On the Convergence of Credit Risk in Current Consumer Automobile Loans

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1. Introduction
2. Data
3. The Probabilistic Model
4. Financial Implications
5. Sensitivity Analysis
6. Conclusion

Table of Contents

1. Introduction
2. Data
3. The Probabilistic Model
4. Financial Implications
5. Sensitivity Analysis
6. Conclusion

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A longstanding debate

American consumers have relied on installment credit to make large purchases, such as automobiles, for over one hundred years (Hughes and Cain, 2011).

And for nearly as long, a central debate of political economy has involved how much protection individual consumers require in financial transactions. For example,

- Franklin D. Roosevelt pledges "a new deal for the American people" in his 1932 acceptance speech for the Democratic nomination (Roosevelt, 1932).
- Exactly thirty years later, the eventual Nobel laureate Milton Friedman wrote, "Underlying most arguments against the free market is a lack of belief in freedom itself" (Friedman, 2002).
- More recently,

"We all win when consumers are protected against abuse. And we all win when folks are rewarded based on how well they perform, not how well they evade accountability" (Obama, 2010).

Figure: Then President Barack Obama signs the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010

Grandiose introductions aside

The literature has naturally followed suit, with noteworthy contributions on payday loans (e.g. Melzer, 2011; Bertrand and Morse, 2011), credit cards (e.g. Gross and Souleles, 2002; Agarwal et al., 2014), and automobile loans (e.g. Adams et al., 2009; Grunewald et al., 2020) to name but a few.

We consider risk-based pricing (Edelberg, 2006; Phillips, 2013), the well-accepted practice of charging a borrower with a higher risk of default a higher cost of borrowing (i.e., a higher interest rate).

The research question(s)

We use our statistical results (Lautier et al., 2021, 2022) generalized for competing risks as the core probabilistic model to continuously evaluate a current borrower's risk profile over the lifetime of the loan. That is, we seek to answer:

(1) How many on-time payments does it take for a high-risk borrower to no longer be considered high-risk (if ever)?

(2) What are the financial and economic implications of loan contracts for borrowers originally charged a high-risk cost of borrowing that remain current?

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Table of Contents

1. Introduction
2. Data
3. The Probabilistic Model
4. Financial Implications
5. Sensitivity Analysis
6. Conclusion

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The Securities and Exchange Commission recently implemented changes to the rules governing the issuance of asset-backed securities (ABS) (Securities and Exchange Commission, 2014, 2016). Notably, it requires public issuers of ABS to make freely available pertinent loan-level information and payment performance on a monthly basis beginning in 2017.

We wrote `Python` code to scrape SEC filings to amass over 275,000 consumer automobile loans from the ABS bonds CarMax Auto Owner Trust 2017-2 (CarMax, 2017), Ally Auto Receivables Trust 2017-3 (Ally, 2017), Santander Drive Auto Receivables Trust 2017-2 (Santander, 2017b), and Drive Auto Receivables Trust 2017-1 (Santander, 2017a).

All bonds span the same macroeconomic environment (actively paying starting in March-April-May 2017 for 44-52 months).

Why auto loans?

- Subject matter expertise (Lautier former ABS auto analyst);
- Auto loans have a high *priority of payment* $\implies$ if default risk doesn't converge for auto loans, it probably doesn't converge.

  (unofficial consumer ABS credit analyst motto: "You can live in your car, but you can't drive your house to work.")

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Loan selection

We selected loans to be as comparable as possible:

- No co-borrowers;
- Income underwriting level: "stated not verified";
- No subvention;
- Used vehicles only;
- No loans in repossession status at ABS start;
- Loan age $\leq$ 18 months at ABS start;
- No credit score field: `NA`;
- Loan term 72-73 months only;
- No unclear loan outcome (i.e., no default but total principle paid less than outstanding balance as of ABS start);

Number of loans left for analysis: 50,107. Largest geographic concentration (TX 13%); manufacturer (Nissan 12%).

Risk band assignment

Borrowers assigned to risk band via credit score, using standard industry ranges (Consumer Financial Protection Bureau, 2019).

