Consumer Credit: Learning Your Customer's Default Risk from What (S)he Buys

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Household finance

- Household assets, end of 2020:
  - Total: $139.2T — Initial focus of household finance: Wealth accumulation, portfolio choice
- Household liabilities, end of 2020:
  - Mortgages: $ 10.9T — A lot of focus on this after the financial crisis
  - Consumer credit: $ 4.2T — Substantial, but comparatively understudied

(For comparison, muni debt is $3.2T, noncorp business debt is $6.6T)

- Reflecting the state of the field:
  - Guiso and Sodini (2013), excellent 121-page survey of household finance:
    A couple of pages on consumer credit in the last section
- If we want to understand household behavior and heterogeneity, let's not censor and study only those without debt
  - Studying consumer credit should be informative more broadly

New developments

Also suggest that increased focus on consumer credit is warranted:

1. Big data revolution in the finance industry: A lot focuses on modeling consumer credit risk
   - Ant Group (an affiliate of Alibaba Group): Has $155B of credit outstanding to Chinese consumers
     Issued by leveraging information on their spending habits and payment histories
   - Fintech: A lot focuses on disrupting markets for household borrowing, including consumer credit
2. Sharp increase in student loan component of consumer credit:
   - Heated debate about fairness of education funding and ability of borrowers to repay

This paper

Focus on big data in consumer credit, specifically the value of transactions data on consumer spending mix

Novel data used to model consumer credit risk in industry

- Granular account-level transactions data: Credit, debit cards, online shopping
- Bill payment data (rent, utilities)
- Social media data
- Mobile payment data
- Clickstream data (the digital footprint created from using a web site)

Not data academics generally have access to → Disconnect between industry and academia/general public

- I seek to understand informativeness of granular account-level data
  - Does the types of good or service purchased have predictive power for understanding credit outcomes?
  - If so, what does that say about fundamental drivers of household borrowing/credit risk and household heterogeneity more generally?
- Pioneering work on digital footprints and credit scoring: Berg, Burg, Gombovic and Puri (2020)
  - Value for default prediction of variables obtained as part of the online shopping process at German retailer
    - Operating system used (iOS or Android, a proxy for cellphone cost and thus income)
    - Name in e-mail address (capturing an aspect of their personality).

I take two approaches

1. Observation: High-quality household surveys contain similar information as detailed account-level data (e.g. checking, debit card, credit card)
    - Consumer Expenditure Survey (CEX):
        - Study 64,000 consumers with consumer credit, 1988Q1-2013Q1
        - How do consumer credit interest and finance charges relate to spending patterns

2. Account-level dataset from large retail chains in Mexico: Sells durables on credit
    - Study default, not just the paying of interest or finance charges
    - Around 500,000 borrowers. Monthly panel data, January 2005 to August 2009
    - Each purchase has its own loan. Make it straightforward to study link between what's purchased and default

CONSUMER CREDIT IN THE US CONSUMER EXPENDITURE SURVEY

1988Q1-2013Q1:

- Amount paid in finance, interest and late charges over the past 12 months on consumer credit
  Available for households in their fifth and last interview
- Detailed expenditures
- Demographics

CEX measure of consumer credit:

- Excludes: Mortgages, home equity loans, vehicle loans, and business related loans
- Includes:
  - Credit card debt (from major credit cards, store credit cards, or gasoline credit cards)
    - 87% of observations with positive consumer credit, 79% of consumer credit finance/interest/late charges
  - Store installment credit
  - Credit from financial institutions (banks, S&Ls, credit unions, finance companies, insurance companies)
  - Credit from health care providers (doctors, dentists, hospitals, and other medical practitioners)
    - I exclude this: May be driven by different factors than other consumer credit
  - Other credit sources

Hundreds of spending categories (UCC codes) in the CEX:

- I include all categories used in CEX total expenditure
  (except "personal insurance and pensions" categories -- savings rather than consumption expenditure)
- 619 categories appear across 1988Q1-2013Q1
  - Drop categories with less than 1% of hh's spending → 448 spending categories remaining
  - Calculate a given household's spending on each category across available interviews
  - Quarterly time dummies as controls: Not all spending categories are used in all survey quarters

Final sample:

- One obs per household, 157,553 households
- 66,997 (43%) have positive consumer credit on 1st of current month
- Focus on 63,691 households with positive consumer credit and positive after-tax income
  - Of these, 69% have positive finance/interest/late charges on consumer credit
  - Among those with positive finance/interest/late charges: Avg=$575, median=$221 (for a 12-month period)

448 spending categories used:

FOOD OR BOARD WHILE AT SCHOOL	OTH REP/MAINT LABOR/MAT OWND	SATELLITE RADIO SERVICE
FOOD AND BEV FOR CATERED AFFAIRS	OTH REP/MAINT LABOR/MAT OWNV	TRASH/GARBAGE COLLECT RNTR
FOOD OUT OF TOWN TRIPS	PROP MANAGEMENT OWND	TRASH/GARBAGE COLLECT OWND
FOOD PREPARED BY CU ON TRIPS	PROP MANAGEMENT OWNV	TRASH/GARBAGE COLLECT OWNV
ALC. BEV. PURCHASED ON TRIPS	PAINT/WALLPAPER AND SUPP RNTR	SEPTIC TANK CLEANING OWND
RENT OF DWELLING	PAINT/WALLPAPER AND SUPP OWND	BATHROOM LINENS
LODGING AWAY FROM HOME	EQUIP FOR PAINT/WPAPER RNTR	BEDROOM LINENS
HOUSING FOR SOMEONE AT SCHOOL	EQUIP FOR PAINT/WPAPER OWND	KITCHEN AND DINING ROOM LINENS
GROUND RENT OWND	MAT FOR PANEL/SIDING, ETC OWND	CURTAINS AND DRAPES
FIRE/EXTENDED COVERAGE OWND	MAT/EQUIP FOR ROOF/GUTTER OWND	SLIPCOVERS/DECORATIVE PILLOWS
HOMEOWNERS INSURANCE OWND	MAT FOR PATIO,MASONRY,ETC OWND	SEWING MATERIALS
HOMEOWNERS INSURANCE OWNV	PLUMBING SUPP/EQUIP OWND	OTHER LINENS
PROPERTY TAXES OWND	ELEC SUPP,HEAT/COOL EQUIP OWND	MATTRESS AND SPRINGS
PROPERTY TAXES OWNV	FUEL OIL OWND	OTHER BEDROOM FURNITURE
MORTGAGE INTEREST OWND	GAS, BOTTLED OR TANK OWND	SOFAS
MORTGAGE INTEREST OWNV	GAS,BOTTLED OR TANK - OWNV & RVS	LIVING ROOM CHAIRS
INTEREST, LMP SUM HM EQ LN, OWND	WOOD/KEROSENE/OTHER FUELS OWND	LIVING ROOM TABLES
CAPITAL IMPROVE MATERIALS OWND	ELECTRICITY RNTR	KITCHEN/DINING ROOM FURNITURE
CAP IMPROVE LABOR/MAT OWND	ELECTRICITY OWND	INFANTS FURNITURE
CAP IMPROVE LABOR/MAT OWNV	ELECTRICITY OWNV	OUTDOOR FURNITURE
PARKING OWND	UTILITY--NATURAL GAS RNTR	WALL UNITS, CABINETS, OCCAS FURN
PAINTING/PAPERING LABOR/MAT OWND	UTILITY--NATURAL GAS OWND	PURCH/INST REFRIG/FREEZER RNTR
PLMB/WTR HEAT LABOR/MAT OWND	UTILITY--NATURAL GAS OWNV	PURCH/INST REFRIG/FREEZER OWND
HEAT/AC/ELEC LABOR/MAT OWND	TELEPHONE SERVICE NOT SPEC	PURCH/INST CLOTHES WASHER RNTR
ROOFING/GUTTERS LABOR/MAT OWND	RESIDENTIAL TELEPHONES/PAY PHONES	PURCH/INST CLOTHES WASHER OWND
OTH REP/MAINT LABOR/MAT OWND	CELLULAR PHONE SERVICE	PURCH/INST CLOTHES DRYER RNTR
REPL DISHWASH/DISP/HOOD OWND	PHONE CARDS	PURCH/INST CLOTHES DRYER OWND
HRD SURFACE FLOOR LABOR/MAT OWND	WATER AND SEWERAGE MAINT RNTR	STOVES, OVENS OWND
W/W CARPET INST REPL OWND	WATER AND SEWERAGE MAINT OWND	MICROWAVE OVENS RNTR
REPAIR-DISPL/DWSHR/RANG HD OWND	WATER AND SEWERAGE MAINT OWNV	MICROWAVE OVENS OWND
REP/MAINT LABOR/MAT RNTR	CABLE/SATELLITE/COM ANTENNA SERV	PURCH/INST WINDOW A/C OWND

