} D_i^* = x_i'\beta + \varepsilon_i & \text{if } D_i^* \geq d_i \\ d_i & \text{if } D_i^* < d_i \end{cases}$$

- Intuition for identification: down payment model allows us to "observe" unobservable drivers of down payment (as the measured residual) and control for them in the default model (as in a "control function" approach).

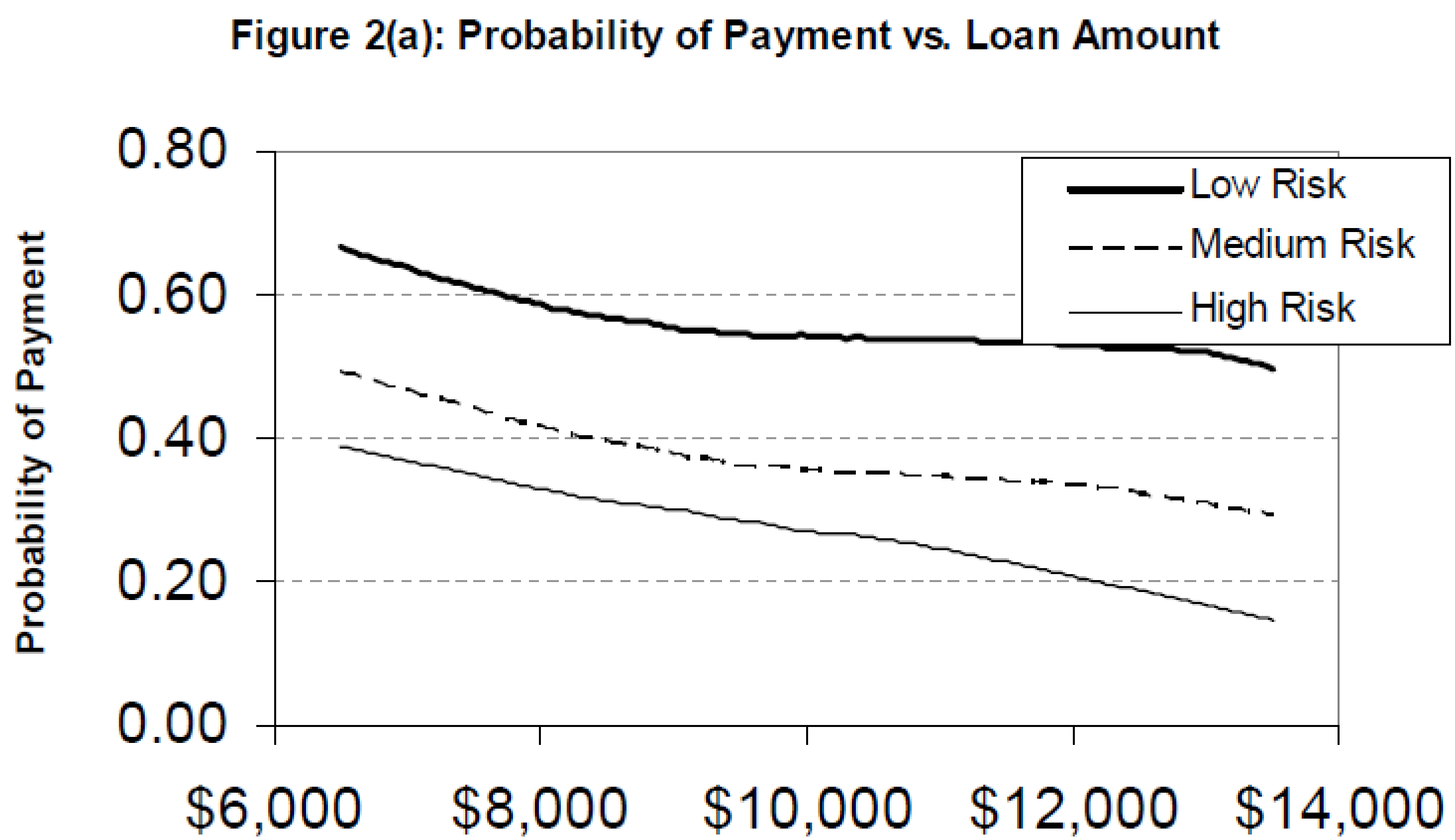


Figure 2(a): Probability of Payment vs. Loan Amount
Probability of Payment
0.80
0.60
0.40
0.20
0.00
$6,000
$8,000
$10,000
$12,000
$14,000
Low Risk
Medium Risk
High Risk

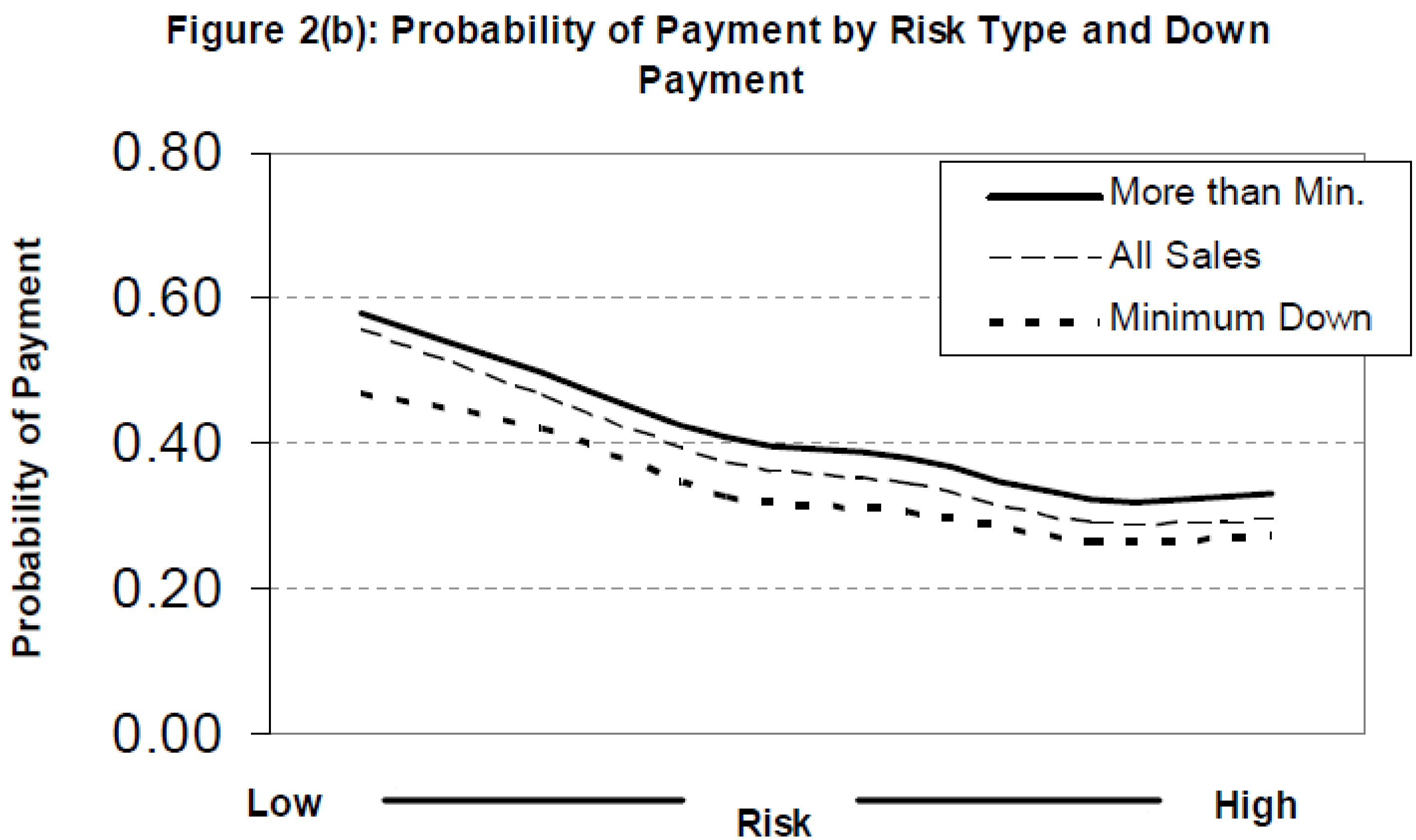


Figure 2(b): Probability of Payment by Risk Type and Down Payment
0.80
0.60
0.40
0.20
0.00
Probability of Payment
More than Min.
All Sales
Minimum Down
Low
Risk
High