Risk Band	Credit Score Range	Count	Default%[1]
deep subprime	< 580	22,093	48%
subprime	$580 \leq x < 620$	11,853	37%
near prime	$620 \leq x < 659$	6,486	28%
prime	$660 \leq x < 719$	6,039	16%
super prime	$720 \leq x$	3,636	7%
		50,107	

[1] We define 3 consecutive months of missed payments = default.

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Estimating recovery upon default (i.e., repo proceeds)

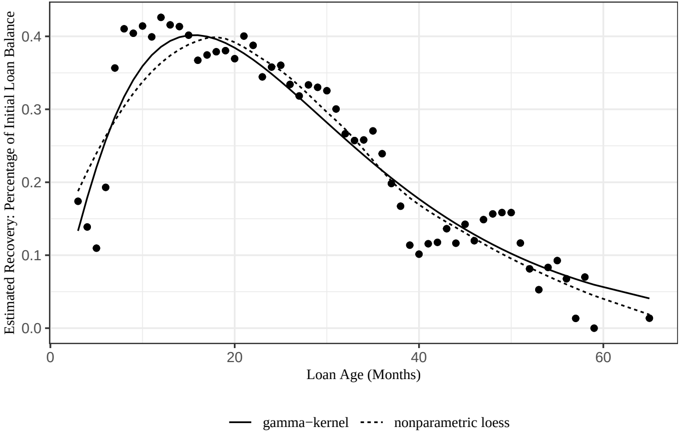

Figure: Estimation of recovery upon default assumption (based on sample of 50,107 loans)

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Summary of 50,107 loans

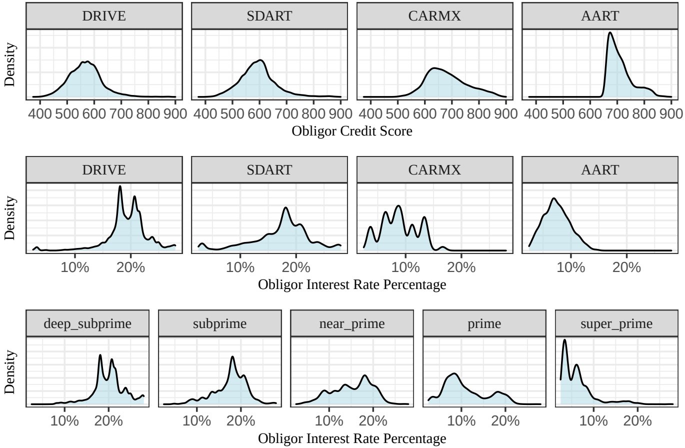

Figure: Details by bond, assigned risk band

Table of Contents

1. Introduction
2. Data
3. The Probabilistic Model
4. Financial Implications
5. Sensitivity Analysis
6. Conclusion

Statistical challenges of ABS data

When trying to estimate the time-to-event distribution from loans sampled from a securitization pool, it is important to consider some incomplete data challenges:

- Left-truncation (there is a delay from loan origination until the trust begins actively paying);
- Right-censoring (many loans will be known to be active but not yet terminated);
- Discrete-time (loan payments due monthly; assuming continuous time req. unrealistic assumptions (i.e., "no ties"))

The papers Lautier et al. (2021) and Lautier et al. (2022) consider these points carefully in the context of ABS.

Hazard rate

We are interested in the time-to-loan termination random variable, X. The classical tool from survival analysis is the *hazard rate*,

$$\lambda(x) = \Pr(X = x \mid X \geq x) = \frac{\Pr(X = x)}{\Pr(X \geq x)}. \tag{1}$$

The probability in (1) is ideal for a current loan analysis, and our goal is to estimate (1) because we can recover the distribution function of X via

$$1 - F(x-) = \Pr(X \geq x) = \begin{cases} 1, & x \leq x_{\text{min}} \\ \prod_{x_{\text{min}} \leq k < x} \{1 - \lambda(x)\} & x > x_{\text{min}}, \end{cases}$$

where x_{min} is the lowest recoverable value of the lifetime X.

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Let T be the random time of a loan origination. Let Y be the left-truncation random variable (it is a linear shift of T until the time the ABS starts paying).