COLOR TV - CONSOLE	LAWN AND GARDEN EQUIPMENT	MENS SPORTCOATS/TAILORED JACKETS
COLOR TV - PORTABLE/TABLE MOD	POWER TOOLS	MENS COATS AND JACKETS
TELEVISIONS	ELECTRIC FLOOR CLEANING EQUIP	MENS UNDERWEAR
VCRS/VIDEO DISC PLAYERS	SEWING MACHINES	MENS HOSIERY
VIDEO CASSETTES/TAPES/DISCS	SMALL ELECTRIC KITCHEN APPLIANCES	MENS NIGHTWEAR/LOUNGEWEAR
VIDEO GAME HARDWARE/SOFTWARE	PORTABLE HEATING/COOLING EQUIP	MENS ACCESSORIES
VIDEO GAME SOFTWARE	CONSTRUCTION MAT OWND	MENS SWEATERS AND VESTS
STREAMING/DOWNLOADING VIDEO	FLOOR REPAIR/REPL MATERIALS OWND	MENS SWIMSUITS/WARM-UP/SKI SUITS
RADIOS	LANDSCAPING MATERIALS OWND	MENS SHIRTS
TAPE RECORDERS AND PLAYERS	OFFICE FURNITURE HOME USE	MENS PANTS
DIGITAL AUDIO PLAYERS	HAND TOOLS	MENS SHORTS/SHORTS SETS
COMPONENTS/COMPONENT SYSTEMS	INDOOR PLANTS, FRESH FLOWERS	MENS PANTS AND SHORTS
ACCESSORIES AND OTH SOUND EQUIP	CLOSET AND STORAGE ITEMS	MENS UNIFORMS
ACCESSORIES AND OTHER SOUND EQUIP	MAT FOR TERMTE/PST CNTRL MAINTCE	MENS COSTUMES
RECORDS,CDS,AUDIO TAPES	BABYSITTING	BOYS COATS AND JACKETS
RCRD/TAPE/CD/VIDEO MAIL ORD CLUB	BABYSIT/CHILD CARE OWN HOME	BOYS SWEATERS
RECORDS,CDS,AUDIO TAPES	BABYSIT/CHILD CARE OTHER HOME	BOYS SHIRTS
STREAMING/DOWNLOADING AUDIO	DOMESTIC SERVICE	BOYS UNDERWEAR
FLOOR COVERINGS (NON-PERM.)	GARDENING/LAWN CARE SERVICE	BOYS NIGHTWEAR
FLOOR COVERINGS (NON-PERM.)	WATER SOFTENING SERVICE	BOYS HOSIERY
WINDOW COVERINGS	MOVING, STORAGE,FREIGHT	BOYS ACCESSORIES
INFANTS EQUIPMENT	HSHLD LNDRY,DRYCLN NOT COIN-OP	BOYS SUITS, SPORTCOATS,VESTS
BARBEQUE GRILLS AND OUTDOOR EQUIP	COIN-OP HSHLD LNDRY, DRY CLN	BOYS PANTS
CLOCKS	REPAIR OF TV/RADIO/SOUND EQUIP	BOYS SHORTS, SHORTS SETS
LAMPS AND LIGHTING FIXTURES	REPAIR OF HOUSEHOLD APPLIANCES	BOYS PANTS AND SHORTS
OTH HOUSEHOLD DECORATIVE ITEMS	REUPHOLSTERY OF FURNITURE	BOYS UNIFORMS/ACTIVE SPORTSWE
TELEPHONES AND ACCESSORIES	RENTAL/REPAIR-TOOLS,LAWN/GARDEN	BOYS COSTUMES
CLOCKS AND OTHER HH DECOR ITEMS	MISC. HOME SERVICES	BOYS UNIFORMS
PLASTIC DINNERWARE	RENTAL OF HOUSEHOLD EQUIPMENT	BOYS SWIMSUITS/WARM-UP/SKI SUITS
CHINA AND OTHER DINNERWARE	MNGMT/SPEC SER/SECURITY OWND	WOMENS COATS AND JACKETS
FLATWARE	SERV FOR TERMT/PST CNTRL	WOMENS DRESSES
GLASSWARE	HOME SECURITY SYS. SERV. FEE	WOMENS SPORTCOATS, TAIL. JKTS
OTHER SERVING PIECES	RENTERS INSURANCE	WOMENS VESTS AND SWEATERS
NONELECTRIC COOKWARE	MENS SUITS	WOMENS SHIRTS, TOPS,BLOUSES

WOMENS SKIRTS	SEWING NOTIONS, PATTERNS	REPAIR TO STEERING OR FRONT END
WOMENS PANTS	WATCHES	REPAIR TO ENGINE COOLING SYSTEM
WOMENS SHORTS,SHORTS SETS	JEWELRY	MOTOR TUNE-UP
WOMENS PANTS AND SHORTS	LUGGAGE	LUBE, OIL CHANGE AND OIL FILTERS
WOMENS SWIMSUITS/WARM-UP/SKI SUIT	SHOE REPAIR, OTH SHOE SERVICE	FRNT END ALIGN, WHEEL BAL/ROTAT
WOMENS SLEEPWEAR	COIN-OP APPAREL LDRY/DRY CLNG	SHOCK ABSORBER REPLACEMENT
WOMENS UNDERGARMENTS	ALTER/REPAIR OF APPAREL, ACCESS	BRAKE ADJUSTMENT
WOMENS HOSIERY	CLOTHING RENTAL	TIRE REPAIR AND OTH REPAIR WORK
WOMENS SUITS	WATCH AND JEWELRY REPAIR	VEHICLE AIR CONDITION REPAIR
WOMENS ACCESSORIES	APPAREL LNDRY/DRY CLNG N/COIN-OP	EXHAUST SYSTEM REPAIR
WOMENS UNIFORMS	NEW CARS	ELECTRICAL SYSTEM REPAIR
WOMENS COSTUMES	TRADE-IN ALLOWANCE/NEW CARS	MOTOR REPAIR/REPLACEMENT
GIRLS COATS AND JACKETS	NEW TRUCKS	VEHICLE ACCESSORIES INCL. LABOR
GIRLS DRESSES, SUITS	TRADE-IN ALLOW/NEW TRUCKS	VEHICLE AUDIO EQ. INCL. LABOR
GIRLS SHIRTS/BLOUSES/SWEATERS	CAR LEASE PAYMENTS	AUTO REPAIR SERVICE POLICY
GIRLS SKIRTS AND PANTS	TRUCK LEASE PAYMENTS	VEHICLE INSURANCE
GIRLS SHORTS, SHORTS SETS	USED CARS	AUTOMOBILE FINANCE CHARGES
GIRLS SKIRTS, PANTS, AND SHORTS	TRADE-IN ALLOWANCE/USED CARS	TRUCK FINANCE CHARGES
GIRLS SWIMSUITS/WARM-UP/SKI SUITS	USED TRUCKS	MOTORCYCLE & PLANE FINANCE CHG
GIRLS UNDERWEAR AND SLEEPWEAR	TRADE-IN ALLOWANCE/USED TRUCKS	VEHICLE REGISTRATION STATE/LOCAL
GIRLS HOSIERY	GASOLINE	State vehicle registration
GIRLS ACCESSORIES	DIESEL FUEL	Local vehicle registration
GIRLS UNIFORMS	GASOLINE ON OUT OF TOWN TRIPS	DRIVERS LICENSE
GIRLS COSTUMES	MOTOROIL	VEHICLE INSPECTION
MENS FOOTWEAR	MOTOR OIL ON OUT OF TOWN TRIPS	AUTO RENTAL
BOYS FOOTWEAR	COOLANT/ADDITIVES/BRK/TRNS FLD	AUTO RENTAL, OUT-OF-TOWN TRIPS
GIRLS FOOTWEAR	TIRES PURCHASED/REPLACED/INSTALL	TRUCK RENTAL
WOMENS FOOTWEAR	PARTS/EQUIP/ACCESSORIES	TRUCK RENTAL, OUT-OF-TOWN TRIP
INFANT COAT/JACKET/SNOWSUIT	VEHICLE PRODUCTS & SERVICES	PARKING FEES
INFANT DRESSES/OUTERWEAR	PARTS/EQUIP/ACCESSORIES	PRKNG FEE IN HME CITY EXCL RSDNC
INFANT UNDERGARMENTS	BODY WORK AND PAINTING	PARKING FEES, OUT-OF-TOWN TRIP
INFANT NIGHTWEAR/LOUNGEWEAR	CLUTCH, TRANSMISSION REPAIR	TOLLS OR ELECTRONIC TOLL PASSES
INFANTS ACCESSORIES	DRIVE SHAFT AND REAR-END REPAIR	TOLLS ON OUT-OF-TOWN TRIPS
MATERIAL FOR MAKING CLOTHES	BRAKE WORK	TOWING CHARGES