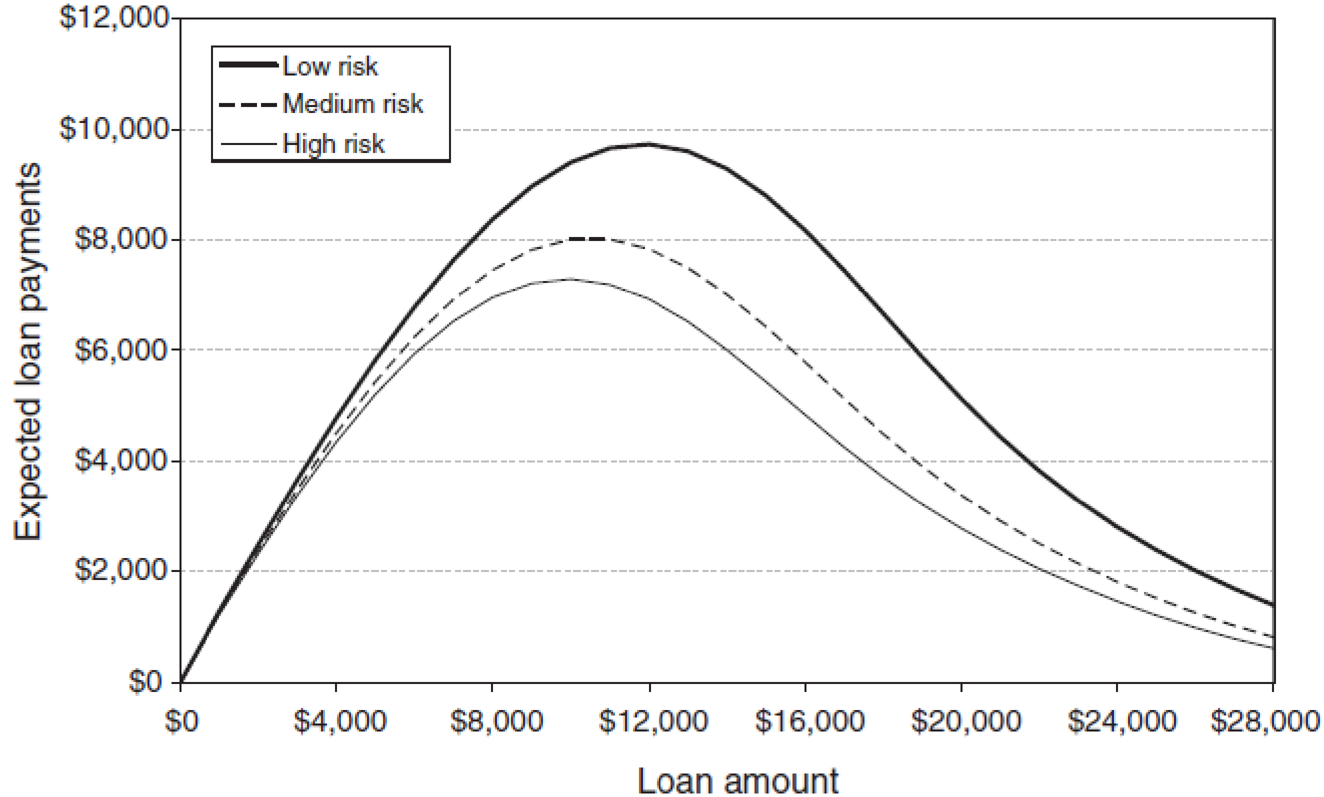
TABLE 3—TOBIT ESTIMATES OF DOWN PAYMENT
(Dependent variable: Down payment ($100s) conditional on purchase)

	Coefficient	Standard error	Coefficient	Standard error
	(1)		(2)[a]	
Offer variables				
Negotiated price ($100s)	0.049	(0.004)	0.177	(0.002)
Maximum interest rate (APR)	0.203	(0.011)	0.242	(0.013)
Term (months)	−0.413	(0.009)	−0.503	(0.018)
Car characteristics				
Car cost ($100s)	0.228	(0.004)	0.100	(0.002)
Premium (cost > $7,500)	3.769	(0.078)	3.759	(0.079)
Car age (years)	0.061	(0.016)	0.065	(0.016)
Odometer (10,000s)	−0.026	(0.012)	−0.022	(0.012)
Lot age (months)	−0.559	(0.016)	−0.331	(0.044)
Individual characteristics				
Income ($1,000s/month)	−0.164	(0.019)	−0.260	(0.026)
Age	−0.169	(0.001)	−0.186	(0.010)
Age squared	0.002	(1E−04)	0.002	(1E−04)
Bank account	0.202	(0.046)	0.235	(0.047)
House owner	0.226	(0.055)	0.241	(0.055)
Lives with parents	0.264	(0.055)	0.266	(0.056)
Credit category fixed effects				
Representative low risk	4.734	(0.119)	4.961	(0.126)
Representative medium risk	3.215	(0.107)	3.270	(0.108)
Representative high risk	0.718	(0.119)	0.733	(0.120)
Month fixed effects				
February (tax season)	3.171	(0.098)	3.259	(0.162)
Other fixed effects	Year, month, city, credit category		Year, month, city, credit category	
Instrument for price[a]	—		List price	

TABLE 4—PROPORTIONAL HAZARD MODEL ESTIMATES OF DEFAULT
(Dependent variable: Fraction of loan payments made)

	Hazard rate (1)	Standard error (1)	Hazard rate (2)	Standard error (2)	Hazard rate (3)	Standard error (3)	Hazard rate (4)	Standard error (4)
Transaction characteristics								
Amount financed ($100s)	1.016	(0.001)	1.024	(0.001)	1.023	(0.001)	1.019	(0.000)
Maximum interest rate (APR)	1.022	(0.002)	1.026	(0.002)	1.025	(0.002)	1.022	(0.002)
Term (months)	1.015	(0.002)	1.006	(0.002)	1.008	(0.002)	1.008	(0.002)
Down payment residual ($100s)	0.982	(0.001)	—	—	—	—	—	—
Car characteristics								
Car cost ($100s)	0.981	(0.001)	0.975	(0.001)	0.974	(0.001)	0.976	(0.001)
Premium (cost > $7,500)	0.867	(0.015)	0.888	(0.015)	0.887	(0.015)	0.819	(0.014)
Car age (years)	1.028	(0.003)	1.028	(0.003)	1.027	(0.003)	1.021	(0.003)
Odometer (10,000s)	1.012	(0.002)	1.012	(0.002)	1.012	(0.002)	1.015	(0.002)
Lot age (months)	1.055	(0.003)	1.065	(0.003)	1.067	(0.003)	1.062	(0.003)
Individual characteristics								
Income ($1,000s/month)	0.955	(0.004)	0.948	(0.004)	—	—	—	—
Age	0.996	(0.002)	0.993	(0.002)	—	—	—	—
Age squared	1.000	(2E−05)	1.000	(7E−03)	—	—	—	—
Bank account	0.818	(0.007)	0.823	(0.007)	—	—	—	—
House owner	0.998	(0.011)	1.004	(0.011)	—	—	—	—
Lives with parents	1.059	(0.011)	1.060	(0.011)	—	—	—	—
Credit category fixed effects								
Representative low risk	0.518	(0.011)	0.509	(0.011)	0.461	(0.009)	—	—
Representative medium risk	0.801	(0.013)	0.789	(0.013)	0.748	(0.012)	—	—
Representative high risk	0.994	(0.018)	0.990	(0.018)	0.963	(0.017)	—	—
Month fixed effects								
February (tax season)	1.071	(0.022)	1.090	(0.022)	0.973	(0.023)	—	—
Other fixed effects	Year, month, city, credit category		Year, month, city, credit category		Year, month, city, credit category		Year, month, city, credit category	

Expected revenues as a function of loan size



Effect is hump-shaped, as in Jaffee and Russell (1976).

"Contract Pricing in Consumer Credit Markets" by Einav, Jenkins, and Levin (*Econometrica*, 2012)

- Same data, but focus on the supply side (pricing)
- Essentially same analysis, except that we now estimate all the equations together in a single model

Pricing in contract markets

- Population of buyers with individual characteristics $\zeta \sim F(\cdot)$.
- Seller offers contract terms ϕ (assume a single contract is offered).
- Buyer purchases if $g(\phi,\zeta) > 0$, transaction outcome is $y(\phi,\zeta)$, resulting in net revenue $r(\phi,y)$.
- Quantity sold is:

$$Q(\phi) = \int \mathbf{1}\{g(\phi,\zeta) \geq 0\} dF(\zeta)$$

- Firm's problem is:

$$\max_{\phi} \Pi(\phi) = Q(\phi)\mathbb{E}\left[r\left(\phi, y(\phi,\zeta)\right) \mid g\left(\phi,\zeta\right) \geq 0\right]$$

- f.o.c:

$$\begin{aligned} \frac{\partial \Pi(\phi)}{\partial \phi} &= \frac{\partial Q(\phi)}{\partial \phi}\mathbb{E}\left[r\left(\phi, y(\phi,\zeta)\right) \mid g\left(\phi,\zeta\right) = 0\right] + \\ & +Q(\phi)\mathbb{E}\left[\frac{\partial r\left(\phi, y(\phi,\zeta)\right)}{\partial \phi} \mid g\left(\phi,\zeta\right) \geq 0\right] \end{aligned}$$

- Optimal pricing decisions must account for:
    - (Adverse) selection: marginal and average buyer are different.
    - Repayment incentives: contract structure may affect outcomes.
    - Information: price can be made contingent on available information.