Then we observe $X \iff X \geq Y$.

Define $C = Y + \tau$, where τ is a constant that depends on when the ABS transaction (observation window) ends.

Then we observe $X \iff (X \geq Y) \cap (X \leq C)$ or we observe $\min(X, C) \iff (X \geq Y) \cap (X > C)$.

We assume $Y \equiv f(T) \perp X$ (reasonable for ABS transactions, see Lautier et al. (2022, Section 4.3)).

Competing risks

We desire to distinguish between a default and prepayment.

Let Z_x be a two-state random variable with probabilities dependent on x. Given a loan terminates at time x, $Z_x \in \{1, 2\}$. This is a mulitstate process (e.g., Beyersmann et al., 2009).

- $\lambda_\tau^{01}(x)$ is the *cause-specific* hazard rate for default (the event of interest).
- $\lambda_\tau^{02}(x)$ is the *cause-specific* hazard rate for prepayment (the competing event).

Formally,

$$\lambda_\tau^{0i}(x) = \Pr(X = x, Z_x = i \mid X \geq x) = \frac{\Pr(X = x, Z_x = i)}{\Pr(X \geq x)}, \quad i = 1, 2,$$

and the *all-cause* hazard is $\lambda_\tau(x) = \lambda_\tau^{01}(x) + \lambda_\tau^{02}(x)$.

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Some references

There are many references on competing risks (e.g., Crowder, 2001; Pintilie, 2006; Kalbfleisch and Prentice, 2011) with some discrete-time specific (e.g., Tutz and Schmid, 2016; Lee et al., 2018; Schmid and Berger, 2021).

Our framing generalizes Lautier et al. (2022) with a multistate process (e.g., Andersen et al., 1993; Beyersmann et al., 2009), however, to avoid unrealistic assumptions, like independence between default and prepayment (e.g., Zhang et al., 2019).

Competing risks also has a long history in modeling loan defaults (e.g., Banasik et al., 1999; Stepanova and Thomas, 2002; Dirick et al., 2017; Frydman and Matuszyk, 2022), but none meet our ABS framework precisely.

Estimating the hazard rate

If we assume $Y \perp (X, Z_x)$ (reasonable for ABS) and define $f^{0i}_{*,\tau}(x) = \Pr(X = x, X \leq C, Z_x = i \mid X \geq Y)$, $i = 1, 2$, $C_\tau(x) = \Pr(Y \leq x \leq \min(X, C) \mid X \geq Y)$, then

$$\lambda^{0i}_\tau(x) = \frac{\Pr(X = x, Z_x = i)}{\Pr(X \geq x)} = \frac{f^{0i}_{*,\tau}(x)}{C_\tau(x)}. \tag{2}$$

Estimation of (2) follows naturally with

$$\hat{f}^{0i}_{*,\tau,n}(x) = \frac{1}{n}\sum_{j=1}^{n} \mathbf{1}_{X_j \leq C_j} \mathbf{1}_{Z_{X_j}=i} \mathbf{1}_{\min(X_j, C_j)=x},$$

$$\hat{C}_{\tau,n}(x) = \frac{1}{n}\sum_{j=1}^{n} \mathbf{1}_{Y_j \leq x \leq \min(X_j, C_j)};$$

that is, $\hat{\lambda}^{0i}_{\tau,n}(x) = \hat{f}^{0i}_{*,\tau,n}(x)/\hat{C}_{\tau,n}(x)$, $i = 1, 2$.

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Proposition 1

For $i \in \{1,2\}$ and $x \in \{\Delta+1,\ldots,\xi\}$, define $\hat{\mathbf{\Lambda}}^{0i}_{\tau,n} = (\hat{\lambda}^{0i}_{\tau,n}(\Delta+1),\ldots,\hat{\lambda}^{0i}_{\tau,n}(\xi))^\top$. Then,

(i)

$$\hat{\mathbf{\Lambda}}^{0i}_{\tau,n} \xrightarrow{\mathcal{P}} \mathbf{\Lambda}^{0i}_{\tau}, \text{ as } n \to \infty;$$