DOCKING/LANDING FEES	HLTH MAINT. ORG (NO BCBS)	CLUB MEMBERSHIP DUES AND FEES
AIRLINE FARES	HLTH MAINT. ORG (BCBS)	SOCIAL/RECRE/CIVIC CLUB MEMBRSHP
INTERCITY BUS FARES	LONG TERM CARE INSURANCE	CREDIT CARD MEMBERSHIPS
INTRACITY MASS TRANSIT FARES	MEDICARE PAYMENTS	AUTOMOBILE SERVICE CLUBS
LOCAL TRANS. OUT OF TOWN TRIPS	COML MEDICAR SUPLMNT/OTH HLTH INS	SHOPPING CLUB MEMB FEES
TAXI FARES ON TRIPS	COML MEDICARE SUPPLEMNT (NO BCBS)	FEES FOR PARTICIPANT SPORTS
TAXI FARES AND LIMOUSINE SERVICE	COML MEDICARE SUPPLEMENT (BCBS)	PARTIC. SPORTS OUT-OF-TOWN TRI
INTERCITY TRAIN FARES	OTHER HEALTH INSURANCE (NO BCBS)	MOVIE, THEATER, OPERA, BALLET
SHIP FARES	MEDICARE PRES. DRUG PREMIUMS	MOVIE, OTH ADM. OUT-OF-TOWN
PRESCRIPTION DRUGS	NEWSPAPERS	ADMISSION TO SPORTING EVENTS
EYEGLASSES AND CONTACT LENSES	NEWSPAPER SUBSCRIPTIONS	ADM TO SPRTS EVENTS OUT-OF-TOW
MEDICAL EQUIP. FOR GENERAL USE	NEWSPAPERS, NON-SUBSCRIPTION	FEES FOR RECREATIONAL LESSONS
SUPPORTIVE/CONVAL MED. EQUIP.	MAGAZINES	PHOTOGRAPHER FEES
HEARING AIDS	MAGAZINE SUBSCRIPTIONS	FILM PROCESSING
PHYSICIANS SERVICES	MAGAZINES, NON-SUBSCRIPTION	PET SERVICES
DENTAL SERVICES	BOOKS THRU BOOK CLUBS	VET SERVICES
EYECARE SERVICES	BOOKS NOT THRU BOOK CLUBS	OTH ENT SERV, OUT-OF-TOWN TRIP
SERV BY PRCTIONER OTH THAN PHYS	MAGAZINE/NEWSPAPER SUBSCRIPTION	RENT/REP MUSIC INSTRUMENTS
LAB TESTS, X-RAYS	MAGAZINE/NEWSPAPER SINGLE COPY	RENT/REPAIR OF MISC SPORTS EQU
SERV BY PROS OTH THAN PHYSICIANS	GENERAL SPORT/EXCERCISE EQUIP	RNTL VIDEO CASS/TAPES/DISCS/FILMS
HOSPITAL ROOM	BICYCLES	LOTTERIES AND PARIMUTUEL LOSSES
HOSPITAL ROOMS & SERVICES	CAMPING EQUIPMENT	ONLINE ENTERTAINMENT AND GAMES
HOSPITAL SERVICE OTH THAN ROOM	HUNTING, FISHING EQUIPMENT	CIGARETTES
OTHER MEDICAL CARE SERVICE	WINTER SPORT EQUIPMENT	OTHER TOBACCO PRODUCTS
RENTAL OF MEDICAL/SURGICAL EQUIP	WATER SPORT/OTHER SPORT EQUIP	WIGS AND HAIRPIECES
RENTAL OF SUPORTIVE/CONVAL EQUIP	WATER SPORT EQUIPMENT	ELECTRIC PERSONAL CARE APPL.
COMMERCIAL HEALTH INSURANCE	OTHER SPORT EQUIPMENT	PERS. CARE SERV FOR FEMALES
TRD FEE FOR SRV HLTH P (NO BCBS)	TOYS GAMES ARTS CRAFTS TRICYCLES	PERS. CARE SERV FOR MALES
TRD FEE FOR SRV HLTH P (BCBS)	PLAYGROUND EQUIPMENT	PERS. CARE SERV.
PREF PROVIDER HLTH PLN (NO BCBS)	MUSIC INSTRUMENTS/ACCESSORIES	SCHOOL BK/SUPL/EQUIP FOR COLLEGE
PREF PROVIDER HLTH PLN (BCBS)	FILM	SCHOOL BK/SUPL/EQUIP FOR ELEM/HS
BLUECROSS/BLUE SHIELD	PHOTOGRAPHIC EQUIPMENT	ENCYL. OTH SETS OF REFRNCE BKS
HEALTH MAINTENANCE PLANS	PET-PURCHASE/SUPPLIES/MEDICINE	SCH BKS/SUPP-DAY CARE,NURS,OTH
	REC EXPNS OUTSIDE HOME CITY	COLLEGE TUITION

ELEM./H.S. TUITION DAY CARE/NURS/PRSCH EXP INCL TUIT OTHER SCHOOL TUITION OTH SCH EXPENSES INCLUD RENTALS LEGAL FEES FUNERAL EXPENSE SAFE DEPOSIT BOX RENTAL CHECK ACCTS / OTH BANK SERV CHGS CEMETERY LOTS,VAULTS,MAINT FEES ACCOUNTING FEES COMPTER/COMPTER HRDWAR N-BUS USE COMPTER SFTWR/CMPTR ACC N-BUS USE REPAIR-CMPTR,CMPTR SYS N-B COMPUTER INFORMATION SERVICES INTERNET SERVICES AWAY FROM HOME PORTABLE MEMORY COMPUTER ACCESSORIES TELEPHONE ANSWERING DEVICES CALCULATORS TYPWRITS/OTH OFF MACH NON-BUS USE SMOKE ALARM PUR/RENT OWND OTH HH APPL RNTR OTH HH APPL OWND REGULAR GROC SHOPPING INCL GOODS FOOD/NONALC BEV AT GROC STORES FD/NONALC BEV AT CONVEN STORE AVG FOOD/NONALC BEV EXPENSES BEER/WINE FOR HOME USE OTHER ALCOHOL FOR HOME USE BEER/WINE/OTH ALC FOR HOME USE DINING OUT AT REST., ETC EXCL ALC ALCOHOL AT RESTAURANTS ETC SCHOOL MEALS	MAINT/REP/UTIL OTH PROP CHILD SUPPORT EXPENDITURES RENT RECEIVED AS PAY CSH GFT/NON-CU, CNTRB/ORG SUPPORT FOR COLLEGE STUDENTS CASH CONTRIBUTIONS TO CHARITIES, OTHER ORGANIZATIONS CASH CONTRIBUTIONS TO CHURCHES OR RELIGIOUS ORGANIZATIONS CASH CONTRIBUTIONS TO EDUCATIONAL INSTITUTIONS CASH CONTRIBUTIONS TO POLITICAL ORGANIZATIONS OTHER CASH GIFTS INT PAID ON OTH VEH INTEREST, HM EQ LN (CRDT), OWND	

Univariate analysis

For each for the 448 spending categories *c*, estimate a linear probability model

$$D(\text{Positive finance/interest/late charges})_i = \gamma_c * D(\text{Positive category spending})_{i,c} + x_i'\beta + \varepsilon_i$$

- *i*=household, *c*=spending category
- x_i=household-level controls:
  ln(C), ln(C)^2, ln(Y), ln(Y)^2, age, age^2, family size, D(male), D(rural), time dummies (quarterly)
- I report 50 categories with largest t-statistics for γ_c (in absolute value)

US data: Relating consumer credit finance/interest/late charges to spending mix. Univariate.

Spending categories related to other borrowing or banking are highlighted in light blue.
Spending categories related to entertainment are highlighted in pink.