- F.o.c. is similar to a standard Lerner equation, but incentive and selection affect the inverse revenue elasticity.

- Estimating the demand for contracts:
    - Consider data consisting of individual choices and outcomes.
    - Goal is to recover fundamentals: $F(\zeta)$, $g(\phi,\zeta)$, $y(\phi,\zeta)$, $r(\phi,y)$.

- Simple econometrics of "selection" and "treatment":
    - Equation for contract choice: $q_i = 1 \Leftrightarrow g(\phi_i, \zeta_i) \geq 0$
    - Equation for contract outcome: $y_i = y(\phi_i,\zeta_i)$

- Incorporating the supply side:
    - Can infer unobserved costs (in r) from first-order conditions.
    - If costs are observed, can assess optimality of prices.

Modeling demand and behavior

- Important point: describe behavior statistically, staying agnostic as to why people do what they do
- Applicant characterized by $\zeta = (x_a, \varepsilon, \eta)$
  - ε, η likely correlated (either b/c of fwd looking behavior, or correlated liquidity)
- Contract characterized by $\phi = (x_c, p, d)$

- Three equations:

$$q_i = 1 \qquad \Leftrightarrow \qquad g(\phi_i, x_i, \varepsilon_i) \geq 0$$

$$D_i(\phi_i, x_i, \varepsilon_i) = \begin{cases} D_i^* = x_i'\beta_x + p_i\beta_p + \varepsilon_i & \text{if } D_i^* > d_i \\ d_i & \text{if } D_i^* \leq d_i \end{cases}$$

$$S_i = \begin{cases} S_i^* = T_i \cdot \exp\left(x_i'\gamma_x + (p_i - D_i)\gamma_l + \eta_i\right) & \text{if } S_i^* < T_i \\ T_i & \text{if } S_i^* \geq T_i \end{cases}$$

- Model has three latent variables but two unobservables, so write:

$$g(\phi_i, x_i, \varepsilon_i) = D_i^* + Z(\phi_i, x_i)$$

and assume

$$Z(\phi_i, x_i) = \alpha_0 + x_i\alpha_x + p_i\alpha_p + d_i\alpha_d.$$

- Finally, assume joint normal:

$$\begin{pmatrix} \varepsilon_i \\ \eta_i \end{pmatrix} \sim N(0, V) \qquad V = \begin{pmatrix} \sigma_\varepsilon^2 & \rho\sigma_\varepsilon\sigma_\eta \\ \rho\sigma_\varepsilon\sigma_\eta & \sigma_\eta^2 \end{pmatrix}$$

- Estimate using ML, “instrument” for sale price using “list” price, and rely on the same variation from the other paper.

Figure 3(a): Purchasing and Down Payment

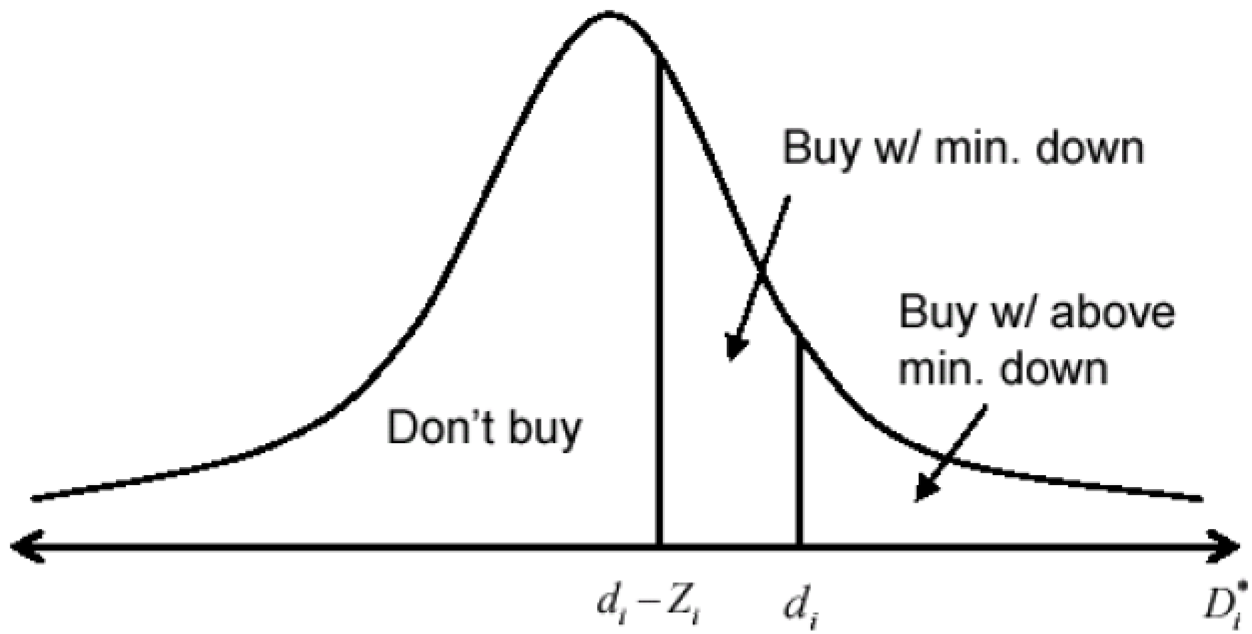


Figure 3(b): An Increase in Minimum Down

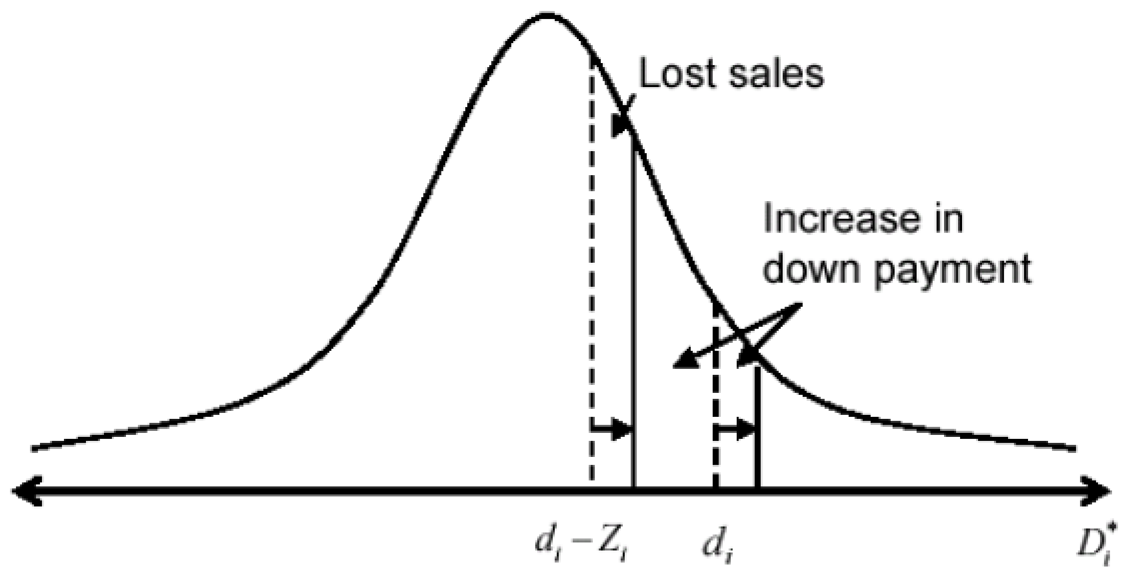
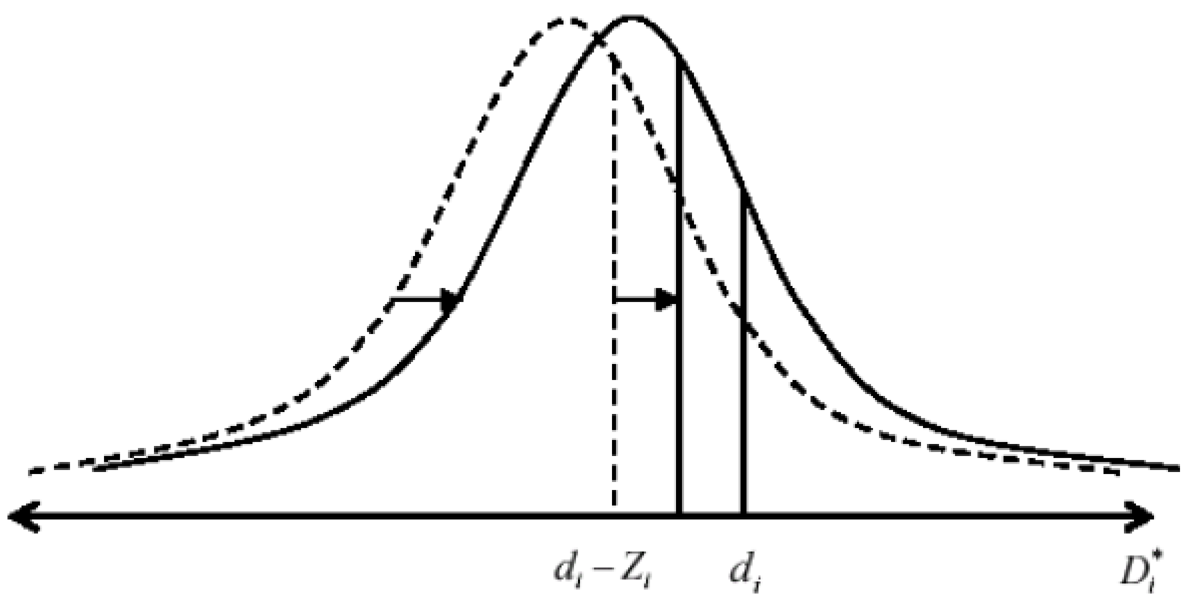