(ii)

$$\sqrt{n}(\hat{\mathbf{\Lambda}}^{0i}_{\tau,n} - \mathbf{\Lambda}^{0i}_{\tau}) \xrightarrow{\mathcal{L}} N(\mathbf{0}, \mathbf{\Sigma}^{0i}), \text{ as } n \to \infty,$$

where $\mathbf{\Lambda}^{0i}_{\tau} = (\lambda^{0i}_{\tau}(\Delta+1),\ldots,\lambda^{0i}_{\tau}(\xi))^\top$ and

$$\mathbf{\Sigma}^{0i} = \text{diag}\left(\cdots, \frac{f^{0i}_{*,\tau}(x)\{C_\tau(x) - f^{0i}_{*,\tau}(x)\}}{C_\tau(x)^3}, \cdots\right).$$

That is, the cause-specific hazard rate estimators $\hat{\lambda}^{0i}_{\tau,n}(\Delta+1),\ldots,\hat{\lambda}^{0i}_{\tau,n}(\xi)$ are consistent, asymptotically normal, and independent.

Lemma 1

The $(1-\theta)\%$ asymptotic confidence interval bounded within $(0,1)$ for $\lambda_{\tau}^{0i}(x)$, $x \in \{\Delta+1,\ldots,\xi\}$, $i=1,2$ is

$$\exp\left\{ \ln \hat{\lambda}_{\tau,n}^{0i}(x) \pm \mathcal{Z}_{(1-\theta/2)} \sqrt{\frac{\hat{C}_{\tau,n}(x) - \hat{f}_{*,\tau,n}^{0i}(x)}{n\hat{C}_{\tau,n}(x)\hat{f}_{*,\tau,n}^{0i}(x)}} \right\}, \quad (3)$$

where $\mathcal{Z}_{(1-\theta/2)}$ represents the $(1-\theta/2)$th percentile of the standard normal distribution.

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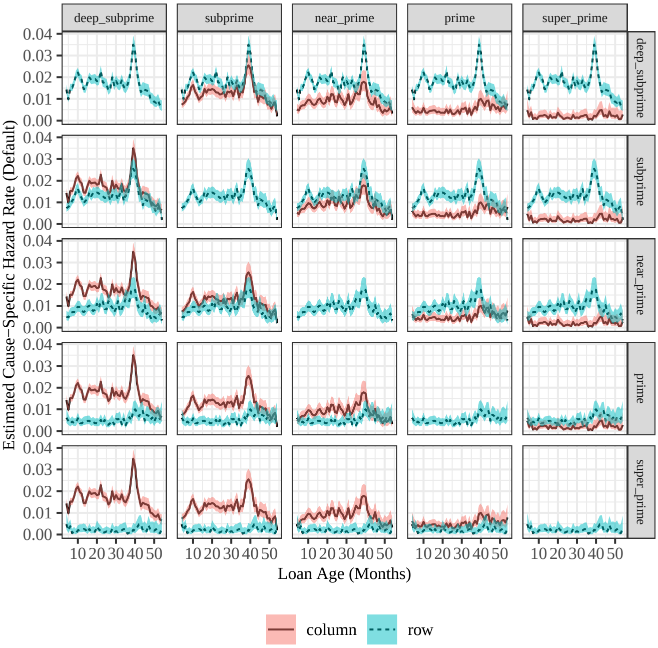
Hypothesis test

The combination of Proposition 1 and Lemma 1 leads to an asymptotic hypothesis test. Let a, a' be two different risk bands (e.g., subprime vs. prime, etc.). Then we may test

$$H_0 : \lambda^{0i}_{\tau,(a)} = \lambda^{0i}_{\tau,(a')} \quad \text{v.s.} \quad H_1 : \lambda^{0i}_{\tau,(a)} \neq \lambda^{0i}_{\tau,(a')},$$

for each age x by determining if the asymptotic confidence intervals in (3) overlap (if so, fail to reject H_0).



deep_subprime
subprime
near_prime
prime
super_prime
Estimated Cause−Specific Hazard Rate (Default)
0.00
0.01
0.02
0.03
0.04
10 20 30 40 50
Loan Age (Months)
column
row

Credit risk convergence matrix (months)

	deep sub.	subprime	near-prime	prime	sup.-prime
deep sub.	10	23	34	46	NA
subprime		10	11	42	49
near-prime			10	28	42
prime				10	10
sup.-prime					10

Note: The first of three consecutive months of confidence interval overlap after month 10. The recoverable range of X is $4 \leq X \leq 54$ for 72-73 month loans (i.e., "NA" $\implies$ no conv. by loan age 54).