Spending category	t-statistic for γ_c	Coefficient (γ_c)	Fraction of hh's with positive spending on category
CHECK ACCTS / OTH BANK SERV CHGS	25.53	0.094	0.438
VEHICLE INSURANCE	13.93	0.070	0.819
AUTOMOBILE FINANCE CHARGES	13.83	0.055	0.318
MORTGAGE INTEREST OWND	12.07	0.049	0.518
RNTL VIDEO CASS/TAPES/DISCS/FILMS	11.69	0.047	0.553
TRUCK FINANCE CHARGES	11.30	0.051	0.219
VIDEO CASSETTES/TAPES/DISCS	9.02	0.035	0.402
COOLANT/ADDITIVES/BRK/TRNS FLD	8.90	0.037	0.273
PHYSICIANS SERVICES	8.73	0.034	0.613
WOMENS HOSIERY	8.71	0.035	0.430
PRESCRIPTION DRUGS	8.59	0.036	0.699
VET SERVICES	8.39	0.034	0.290
INTEREST, LMP SUM HM EQ LN, OWND	8.27	0.068	0.056
MAGAZINE/NEWSPAPER SINGLE COPY	8.19	0.057	0.328
PET-PURCHASE/SUPPLIES/MEDICINE	8.17	0.031	0.430
TOYS GAMES ARTS CRAFTS TRICYCLES	8.17	0.031	0.493
VIDEO GAME HARDWARE/SOFTWARE	8.11	0.040	0.186
SCHOOL MEALS	7.87	0.039	0.223
LOTTERIES AND PARIMUTUEL LOSSES	7.66	0.044	0.276
RECORDS,CDS,AUDIO TAPES	7.66	0.034	0.473
RCRD/TAPE/CD/VIDEO MAIL ORD CLUB	7.38	0.048	0.121
FILM	7.37	0.031	0.443
CIGARETTES	7.20	0.028	0.329

WOMENS ACCESSORIES	7.01	0.029	0.305
MAGAZINES, NON-SUBSCRIPTION	6.87	0.037	0.374
WOMENS UNDERGARMENTS	6.79	0.026	0.405
NEWSPAPERS, NON-SUBSCRIPTION	6.77	0.036	0.416
BOOKS NOT THRU BOOK CLUBS	6.71	0.025	0.507
BATHROOM LINENS	6.64	0.028	0.255
WOMENS SHIRTS, TOPS,BLOUSES	6.54	0.025	0.580
RENTERS INSURANCE	6.16	0.047	0.060
TELEPHONE SERVICE NOT SPEC	6.15	0.146	0.960
GIRLS ACCESSORIES	6.10	0.040	0.086
JEWELRY	5.99	0.024	0.344
OTHER GASH GIFTS	5.99	0.032	0.368
GIRLS SWIMSUITS/WARM-UP/SKI SUITS	5.92	0.037	0.097
MENS HOSIERY	5.87	0.025	0.269
INT PAID ON OTH VEH	5.81	0.066	0.026
OTH HOUSEHOLD DECORATIVE ITEMS	5.80	0.025	0.350
WOMENS PANTS	5.66	0.024	0.521
WOMENS FOOTWEAR	5.60	0.021	0.550
BOOKS THRU BOOK CLUBS	5.60	0.032	0.114
CREDIT CARD MEMBERSHIPS	5.58	0.039	0.085
ELECTRIC PERSONAL CARE APPL.	5.44	0.027	0.153
COMPTER SFTWR/CMPTR ACC N-BUS USE	5.40	0.029	0.146
WOMENS DRESSES	5.39	0.021	0.365
SCHOOL BK/SUPL/EQUIP FOR ELEM/HS	5.29	0.030	0.138
	…		
ELECTRICITY OWNV	-5.79	-0.072	0.022
CAP IMPROVE LABOR/MAT OWND	-6.04	-0.031	0.158
SAFE DEPOSIT BOX RENTAL	-9.96	-0.060	0.109

1. Consistent with usefulness of account-level data for (potential) lenders:
   - Even controlling for C, Y, demographics, many categories have sign. explanatory power (economic & statistical)
   - Easier to predict high-risk than low-risk borrowers. Of the 50 strongest predictors, 47 have positive coefficients

2. Consistent with usefulness of traditional credit scoring:

   Significance of categories related to payments on other borrowing or banking products
   - Other distress indicator: Checking accounts & other bank service charges (includes below minimum balance fees)
   - Cheaper sources of credit: Mortgage interest on owned dwellings, interest on lump sum home equity lines of credit for owned dwellings, automobile finance charges, truck finance charges, and interest paid on other vehicles

3. Novel finding: Entertainment-related items matter, with positive coefficients. 16 of the top 50 categories
   - Five categories related to video and audio
   - Five categories related to magazines, newspapers, and books (of which four are single-copy)
   - Two pet-related categories, toys/games/arts/crafts/tricycles, lotteries, film (for cameras), and telephone service

Multivariate analysis

D(Positive finance/interest/late charges)$_i$ =γ_1*D(Pos. category spending)$_{i,1}$ +…+γ_C*D(Pos. category spending)$_{i,C}$ +$x_i'\beta+\varepsilon_i$

LASSO approach:

- Avoid overfitting in settings with many regressors
- Better statistical properties than simply adding or deleting variables using a stepwise OLS approach

For a linear model, $y=\beta_1x_1+\beta_2x_2+\ldots+\beta_px_p+\varepsilon$, the LASSO objective is to minimize

$$\frac{1}{2N}(y-X\beta)'(y-X\beta)+\lambda\sum_{j=1}^{p}|\beta_j|$$

- First term: OLS objective

  Second term: Penalizes non-zero coefficients. Kink in absolute value function → Some coefficients are set to zero

  - Value of λ determines how sparse the chosen model will be
  - I pick λ using extended Bayesian information criterion. Tends to result in fewer predictors than other criteria
  - Same x_i. No penalty on time dummies included in controls (to ensure that they are included)

US data: Relating consumer credit finance/interest/late charges to spending mix. Multivariate approach: LASSO

The table lists the spending mix variables chosen by LASSO, sorted based on the post-estimation OLS t-statistics. The t-statistic for γ_c and the coefficients for γ_c are based on the post-estimation OLS regression. These are biased and are not to be used for inference but as indicators of the relative importance of variables. The controls chosen by LASSO are shown at the bottom of the table.

Spending category	t-statistic for γ_c	γ_c
CHECK ACCTS / OTH BANK SERV CHGS	21.23	0.079
MORTGAGE INTEREST OWND	17.00	0.081
AUTOMOBILE FINANCE CHARGES	11.36	0.045
ELECTRICITY RNTR	10.07	0.053
TRUCK FINANCE CHARGES	9.41	0.042
VEHICLE INSURANCE	9.25	0.046
INTEREST, LMP SUM HM EQ LN, OWND	7.84	0.064
CIGARETTES	5.66	0.022
CAR LEASE PAYMENTS	5.11	0.049
MAGAZINE/NEWSPAPER SINGLE COPY	4.67	0.032
RNTL VIDEO CASS/TAPES/DISCS/FILMS	4.65	0.019
RENTERS INSURANCE	4.27	0.034
PHYSICIANS SERVICES	4.06	0.016
COIN-OP HSHLD LNDRY, DRY CLN	3.97	0.023
RCRD/TAPE/CD/VIDEO MAIL ORD CLUB	3.95	0.026
INT PAID ON OTH VEH	3.82	0.043
WOMENS HOSIERY	3.56	0.015
SCHOOL MEALS	3.52	0.017
LOTTERIES AND PARIMUTUEL LOSSES	3.43	0.019
VET SERVICES	3.35	0.015
NEWSPAPERS, NON-SUBSCRIPTION	3.35	0.018
COOLANT/ADDITIVES/BRK/TRNS FLD	3.22	0.014

BATHROOM LINENS	2.60	0.011
VIDEO GAME HARDWARE/SOFTWARE	2.34	0.012
MAGAZINES, NON-SUBSCRIPTION	2.27	0.013
GIRLS ACCESSORIES	2.05	0.015
RECORDS,CDS,AUDIO TAPES	1.97	0.009
VIDEO CASSETTES/TAPES/DISCS	1.90	0.008
GIRLS SWIMSUITS/WARM-UP/SKI SUITS	1.74	0.012
WOMENS ACCESSORIES	1.48	0.006
TOYS GAMES ARTS CRAFTS TRICYCLES	1.23	0.005
PET-PURCHASE/SUPPLIES/MEDICINE	0.69	0.003
ELECTRICITY OWNV	-4.39	-0.053
DOMESTIC SERVICE	-5.56	-0.034
CASH CONTRIBUTIONS TO EDUCATIONAL INSTITUTIONS	-5.76	-0.054
MEDICARE PAYMENTS	-6.00	-0.030
CAP IMPROVE LABOR/MAT OWND	-6.68	-0.034
SAFE DEPOSIT BOX RENTAL	-9.75	-0.057
ln(Real after-tax income)	3.23	0.006
D(Male)	-5.37	-0.020
D(Rural)	-5.79	-0.038
Time dummies included without penalty, coefficients omitted for brevity		

- LASSO (with the chosen approach to pick λ) selects: 38 spending categories, ln(Y), D(male), D(rural)
  - Of the 32 with positive signs, 7 relate to other debt and banking and 12 are entertainment-related categories

- Predictive power of various sets of variables: Re-estimate the final model using logit and calculate the area under the ROC curve (called AUC), a standard measure of fit in binary dept. var. models. Lies between 0.5 and 1

Time dummies and 3 controls	AUC=0.605
+7 var's related to other debt and banking	AUC=0.646
+12 entertainment-related categories	AUC=0.653
+19 other spending category	AUC=0.666

Iyer, Khwaja, Luttmer and Shue (2016): "an AUC of 0.6 or greater is generally considered desirable in information-scarce environments, and AUCs of 0.7 or greater are the goal in more information-rich environments"

Mechanism: Where does predictive power of spending mix for credit outcomes come from?