Figure 3(c): An Increase in Car Price



Pricing

$$\Pi(\phi) = \int \underbrace{\mathbf{1}\{g(\phi,\zeta) \geq 0\} r\left(\phi, y(\phi,\zeta)\right)}_{\pi(\phi,\zeta)} dF(\zeta)$$

So we just need to "fill in" the details.

g and *y* are given from the demand estimation. Net revenues is given by:

$$r\left(\phi, y(\phi,\zeta)\right) = D + \frac{\frac{1}{\kappa}\left(1 - e^{-\kappa S}\right)}{\frac{1}{z}\left(1 - e^{-zT}\right)}(p - D) + e^{-\kappa S} k(x,S) - C(x)$$

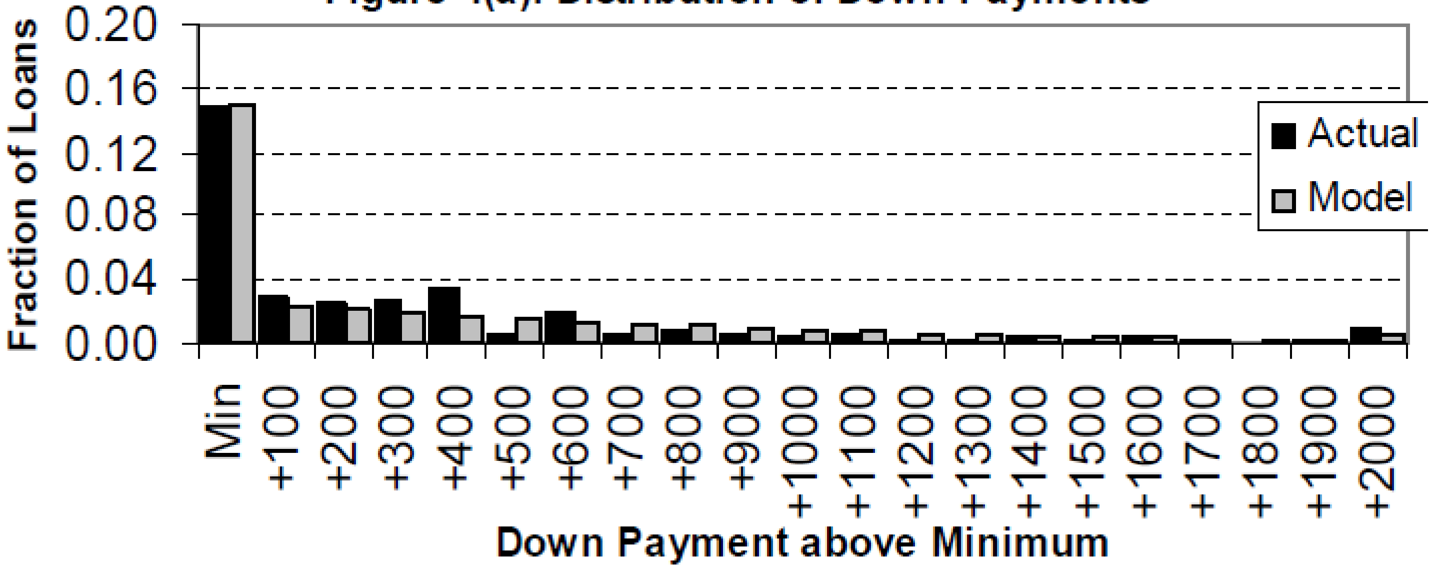
An important issue is how to define alternative pricing structures to consider. That is, over which set ϕ is optimal, or even more broadly how much optimality to impose.

Our baseline strategy is to require the following:

$$\int \pi\left(p_x, d_x, x, \omega\right) dF_{x,\omega} \geq \int \pi\left(p_x + a, d_x + b, x, \omega\right) dF_{x,\omega}$$

For all *a*,*b*.

Figure 4(a): Distribution of Down Payments



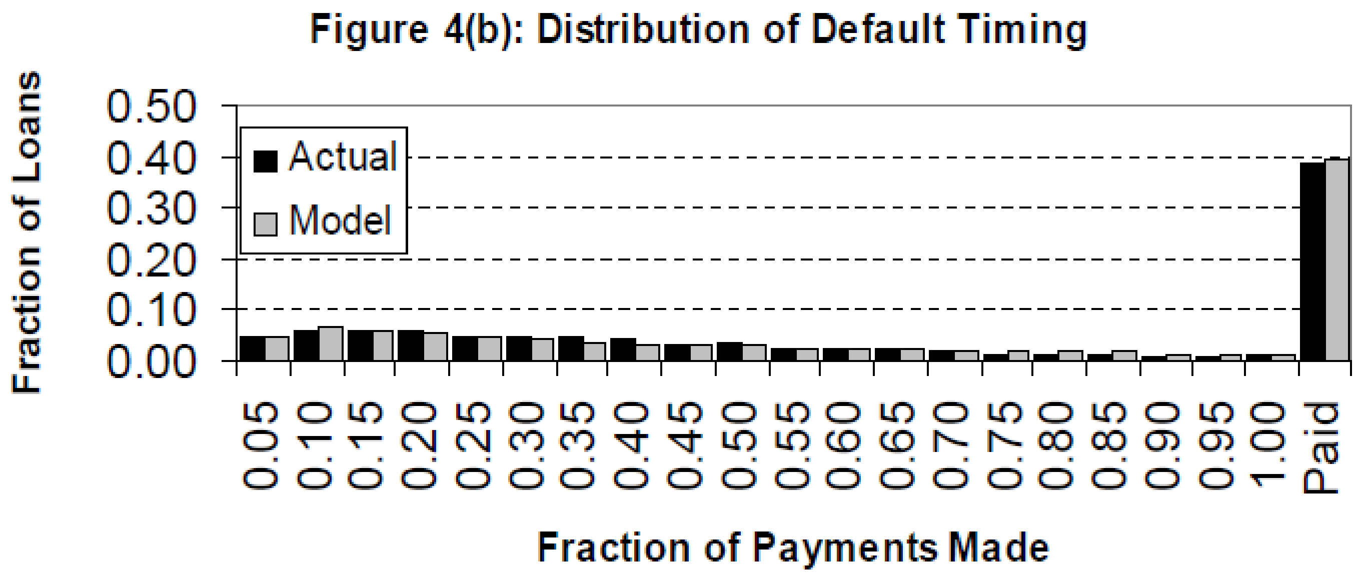


Figure 4(b): Distribution of Default Timing
Fraction of Loans
0.50
0.40
0.30
0.20
0.10
0.00
Actual
Model
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
Paid
Fraction of Payments Made