Table of Contents

1. Introduction
2. Data
3. The Probabilistic Model
4. **Financial Implications**
5. Sensitivity Analysis
6. Conclusion

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Risk-based pricing

Risk-based pricing is the standard in consumer credit (Edelberg, 2006). It has been attributed to lowering the cost of borrowering (Staten, 2015), and has grown in sophistication to filter prospective borrowers based on contract terms (Einav et al., 2012).

Following Phillips (2013), the interest rate for risk band a, r_a, can be divided into three components,

$$r_a = r_c + m + l_a,$$

where r_c is the cost of capital, m is the added profit margin, and l_a is a factor that varies by risk band.

Law of One Price $\implies$ $r_c + m$ consistent between risk bands.

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Actuarial approach

The factor l_a has a component attributable to the expected (actuarial) present value for loans in risk band a, e_a, and a component attributed to the uncertainty of loans in risk band a, π_a. That is,

$$r_a = r_c + m + e_a + \pi_a.$$

Interpretation:

- $r_c + m + e_a$ is the "risk indifferent" or "fair" price;
- π_a is the market implied credit spread.

With reliable probability estimates of loan default and prepayment (see Proposition 1), we can estimate the expected return for a loan in risk band a,

$$\rho_a = r_c + m + e_a,$$

given a loan has survived to at least month x. That is, a *conditional expected rate of return*, $\rho_{a|x}$, by risk band.

A pleasing property

Proposition 2

Suppose a loan is originated with an initial balance, B, a monthly rate of interest, r_a, and a term of ψ months. Let $\rho_{a|x}$ denote the expected rate of return given the loan has survived to month x. If the probability that all payments will follow the amortization schedule exactly is unity (i.e., no payment uncertainty), then $\rho_{a|x} = r_a$ for all $x \in \{1, \ldots, \psi\}$.

Calculation details

Suppose $1 \leq X \leq \psi$, and the current age of a loan is x. If we denote $p_x^{0i}(j) = \Pr(X = j, Z_j = i \mid X \geq x)$, $x \leq j \leq \psi$, $i = 1, 2$, then we can show for $x \leq j \leq \psi$,

$$p_x^{0i}(j) = \begin{cases} \lambda^{0i}(x), & j = x \\ \lambda^{0i}(j) \prod_{k=x}^{j-1} \{1 - \lambda(k)\}, & j > x, \end{cases} \quad i = 1, 2.$$

For every x, $\sum_{j=x}^{\psi} \sum_{i=1}^{2} p_x^{0i}(j) = 1$.

Let B_x denote the scheduled amortization balance at month x (and so $B_\psi = 0$), P denote the schedule payment, and R_x the assumed recovery of a defaulted consumer auto loan at month x.

Default and recovery cash flow matrices

$$
\mathbf{DEF}_x = \begin{bmatrix} R_x & 0 & 0 & \dots & 0 & 0 \\ P & R_{x+1} & 0 & \dots & 0 & 0 \\ P & P & R_{x+2} & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ P & P & P & \dots & R_{\xi-1} & 0 \\ P & P & P & \dots & P & R_\psi \end{bmatrix}
$$

$$
\mathbf{PRE}_x = \begin{bmatrix} B_x + P & 0 & 0 & \dots & 0 & 0 \\ P & B_{x+1} + P & 0 & \dots & 0 & 0 \\ P & P & B_{x+2} + P & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ P & P & P & \dots & B_{\psi-1} + P & 0 \\ P & P & P & \dots & P & P \end{bmatrix}
$$

Note: dimensions $(\psi - x + 1) \times (\psi - x + 1)$.