Standard models of household life-cycle consumption and savings: Consumers borrow to smooth consumption

- Across age: Mismatch in timing between income profile and desired spending, and including for durables consumption
- Across states: Smoothing transitory shocks to income or to needed expenditures

Repayment difficulties could be driven by:

- Bad planning: Taking on more debt than one would if fully understanding the optimization problem
- Sufficiently bad news about realized income and expenditure needs (or house prices)
- Impatience: The impatient are willing to borrow more even if it increases risk of default and low consumption later

Role for expenditure shocks appears modest: Physician services, vet services, and prescription drugs perhaps

Categories related to other borrowing and banking are not informative

- If some people tend to borrow in many ways: Does not inform us about why they made this choice

Predictive power of categories related to entertainment is more informative

- Hypothesis: More impatient households are more likely to spend on particular categories
  - Those who are less patient may also have stronger preferences for products that provide immediate experiences
  - They may be willing to borrow to pay for it
- Regressions control for Y: Not simply the case that those who spend money on entertainment have lower Y and therefore worse credit outcomes

Proxy for discount rate in the CEX data: Smoking (positive spending on cigarettes or other tobacco products)

- Smoking: Immediate utility but negative health consequences later
  → More impatient should be more likely to smoke
- Does spending on categories with higher γ_c predict smoking?
- Note: Cigarette spending is significant predictor in both univariate and multivariate results

Alternative proxy for discount rate in CEX: Fewer years of education

- Education: Requires upfront study effort and delay of consumption, returning higher consumption later
  → More impatient individuals should tend to choose less education
- Does spending on categories with higher γ_c predict shorter education?

For each spending category *c*, I estimate the univariate model, replacing dependent variable with D(Smoking):

$$D(\text{Positive smoking spending})_i = \gamma_c^{smoke} * D(\text{Positive category spending})_{i,c} + x_i'\beta + \varepsilon_i$$

- Positive value for γ_c^{smoke}: Category *c* tends to attract less patient households
- Across 448 spending categories: Relate γ_c^{smoke} to γ_c (t-statistics and coefficient magnitudes)

US data: Does spending mix capture time preferences?

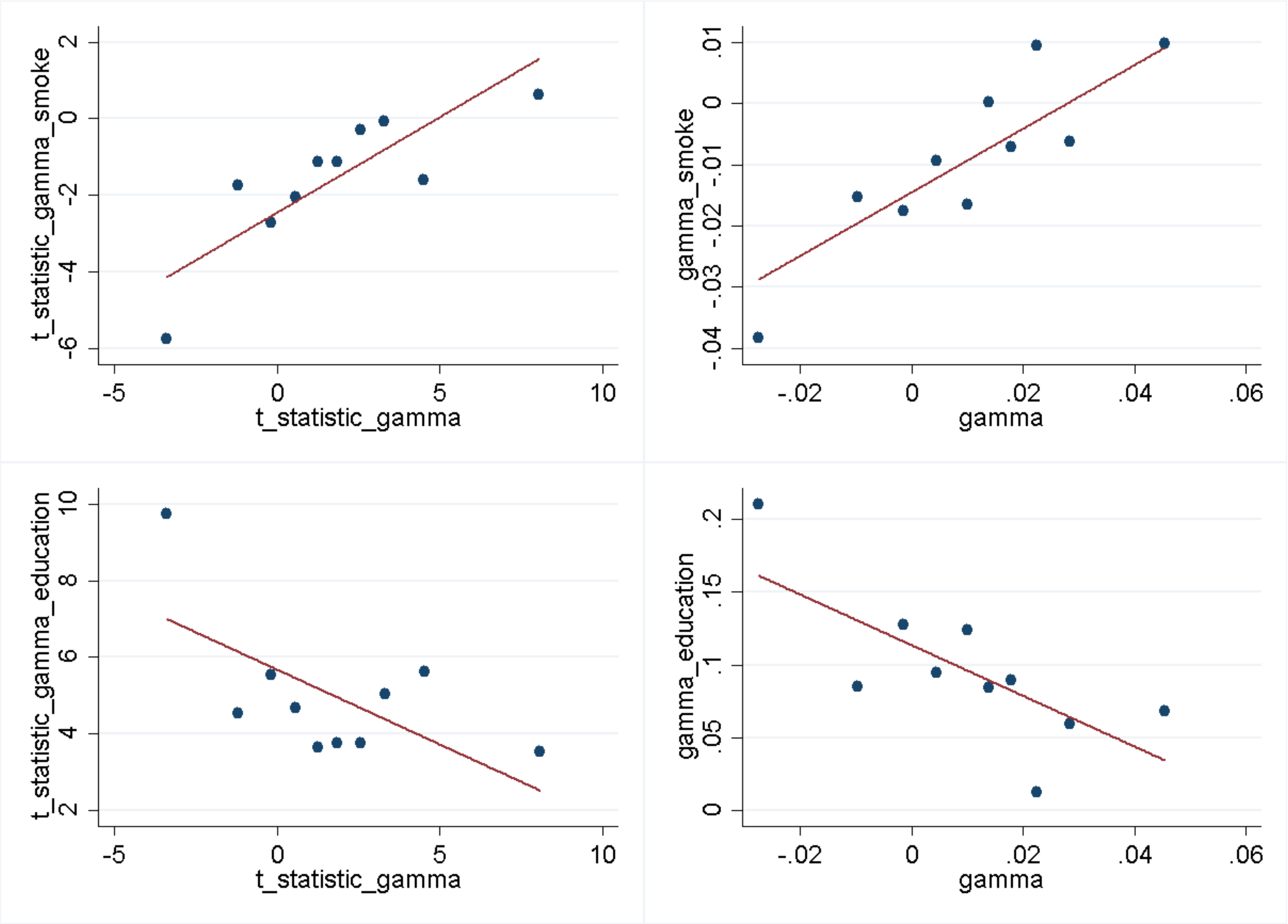
The table relates categories' ability to predict positive finance/interest/late change on consumer credit (γ_c) to categories' ability to predict smoking (γ_c^{smoke}) or years of education ($\gamma_c^{education}$).

	Dependent variable:			
	t-statistic for		t-statistic for	
	γ_c^{smoke}	γ_c^{smoke}	$\gamma_c^{education}$	$\gamma_c^{education}$
	(1)	(2)	(3)	(4)
t-statistic for γ_c	0.663***		-0.705***	
	(7.46)		(-5.33)	
γ_c		0.624***		-2.231***
		(7.17)		(-5.64)
Fraction of households with positive spending on category	-7.545***	-0.0370***	14.44***	0.172***
	(-5.16)	(-4.00)	(6.62)	(4.09)
Constant	-1.337***	-0.00874***	3.548***	0.0867***
	(-3.60)	(-3.64)	(6.40)	(7.94)
N (spending categories)	446	448	448	448
R^2	0.124	0.110	0.108	0.079

- Gammas and their t-statistics are estimated. Accounting for estimation error would likely only strengthen the results
- I include fraction of hh's with positive spending on a given category as a control: May affect both sets of t-statistics

US data: Does spending mix capture time preferences?

The figures relate categories' ability to predict positive finance/interest/late change on consumer credit (γ_c) to categories' ability to predict smoking (γ_c^{smoke}) or years of education ($\gamma_c^{education}$). The figures present bin-scatter plots with 10 bins.



How does impatience drive consumer credit outcomes? More work needed

- Are those with higher entertainment spending more likely to be hyperbolic discounters?
- Do more impatient household have time consistent preferences with higher discount rates? How exactly?