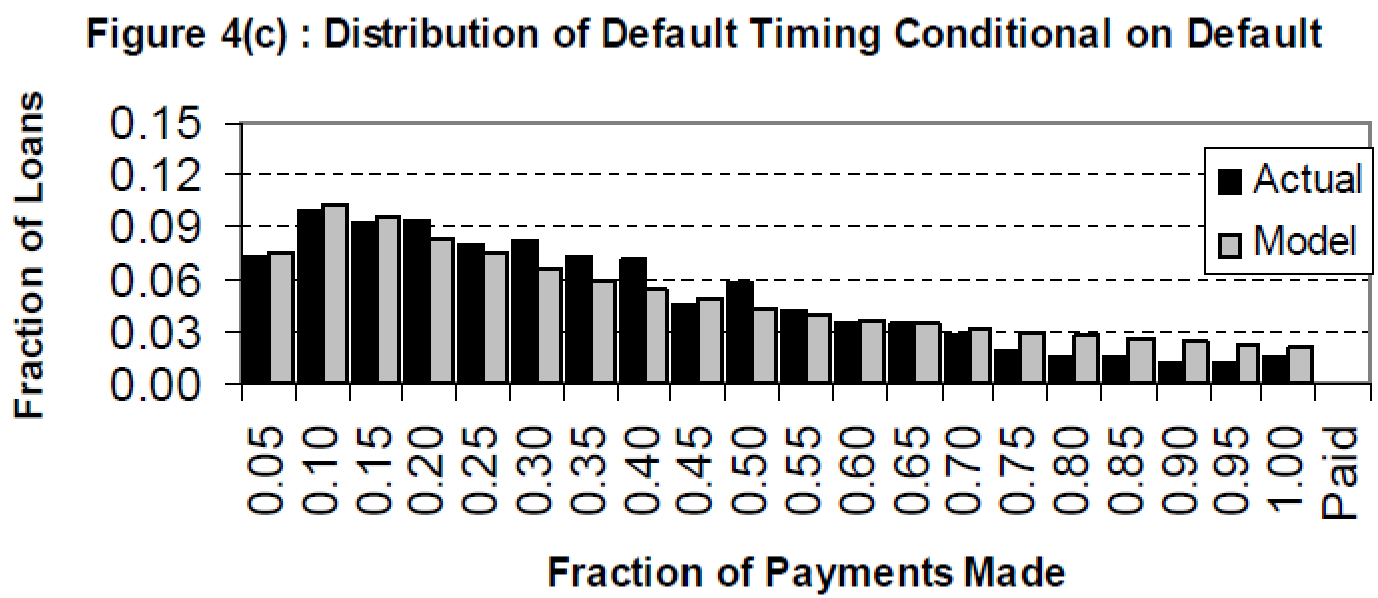
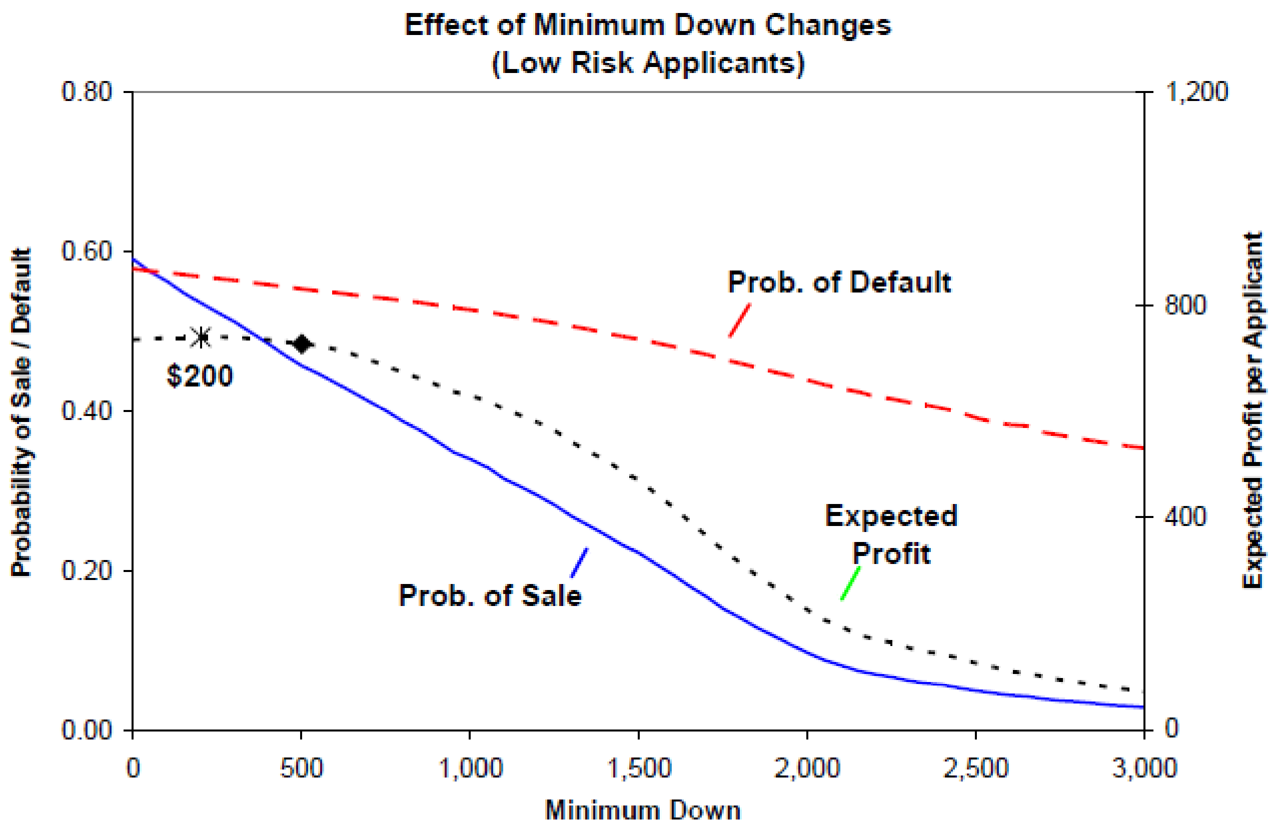
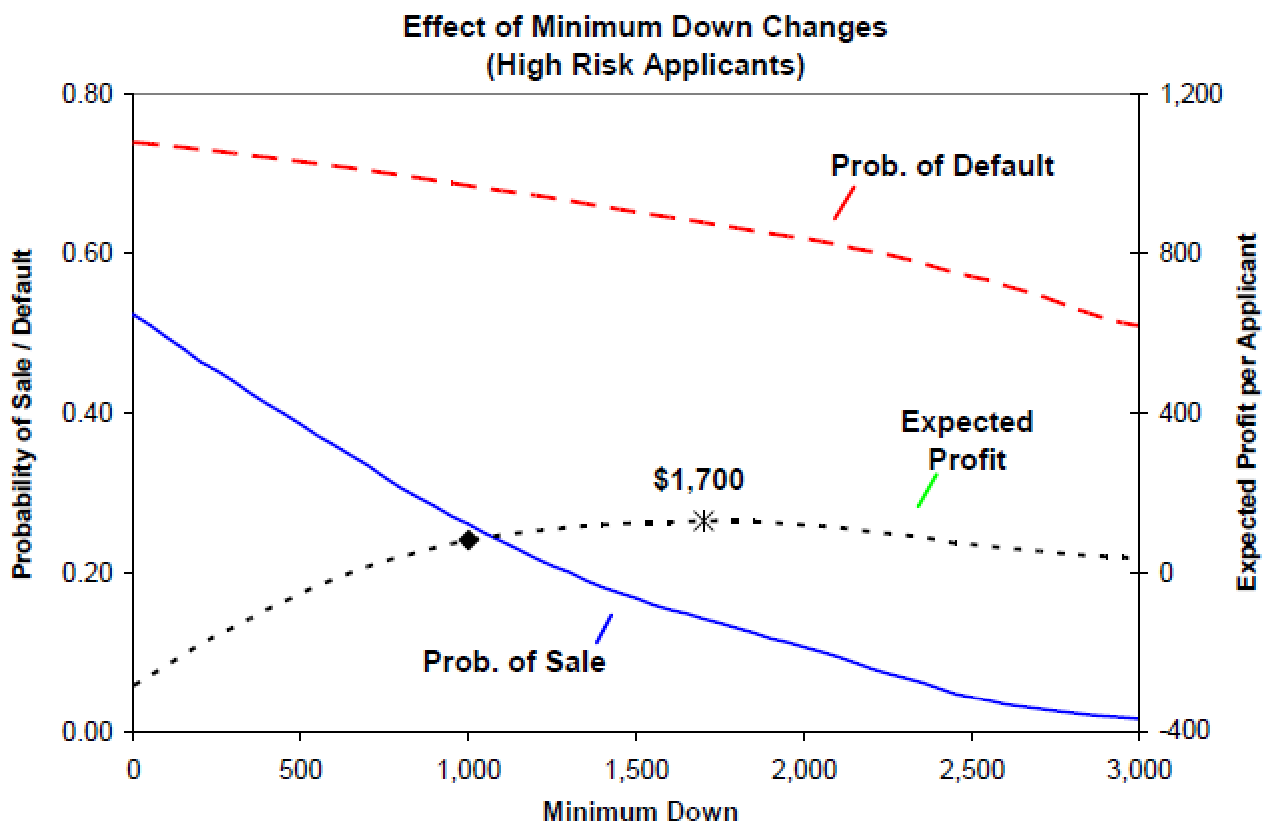
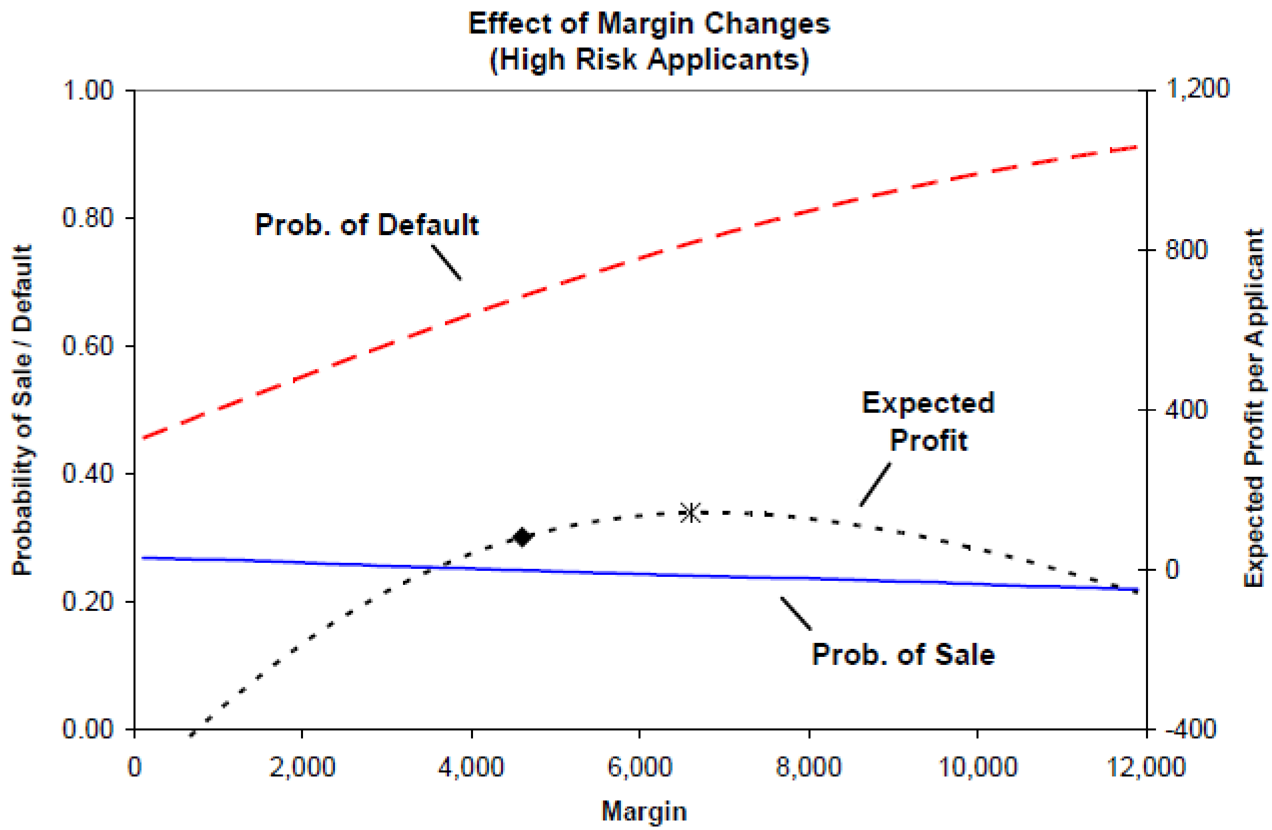
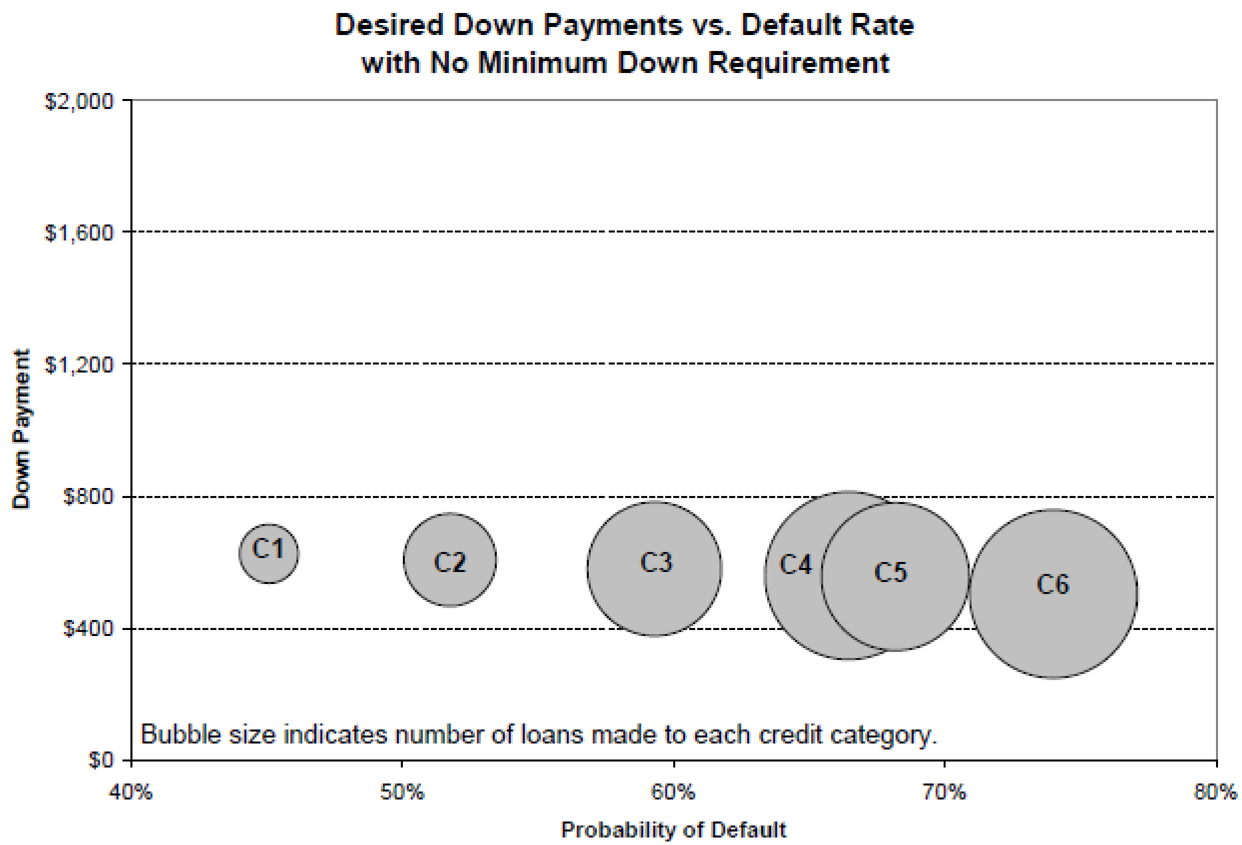