Consider a setting with two periods (1 and 2) and two goods (A and B). Think of B as entertainment.

$u(c_1^A, c_1^B) + \beta u(c_2^A, c_2^B)$ Do those w/stronger preference for B have lower β?

$u(c_1^A) + \beta^A u(c_2^A) + v(c_1^B) + \beta^B v(c_2^B)$ If $\beta^B < \beta^A$ those w/stronger pref for B spend more upfront

- Alternatively, perhaps we should think of impatience as related to impulsiveness and impulse shopping

  Are consumers who spend a large fraction on the entertainment-related categories succumbing to a desire for immediate gratification both when shopping and when deciding what to do with their time?

  - Gathergood (2012) documents a relation between impulse buying and financial distress
  - Singly-copy magazines and newspapers

  Add patience and impulsiveness-related survey questions to CEX (Rook and Fisher (1995) or Puri (1996))
  Combine account-level data with customer surveys at financial institutions

CONSUMER CREDIT AT A MEXICAN RETAIL CHAIN

Basics of data set

499,906 new customers who purchased one or more products on credit at retail chain between January 2005 and December 2006

- Chain sells about 90% on credit, rest paid in cash or using credit or debit cards. Data covers credit purchases
- A total of 1,364,864 credit-financed purchases, across 220 stores
- Payment history of these purchases is followed up to August 2009:
    - Sufficient to assess repayment of 2005/2006 loans
    - Takes about two years before accounts are declared "lost"

- Target customers: Middle and lower income households

	My sample	Mexican population (ENIGH 2005)
Monthly household income<16,800 pesos ($1,268)	88%	85%
Monthly household income< 4,200 pesos ($317)	52%	26%

- Monthly information by customer:
  1. Demographics: Age, gender, marital status, household income, education, home ownership, years at current address, and household size
  2. New purchases: Store, amount of purchase, down-payment, interest rate, loan term, type of product
     Payments on past purchases, assignment of additional interest (due to late payments) and merchandise returns
  3. Account balances, track record of repaying loans, and customer's credit limit
  4. “Lost loans" (loans on which company has given up collecting any further payments)
     For such accounts: Date of purchase, date account was declared lost, loss amount

- Separate loan for each purchase
  (Except for clothing and cell phone minutes: charged to a revolving account much like a credit card,. I exclude these)

Type of product purchased information:

- ``DVD player", ``lamp", or ``washing machine": Refers to largest item purchased on a given visit to the store
- Company categorizes products into nine broad categories, each further sub-divided into classes
    - Purchases in the 2005-2006 sample: Fall into 124 product categories, some with few purchases
      I group some together and work with 32 more detailed product categories
- Diverse set of products (but excludes important spending categories like food and housing)

Loan features

Required minimum downpayment:

Function of cost of the relative to customer's authorized credit (credit limit) and customer's internal credit score

% of customer's authorized credit	Internal credit score				
	A	B	N	C	D
From 0 to 100	0	20	10	30	30
101 to 150	10	20	20	30	40
151 to 200	20	30	30	40	50
201 to 300	20	40	40	50	60
301 to 400	30	50	50	60	70

- Authorized credit (credit limit) = 25% of the customer's annual income for new customers
  - Subsequent limits are updated based on the client's payment history
  - Can borrow more than limit but with higher down-payment as laid out in table
- Internal credit score: Based on customer's repayment efficiency to date
  - Repayment efficiency=(Sum of actual payments)/(Sum of payments due while customer)
    - A: > 75%. B: 50 to 75%, C: 25 to 50%, D: <25%. New customer: N

Monthly payment on a loan:

Monthly payment=Loan amount*(1+r)/Loan term

- r is the "flat interest rate" on the loan. Implied APR is higher than r (you don't owe the full amount all year)
- r=24% on a 12-month loan leads to same monthly payment as APR=41.6% with monthly compounding would

Interest rate:

- Does *not* depend on downpayment, credit score, or size of purchase.
- Higher for cell phones than for other product categories, higher for 18-month loans than 12-month loans
- Higher for cities considered high risk

Schedule of interest rates as of end of sample:

City type:	Zone 1 (low risk)	Zone 2 (high risk)
Furniture/household item (12 month loan)	24%	30%
Furniture/household item (18 month loan)	36%	45%
Cell phone (12 month loan)	32%	38%
Cell phone (18 month loan)	44%	38%

If a customer misses payments: Customer returns product, or loan is declared a loss

Differences in loan loss rates across product categories

$$\text{Loss} = \text{Loan}*(1+r)-\text{Payments}$$

Approximate realized return:

$$1+\text{realized return} = \text{Payments}/\text{Loan} = (1+r) - \text{Loss}/\text{Loan}$$

- True return is higher since payments are monthly, not all at end of loan
- But true return is lower if some payments are late

Mexican data: Loss rates by product category

	Pct of sales	Excl. products with no default information (clothes, cell phone minutes)				
		Pct. of sales	Pct. of loans	Loss rate	Avg. interest rate	Lender return
Product category	(1)	(2)	(3)	(4)	(5)	=(5)-(4)
Kitchen equipment, various hh. items	2.40	3.50	3.50	11.50	24.90	13.40
Electronics	40.60	60.00	60.20	21.30	27.60	6.30
Mattresses, dining sets, other furniture	4.90	7.20	7.20	11.30	24.90	13.60
Living room and bedroom furniture	3.40	5.10	5.00	11.10	25.70	14.60
Kids gear and toys, auto parts, bikes	5.50	8.20	8.30	16.50	24.90	8.40
Appliances	9.20	13.50	13.40	11.80	25.50	13.70
Watches	0.60	0.90	0.90	17.00	25.00	8.00
Jewelry	0.70	1.10	1.10	39.20	25.20	-14.00
Eye glasses etc.	0.30	0.50	0.50	15.40	25.00	9.60
Cell phone minutes	1.80					
Clothes	30.50					
All above categories	100	100	100	18.20	26.60	8.40

- Low loss rates on useful but unexciting stuff (green)
- High loss rates on electronics (pink), which is mainly entertainment (next slide) and jewelry
- Return differences given similar interest rates (except for cell phones)
- Limited data on product markups across categories: Markups are not systematically related to loss rates

Mexican data: Loss rates by detailed product category

	Pct. of sales	Excl. products with no default information (clothes, cell phone minutes)				
		Pct. of sales	Pct. of loans	Loss rate	Avg. interest rate	Lender return
Product category	(1)	(2)	(3)	(4)	(5)	=(5)-(4)
Kitchen equipment, various household items						
1. Kitchen electronics	1.3	1.9	1.9	11.1	25.0	13.9
2. Cook and tableware	0.4	0.6	0.6	11.8	24.9	13.1
3. Personal care	0.3	0.5	0.5	13.3	24.8	11.5
4. Luggage	0.3	0.4	0.4	12.2	24.6	12.4
Electronics						
5. Audio, for cars	3.0	4.4	4.5	20.5	25.0	4.4
6. Audio, not for cars	5.6	8.2	8.2	16.2	25.8	9.6
7. TVs	5.0	7.4	7.4	18.7	25.4	6.7
8. DVD, video	2.3	3.4	3.5	15.8	25.2	9.4
9. Entertainment electronics	2.9	4.2	4.2	18.5	25.0	6.4
10. Phones (not cell)	0.4	0.6	0.6	9.7	25.1	15.4
11. Cell phones	20.8	30.8	31.0	24.9	29.7	4.8
12. Microwave ovens	0.5	0.8	0.8	13.5	25.1	11.7
Mattresses, dining sets, other furniture						
13. Mattresses	2.2	3.2	3.2	12.6	24.9	12.4
14. Dining sets, chairs	1.1	1.7	1.6	11.3	24.8	13.5
15. Office furniture	0.2	0.3	0.3	7.7	24.9	17.2

16. Wardrobes, cupboards	1.0	1.4	1.4	8.4	24.8	16.4
Living room and bedroom furniture						
17. Living room furniture	2.6	3.9	3.8	11.4	25.8	14.5
18. Bedroom furniture	0.5	0.7	0.7	12.1	25.3	13.2
19. Sewing machines	0.3	0.5	0.5	7.3	25.1	17.8
Kids gear and toys, auto parts, bikes						
20. Baby items (e.g. stroller)	0.9	1.4	1.4	17.6	24.9	7.3
21. Toys	0.8	1.2	1.2	17.2	24.9	7.7
22. Tires, car batteries	2.1	3.0	3.1	16.0	24.8	8.8
23. Kids bikes	1.7	2.5	2.5	16.4	24.9	8.5
Appliances						
24. Fans, AC units	0.9	1.4	1.4	13.9	25.0	11.1
25. Water heaters, other heaters	0.4	0.6	0.6	11.3	25.3	14.0
26. Stoves, ovens	1.7	2.5	2.5	11.4	25.2	13.8
27. Fridges, water coolers	3.0	4.4	4.3	12.4	25.7	13.3
28. Washer/dryer/dishwasher	3.1	4.6	4.6	10.9	25.5	14.7
29. Other (from above categories)	0.7	1.1	1.1	11.2	24.9	13.7
30. Watches	0.6	0.9	0.9	17.0	25.0	8.0
31. Jewelry	0.7	1.1	1.1	39.2	25.2	-14.0
32. Glasses etc.	0.3	0.5	0.5	15.4	25.0	9.6
33. Cell phone minutes	1.8					
34. Clothes	30.5					
All above categories	100	100	100	18.2	26.6	8.4

Mexican data: Loss rate by product category and time as customer

Product category	Loss rate, by months as customer at time of current purchase				
	<1	1 to 6	6 to 12	12 to 18	18 to 24
Kitchen equipment, various household items	14.3%	12.9%	6.9%	6.7%	8.3%
Electronics	25.4%	22.4%	14.3%	14.2%	16.3%
Mattresses, dining sets, other furniture	12.6%	12.5%	8.7%	8.4%	10.1%
Living room and bedroom furniture	11.8%	12.6%	9.1%	8.8%	11.0%
Kids gear and toys, auto parts, bikes	19.0%	19.1%	10.7%	11.4%	13.9%
Appliances	13.2%	13.3%	8.7%	8.7%	10.1%
Watches	21.6%	18.4%	9.4%	10.4%	12.1%
Jewelry	51.5%	34.6%	20.1%	24.0%	28.7%
Eye glasses etc.	18.5%	16.7%	9.4%	10.2%	14.6%
All above categories	21.5%	19.6%	12.3%	12.2%	14.4%

- Loss rates are lower for more seasoned borrowers
- Differences across product categories remain about as large in relative terms for seasoned as for new borrowers

Consistent with findings: In early 2009, the company increased down-payment requirement for new clients from 10% to 20% for cell phones, stereos, video games, iPods, computers, laptops, and jewelry

Predictive power of product mix for losses, controlling for standard default predictors

- Do standard explanatory variables matter?
- Are product categories saying something beyond known determinants of default?
- How much extra predictive power do the product effects generate?

- Linear model for loss rate:
  - Tobit better, but later I include fixed effects and no unbiased fixed effects Tobit approach exists

- Standard explanatory variables:
  - Time as customer dummies
  - Transaction characteristics (loan amount, down payment/purchase price, interest rate, and loan term)
  - Measures of borrower credit risk (including the company's internal credit rating)
  - Demographics
  - Store fixed effects

Mexican data: Predicting loss rates using standard predictors (only)

Significance indicated with *** (1%), ** (5%) and * (10%).

	Dependent variable: Loss rate=Amount not repaid/Loan amount				
	(1)	(2)	(3)	(4)	(5)
Fixed effects (month dummies) for time as customer	Yes	Yes	Yes	Yes	Yes
Transaction characteristics					
Loan amount (1000s of pesos)		0.0100***	0.0100***	0.0093***	0.0087***
Downpayment/Purchase price		-0.0525***	-0.1339***	-0.1240***	-0.1132***
Interest rate		1.0649***	1.0260***	0.9892***	1.3823***
Term of loan (months)		-0.0133***	-0.0131***	-0.0123***	-0.0205***
Measures of borrower credit risk					
Credit score (omitted: New customer, no score)					
A (best credit)			-0.0621***	-0.0618***	-0.0597***
B			0.0292***	0.0252***	0.0250***
C			0.0674***	0.0625***	0.0642***
D			0.1546***	0.1554***	0.1543***
Repayment efficiency, main account			-0.0012***	-0.0011***	-0.0011***
Repayment efficiency, clothing account			-0.0011***	-0.0011***	-0.0010***
Credit limit (omitted: limit=4200 pesos)					
Limit=8400 pesos			-0.0055***	-0.0086***	0.0003
Limit=12600 pesos			-0.0082***	-0.0029**	0.0163***
Number of purchases made to date			0.0094***	0.0080***	0.0080***

Account balance, main account (1000s of pesos)	0.0188***	0.0186***	0.0178***
Account balance, clothing account (1000s of pesos)	0.0646***	0.0664***	0.0641***
Late balance, main account (1000s of pesos)	0.1091***	0.1048***	0.1037***
Late balance, clothing account (1000s of pesos)	0.0905***	0.0870***	0.0869***
Moratory interest accumulated, main account (1000s of pesos)	0.6919***	0.6505***	0.6374***
Moratory interest accumulated, clothing account (1000s of pesos)	0.7327***	0.7259***	0.7196***
Maximum credit level in the past, main account (1000s of pesos)	-0.0112***	-0.0109***	-0.0108***
Maximum credit level in the past, clothing account (1000s of pesos)	-0.0093***	-0.0080***	-0.0079***
Demographics			
Age		-0.0021***	-0.0021***
Minor (age<21 for men, age<18 for women)		-0.0011	0.0011
Male		0.0255***	0.0214***
Marital status (omitted: married)			
Divorced		0.0672***	0.0650***
Single		0.0140***	0.0114***
Couple, not married		0.0374***	0.0359***
Widow		0.0395***	0.0376***
Income category (omitted: income<4200 pesos)			
>=4200, <8400 pesos		-0.0118***	-0.0124***
>=8400, <12600 pesos		-0.0099***	-0.0117***
>=12600, <16800 pesos		-0.0132***	-0.0115***
>=16800 pesos		-0.0104***	-0.0097***
Highest education (omitted: no schooling)			
<=Elementary school		0.0096***	0.0013
<=Junior high		0.0154***	-0.0016
<=Technical college		-0.0050*	-0.0275***
<=High school		0.0110***	-0.0086***

<=University				-0.0217***	-0.0414***
Living situation (omitted: home owner)					
Renter				0.0540***	0.0534***
Lives with family				0.0072***	0.0040***
Guest				0.0040	0.0059
Years living at home address				-0.0016***	-0.0018***
Number of people living in customer's house				-0.0076***	-0.0072***
Number of people who live in customer's house and work				0.0138***	0.0141***
Number of people who are economically dependent on the client				-0.0001	0.0003
Store fixed effects	No	No	No	No	Yes
N	1,364,864	1,364,864	1,364,864	1,364,864	1,364,864
R2	0.015	0.027	0.068	0.084	0.097

Yes, standard predictors matter. Estimated effect on loss rate based on col 5:

- Loan size +1σ (+1309 pesos): +1.1 pp Adverse selection (high-risk hh's select into larger loans)
  Moral hazard (larger loan → strategic default or lack of affordability)
- Down payment/Price +1σ (+0.083): -0.9 pp
- Interest rate +1 σ (+3.9 pp): +5.4 pp
- "A" credit score: -6.0 pp
- Age +1 σ (10.8 years): -2.3 pp
- Years at home address +1σ (11.3 yrs): +2.0 pp

R2=0.015 to 0.097

Mexican data: Predicting loss rates using product categories and standard predictors

	Dependent variable: Loss rate=Amount not repaid/Loan amount						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Controls:							
Time as customer fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Transactions characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Measures of borrower credit risk	No	No	No	Yes	Yes	Yes	Yes
Demographics	No	No	No	No	Yes	Yes	Yes
Store fixed effects	No	No	No	No	No	Yes	No
Individual fixed effects	No	No	No	No	No	No	Yes
Product category (omitted=sewing machines)							
Kitchen equipment, various household items							
Kitchen electronics	0.030	0.029	0.054	0.052	0.049	0.048	0.008
Cook and tableware	0.025	0.026	0.052	0.050	0.048	0.049	0.015
Personal care	0.047	0.047	0.074	0.065	0.056	0.053	0.009
Luggage	0.038	0.041	0.067	0.060	0.057	0.058	0.009
Electronics							
Audio, for cars	0.122	0.122	0.121	0.110	0.100	0.096	0.028
Audio, not for cars	0.074	0.074	0.080	0.071	0.064	0.061	*0.006*
TVs	0.102	0.099	0.090	0.083	0.074	0.072	*0.000*
DVD, video	0.078	0.075	0.087	0.078	0.067	0.063	*0.003*
Entertainment electronics	0.089	0.096	0.092	0.080	0.071	0.068	*0.007*
Phones (not cell)	0.018	0.020	0.043	0.037	0.038	0.031	*0.005*
Cell phones	0.167	0.163	0.151	0.138	0.128	0.129	0.043
Microwave ovens	0.053	0.054	0.067	0.062	0.056	0.051	*0.009*
Mattresses, dining sets, other furniture							