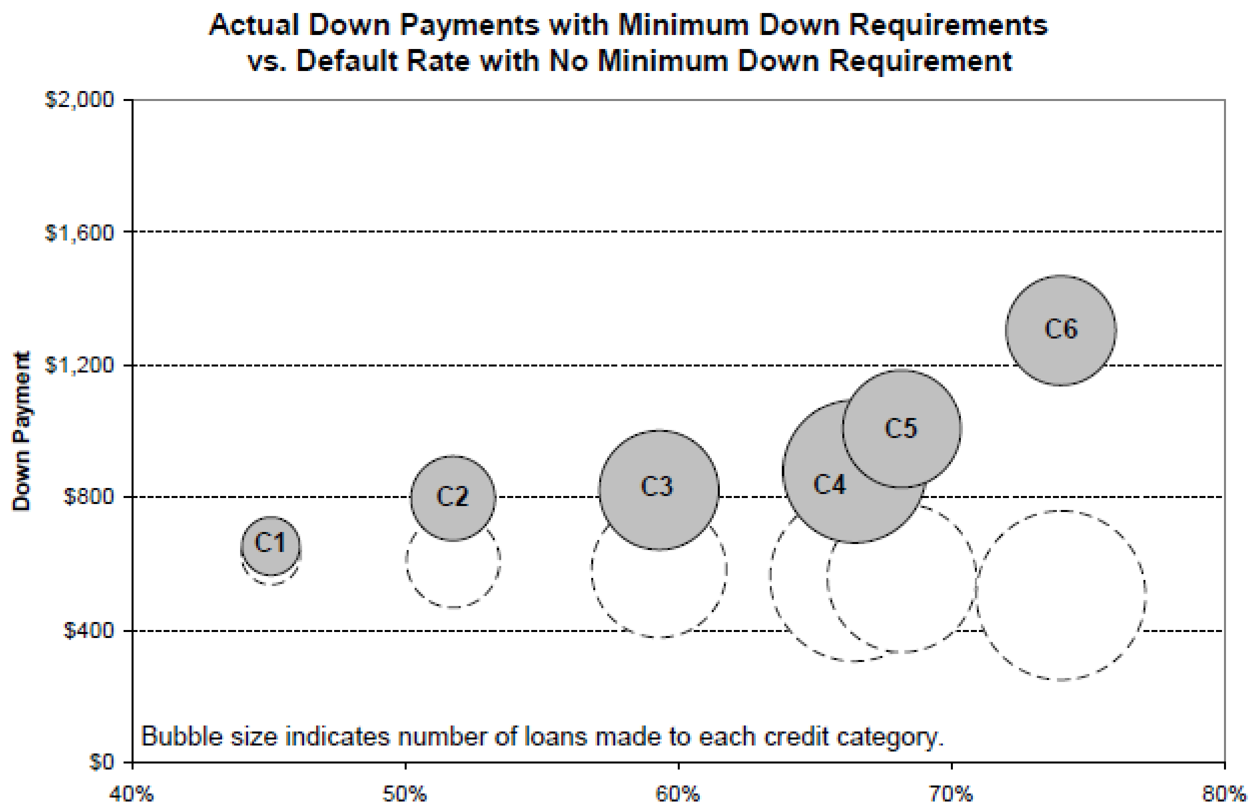
Figure 4(c) : Distribution of Default Timing Conditional on Default
Fraction of Loans
0.15
0.12
0.09
0.06
0.03
0.00
Actual
Model
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
Paid
Fraction of Payments Made