Mattresses	0.044	0.044	0.045	0.043	0.042	0.039	0.021
Dining sets, chairs	0.030	0.033	0.027	0.023	0.020	0.019	*-0.001*
Office furniture	*-0.003*	*-0.004*	*0.011*	*0.009*	*0.012*	*0.009*	0.013
Wardrobes, cupboards	*0.009*	*0.011*	0.016	0.015	*0.010*	*0.009*	0.010
Living room and bedroom furniture							
Living room furniture	0.026	0.027	*0.004*	*0.000*	*-0.002*	*-0.003*	*-0.006*
Bedroom furniture	0.032	0.033	*-0.013*	*-0.014*	-0.020	-0.019	-0.019
Sewing machines	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Kids gear and toys, auto parts, bikes							
Baby items (e.g. stroller)	0.090	0.087	0.106	0.096	0.086	0.084	0.023
Toys	0.095	0.095	0.114	0.099	0.090	0.088	0.019
Tires, car batteries	0.083	0.086	0.101	0.094	0.097	0.093	0.033
Kids bikes	0.084	0.083	0.092	0.080	0.075	0.077	0.011
Appliances							
Fans, AC units	0.047	0.046	0.061	0.056	0.051	0.050	*0.000*
Water heaters, other heaters	0.036	0.041	0.049	0.046	0.049	0.038	0.015
Stoves, ovens	0.040	0.041	0.035	0.034	0.030	0.031	*-0.001*
Fridges, water coolers	0.044	0.042	*0.004*	*0.002*	*-0.006*	*-0.006*	-0.022
Washer/dryer/dishwasher	0.029	0.028	*0.007*	*0.005*	*0.000*	*-0.001*	-0.015
Other (from above categories)	0.017	0.021	0.037	0.033	0.033	0.032	*0.005*
Watches	0.075	0.076	0.096	0.084	0.079	0.080	0.025
Jewelry	0.186	0.184	0.202	0.184	0.175	0.175	0.031
Eye glasses etc.	0.079	0.078	0.091	0.084	0.084	0.081	0.036
N=1,364,864							
R2	0.021	0.035	0.039	0.077	0.092	0.103	0.819

- Yes, product categories say something beyond known determinants of default: Small effect of controlling
- R2 up 0.01-0.02 in each column when adding product category dummies

Mechanism: Are differential loss rates across product categories about people or products?

- Which types of individuals buy particular products or
- High loss rates on certain products regardless of who buys them

Simple framework: i=individual, p=product, x=observables

$$Loss\ rate_{i,p} = f_p + f_i + x_{i,p}'\beta.$$

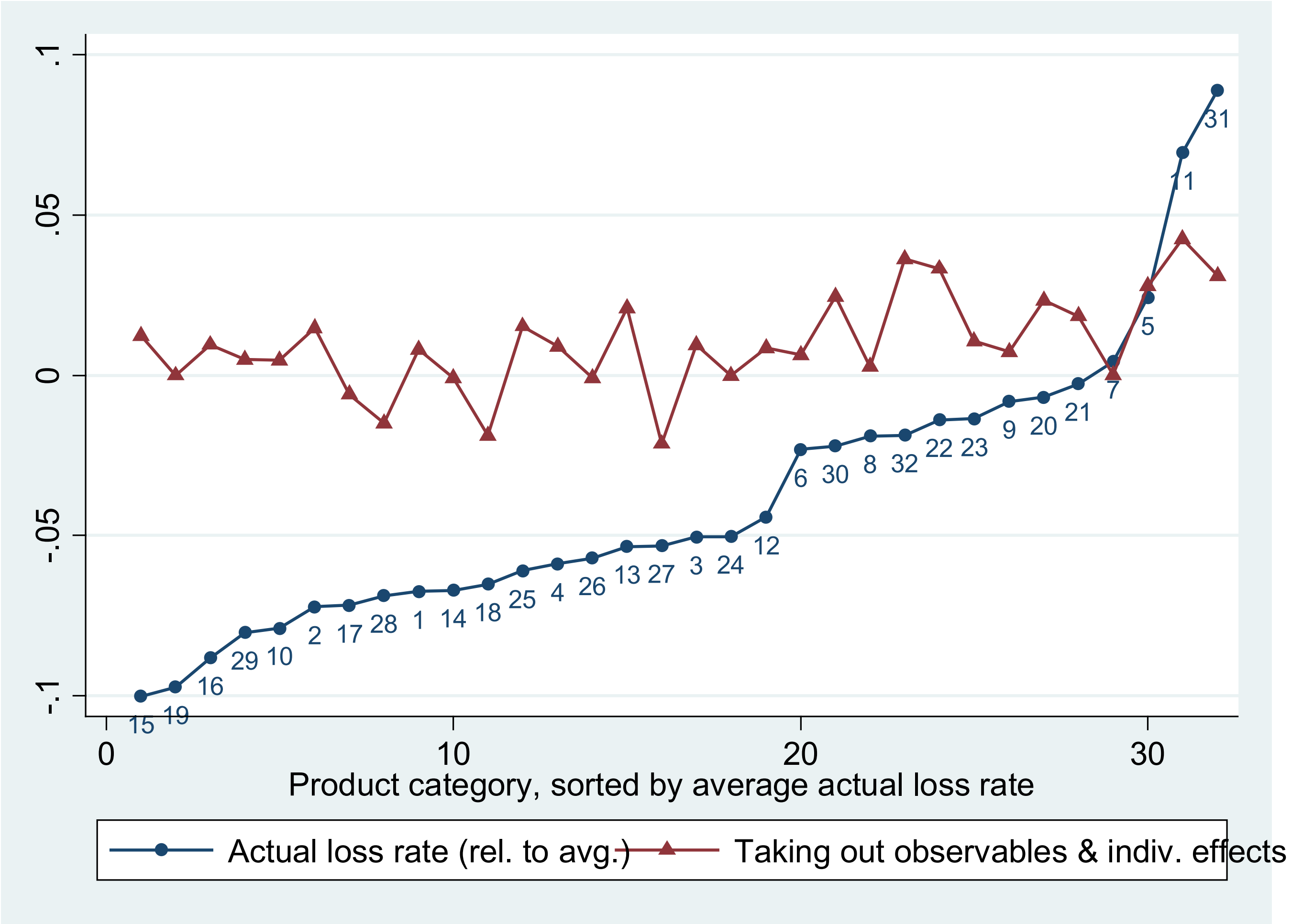
$$Average\ Loss\ Rate_p = \frac{1}{I}\sum_{i=1}^{I} Loss\ rate_{i,p} = \left[f_p + \left(\frac{1}{I}\sum_{i=1}^{I} f_i\right)_p\right] + \frac{1}{I}\sum_{i=1}^{I} x_{i,p}'\beta$$

- Without individual fixed effects, estimated product dummy coefficients combine true product+individual effects
- With individual fixed effects, product dummy coefficients isolate product effect

Variation in data allowing identification: Multiple purchases by each individual across product categories

- Of 499,906 customers, 179,311 made purchases in one/more of 4 lowest *and* one/more of 5 highest default categories
- Result: Default is about people, not products. Products differ in the risk of the customer pool they attract

Mexican data: Average loss rates with and without individual fixed effects



- Blue: Product dummy coefficients from regression without individual fixed effects or controls (omitted=sewing machines)
- Red: Product dummy coefficients from regression with individual fixed effects and controls
- Vertical difference between blue and red: Avg. individual effect for those with loans in category (plus small effect of observables)

Summary:

What's going on inside big data credit risk analysis? What can it teach us about consumers?

- Survey (CEX) + account-level data from Mexican retailer
- Spending on entertainment (video, audio, magazines, newspapers, toys and pets) predicts worse credit outcomes
  - A higher probability of paying positive finance/interest/late charges (in US data)
  - Consumer credit default (in Mexican data)
- Mix of consumption *within time periods* relevant for understanding consumption *across periods*

Economics: It's about people, not products, possibly about time preference

- Mexico: Multiple purchases by each individual allows separation of product and individual effects
- US: Smoking and lower education used to proxy impatience
- Time preference heterogeneity also relevant for net worth, portfolio choice
  - Calvet, Campbell, Gomes and Sodini (2021): Swedish data+model of saving and portfolio choice: Modest heterogeneity in risk aversion but considerable heterogeneity in the time preference rate and EIS