Effect of Minimum Down Changes
(Low Risk Applicants)
0.80
0.60
0.40
0.20
0.00
1,200
800
400
0
0
500
1,000
1,500
2,000
2,500
3,000
Minimum Down
Probability of Sale / Default
Expected Profit per Applicant
Prob. of Default
Prob. of Sale
Expected
Profit
$200


Effect of Minimum Down Changes
(High Risk Applicants)
Probability of Sale / Default
0.80
0.60
0.40
0.20
0.00
Expected Profit per Applicant
1,200
800
400
0
-400
Minimum Down
0
500
1,000
1,500
2,000
2,500
3,000
Prob. of Default
Expected
Profit
$1,700
Prob. of Sale


Effect of Margin Changes
(High Risk Applicants)
Prob. of Default
Expected Profit
Prob. of Sale
Probability of Sale / Default
Expected Profit per Applicant
Margin
1.00
0.80
0.60
0.40
0.20
0.00
1,200
800
400
0
-400
0
2,000
4,000
6,000
8,000
10,000
12,000


Desired Down Payments vs. Default Rate
with No Minimum Down Requirement
$2,000
$1,600
$1,200
$800
$400
$0
Down Payment
C1
C2
C3
C4
C5
C6
Bubble size indicates number of loans made to each credit category.
40%
50%
60%
70%
80%
Probability of Default


Actual Down Payments with Minimum Down Requirements vs. Default Rate with No Minimum Down Requirement
$2,000
$1,600
$1,200
$800
$400
$0
Down Payment
C1
C2
C3
C4
C5
C6
Bubble size indicates number of loans made to each credit category.
40%
50%
60%
70%
80%

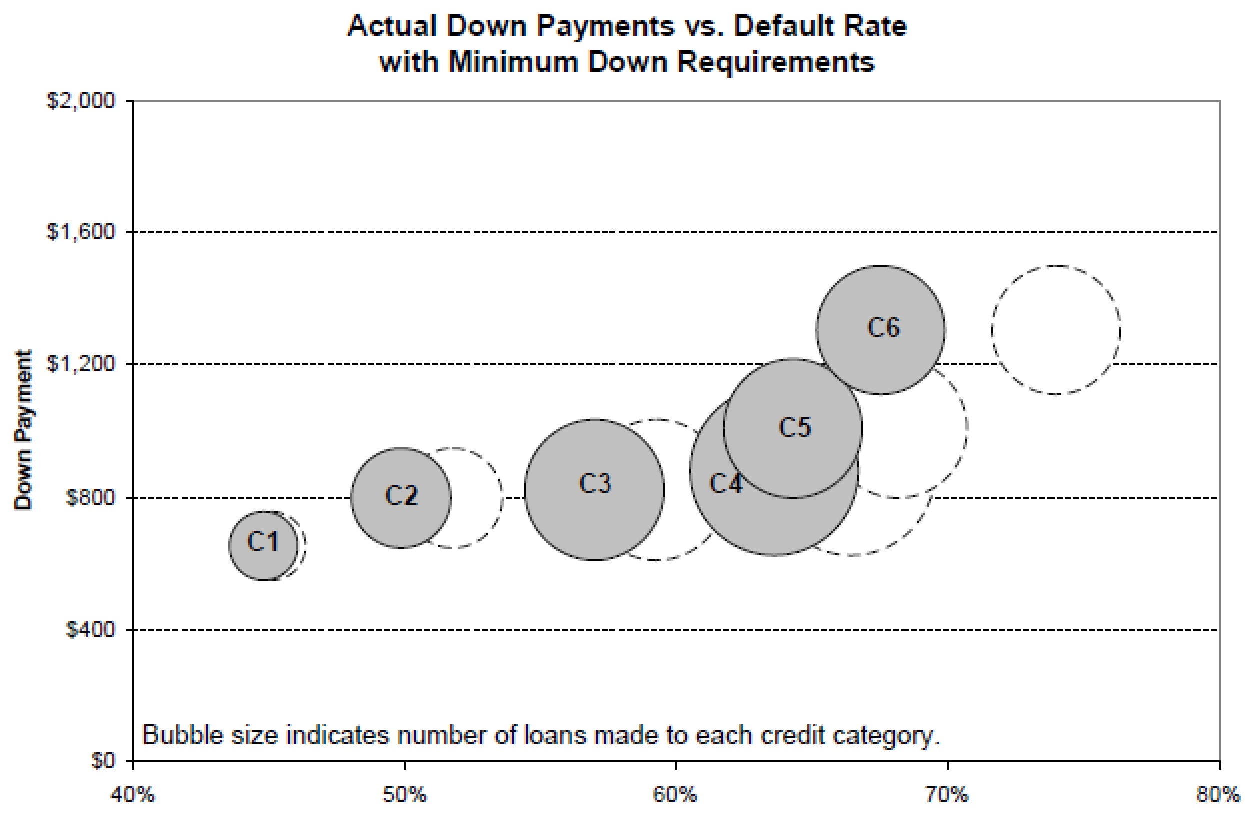

Actual Down Payments vs. Default Rate
with Minimum Down Requirements
$2,000
$1,600
$1,200
$800
$400
$0
Down Payment
C1
C2
C3
C4
C5
C6
Bubble size indicates number of loans made to each credit category.
40%
50%
60%
70%
80%

Figure 7: Expected Profit vs. Minimum Down Payment

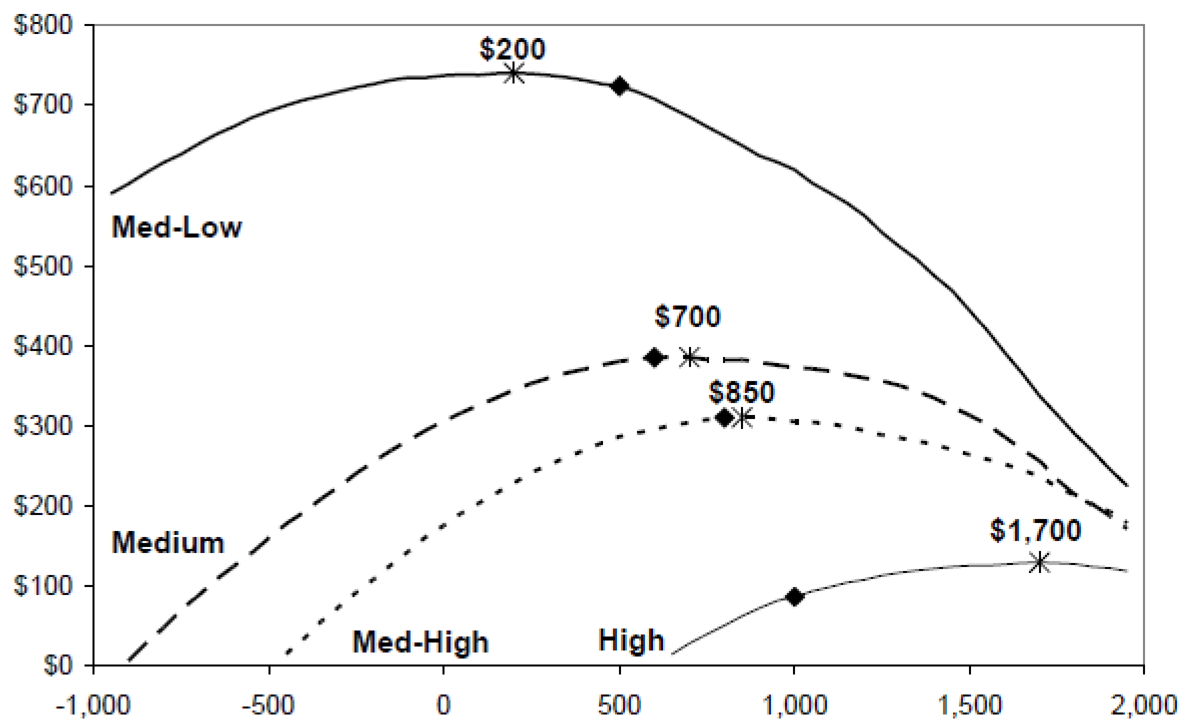


Table 5(a): Value of Credit Scoring

	Low Risk	Med Risk	High Risk	All Applicants
Minimum Down Payment				
Observed pricing	$400	$600	$1,000	-
Optimal credit-based pricing	$0	$700	$1,550	-
Optimal uniform pricing	$800	$800	$800	$800
Pricing with perfect knowledge of liquidity	-	-	-	-
Close Rate				
Observed pricing	0.451	0.398	0.249	0.343
Optimal credit-based pricing	0.568	0.377	0.150	0.340
Optimal uniform pricing	0.381	0.352	0.291	0.328
Pricing with perfect knowledge of liquidity	0.577	0.472	0.273	0.408
Profit Conditional on Sale				
Observed pricing	$2,137	$969	$348	$1,174
Optimal credit-based pricing	$1,924	$1,026	$914	$1,258
Optimal uniform pricing	$2,254	$1,092	$218	$1,112
Pricing with perfect knowledge of liquidity	$2,499	$1,543	$1,154	$1,695
Expected Profit per Applicant				
Observed pricing	$963	$385	$87	$402
Optimal credit-based pricing	$1,093	$387	$137	$428
Optimal uniform pricing	$859	$384	$63	$364
Pricing with perfect knowledge of liquidity	$1,443	$728	$314	$692

Table 5(c): Credit Scoring as a Barrier to Entry

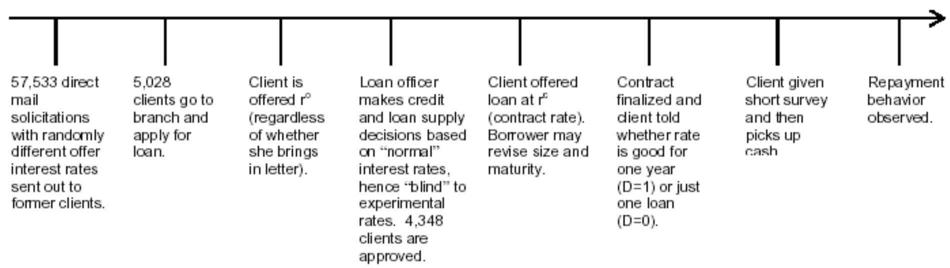
(Incumbent Profit per Applicant, Entrant Profit per Applicant)

	Incumbent Prices Uniformly	Incumbent Prices by Risk Category
No Entrant (Monopoly)	($364, $0)	($428, $0)
Entrant Prices Uniformly	($168, $168)	($249, $123)
Entrant Prices by Grade	($123, $249)	($202, $202)

"Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment" by Karlan and Zinman (*Econometrica*, 2009)

- Large scale field experiment in the high risk consumer credit market in South Africa.
- Good place to do this: individuals are used to see individualized "random looking" prices, unlikely to get "upset," so firms less reluctant to experiment compared to other settings.
- Allows disentangling between:
    - Adverse selection (randomizing offer rates)
    - "Total" moral hazard (randomizing, by surprise, a reduction in repayment burden)
    - "Pure" moral hazard (randomizing an incentive to repay)

Figure 2: Operational Steps of Experiment



Setting

- Seems similar to PayDay Loans in the US.
- Large lenders who focus on the working poor, who have no access to regular loans.
- Cash loans with high interest rates (4-12% per <u>month</u>) for durations of about 4 months, and high default rates (15% for repeat customers, 30% for new ones).
- Careful design to make sure that the subsequent decisions by loan officers are done independently of the randomized rates and incentives.

Table 3. Identifying Adverse Selection, Repayment Burden, and Moral Hazard: Comparison of Means

		Selection Effects			Repayment Burden Effects			Moral Hazard Effects		
		High Offer, Low Contract	Low Offer, Low Contract	t-stat: diff≠0	High Offer, High Contract	High Offer, Low Contract	t-stat: diff≠0	No Dynamic Incentive, Low Contract	Dynamic Incentive, Low Contract	t-stat: diff≠0
Full Sample		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Average Monthly Proportion Past Due	0.102	0.082	1.90*	0.105	0.102	0.23	0.094	0.079	1.94**
		(0.009)	(0.004)		(0.006)	(0.009)		(0.006)	(0.005)	
	Proportion of Months in Arrears	0.211	0.202	0.72	0.244	0.211	2.38**	0.217	0.188	2.70***
		(0.011)	(0.006)		(0.008)	(0.011)		(0.008)	(0.008)	
	Account in Collection Status	0.123	0.101	1.50	0.139	0.123	0.99	0.118	0.092	2.16**
		(0.013)	(0.007)		(0.009)	(0.013)		(0.008)	(0.008)	
	# of observations	625	2087		1636	625		1458	1254	
Female										
	Average Monthly Proportion Past Due	0.101	0.067	2.42**	0.089	0.101	-0.85	0.078	0.071	0.65
		(0.013)	(0.005)		(0.007)	(0.013)		(0.007)	(0.007)	
	Proportion of Months in Arrears	0.209	0.181	1.55	0.221	0.209	0.64	0.194	0.180	0.97
		(0.02)	(0.008)		(0.011)	(0.02)		(0.010)	(0.010)	
	Account in Collection Status	0.121	0.082	1.88*	0.107	0.121	-0.65	0.102	0.078	1.57
		(0.019)	(0.008)		(0.121)	(0.019)		(0.011)	(0.011)	
	# of observations	307	1047		779	307		724	630	
Male										
	Average Monthly Proportion Past Due	0.103	0.099	0.30	0.120	0.103	1.05	0.111	0.087	1.97**
		(0.013)	(0.007)		(0.008)	(0.013)		(0.009)	(0.008)	
	Proportion of Months in Arrears	0.213	0.223	-0.51	0.264	0.213	2.60***	0.240	0.197	2.77***
		(0.016)	(0.009)		(0.011)	(0.016)		(0.011)	(0.011)	
	Account in Collection Status	0.126	0.120	0.26	0.168	0.126	1.87*	0.134	0.107	1.48
		(0.019)	(0.010)		(0.013)	(0.019)		(0.013)	(0.012)	
	# of observations	318	1040		857	318		734	624	

"High" is defined as above the median offer rate for that risk category. This is equal to 7.77% for high risk clients, 7.50% for medium risk clients and 6.00% for low risk clients. Sample sizes vary due to exclusions motivated by the formal derivation of our identification strategy, please see Section V for details. The column headings indicate which rate cells are included in any given analysis. T-tests assume unequal variances across columns.

Table 4. Identifying Adverse Selection, Repayment Burden, and Moral Hazard: OLS on the Full Sample

OLS

Dependent Variable:	*Monthly Average Proportion Past Due*		*Proportion of Months in Arrears*		*Account in Collection Status*	
	(1)	(2)	(3)	(4)	(5)	(6)
Offer Rate (Selection)	0.004	0.004	0.002	0.002	0.007	0.007
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Contract Rate (Repayment Burden)	-0.000	-0.002	0.007*	0.003	0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Dynamic Repayment Incentive Dummy (Moral Hazard)	-0.011*	0.003	-0.016**	0.013	-0.019**	0.000
	(0.005)	(0.011)	(0.008)	(0.018)	(0.009)	(0.019)
Dynamic Repayment Incentive Size (Moral Hazard)		-0.004		-0.008**		-0.005
		(0.003)		(0.004)		(0.004)
Constant	0.079***	0.094***	0.139***	0.171***	0.069***	0.090***
	(0.014)	(0.019)	(0.025)	(0.027)	(0.024)	(0.028)
Observations	4348	4348	4348	4,348	4348	4348
Adjusted R-squared	0.04	0.04	0.11	0.11	0.03	0.03
Mean of dependent variable	0.09	0.09	0.22	0.22	0.12	0.12
Prob(both Dynamic Incentive variables = 0)		0.08*		0.01***		0.05**

Estimate that moral hazard account for 7-16% of difference in repayment.

Table 5. Identifying Adverse Selection, Repayment Burden, and Moral Hazard by Gender

OLS

	Male			Female		
Dependent Variable:	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*	*Monthly Average Proportion Past Due*	*Proportion of Months in Arrears*	*Account in Collection Status*
	(1)	(2)	(3)	(4)	(5)	(6)
Offer Rate	-0.002	-0.004	0.001	0.010***	0.008*	0.013**
	(0.004)	(0.005)	(0.007)	(0.003)	(0.005)	(0.005)
Contract Rate	0.005	0.014***	0.010	-0.005	-0.001	-0.009
	(0.003)	(0.005)	(0.007)	(0.004)	(0.005)	(0.006)
Dynamic Repayment	-0.014	-0.025**	-0.020	-0.007	-0.006	-0.017
Incentive Indicator	(0.009)	(0.012)	(0.015)	(0.008)	(0.012)	(0.012)
Constant	0.108***	0.178***	0.092**	0.050***	0.097***	0.043
	(0.025)	(0.040)	(0.043)	(0.015)	(0.026)	(0.027)
Observations	2215	2215	2215	2133	2133	2133
R-squared	0.05	0.12	0.04	0.05	0.10	0.04