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Estimating $\rho_{a|x}$ (ρ_x to ease notation)

Denote the unknown $(\psi - x + 1) \times 1$ dimension discount vector,

$$(\boldsymbol{\nu}_x)^\top = \left((1+\rho_x)^{-1} \quad (1+\rho_x)^{-2} \quad \dots \quad (1+\rho_x)^{-(\psi - x + 1)}\right)^\top,$$

and the $(\psi - x + 1) \times 1$ dimension cause-specific probability vector,

$$\left(\boldsymbol{p}_x^{0i}\right)^\top = \left(p_x^{0i}(x) \quad p_x^{0i}(x+1) \quad \dots \quad p_x^{0i}(\psi)\right)^\top;$$

then the expected present value (EPV) of a loan at age $x \leq \psi - 1$ is

$$\text{EPV}_x = \left(\boldsymbol{p}_x^{01}\right)^\top \mathbf{DEF}_x \boldsymbol{\nu}_x + \left(\boldsymbol{p}_x^{02}\right)^\top \mathbf{PRE}_x \boldsymbol{\nu}_x.$$

Therefore, ρ_x is the interest rate such that $B_x = \text{EPV}_x$; that is,

$$\rho_x = \{\rho_x : B_x = \text{EPV}_x\}.$$

Note $\rho_x \leq r$ with equality iff conditions of Proposition 2.

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Estimating ρ_x (cont.)

The estimate of ρ_x, $\hat{\rho}_{n,x}$, may be found by replacing the true probabilities in $\boldsymbol{p}_x^{0i}$, with estimates vis-à-vis $\hat{\lambda}_n^{0i}$, $i = 1, 2$. The recovery estimates follow from earlier (Slide 13). The remaining items in EPV_x may be read directly from the data (e.g., P, B_x, ψ).

We can then plot the estimated market-implied credit spread conditional on loan survival, $\hat{\pi}_{n,a|x} = r_a - \hat{\rho}_{n,a|x}$. Interpretation:

- $\hat{\pi}_{n,a|x}$ stable $\implies$ constant profit over the life of a current loan;
- $\hat{\pi}_{n,a|x}$ increases $\implies$ profit declines over the life of a current loan (i.e., profit is "front-loaded");
- $\hat{\pi}_{n,a|x}$ decreases $\implies$ profit increases over the life of a current loan (i.e., profit is "back-loaded");

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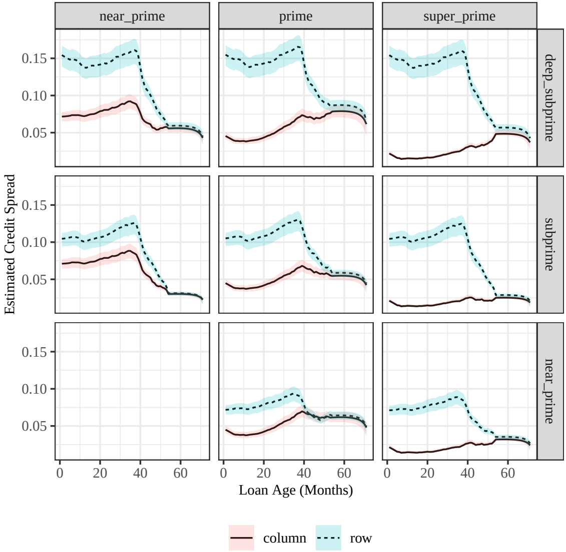

Figure: Estimated market-implied credit spread given survival

The difference in interest rates between two contracts with equivalent credit risk (i.e., after convergence) is a useful estimate of overpayment.

	Avg. APR Diff.		
	near-prime	prime	super-prime
deep subprime	561	905	1,391
subprime	285	630	1,115
near-prime		344	830

	Avg. APR Diff. ($X \geq 40$)		
	near-prime	prime	super-prime
deep subprime	601	956	1,366
subprime	316	670	1,080
near-prime		354	765

Table of Contents

1. Introduction
2. Data
3. The Probabilistic Model
4. Financial Implications
5. Sensitivity Analysis
6. Conclusion

Robustness checks considered

- Influence of COVID-19
- Risk Band Definition
- Assumptions
- Loan Type

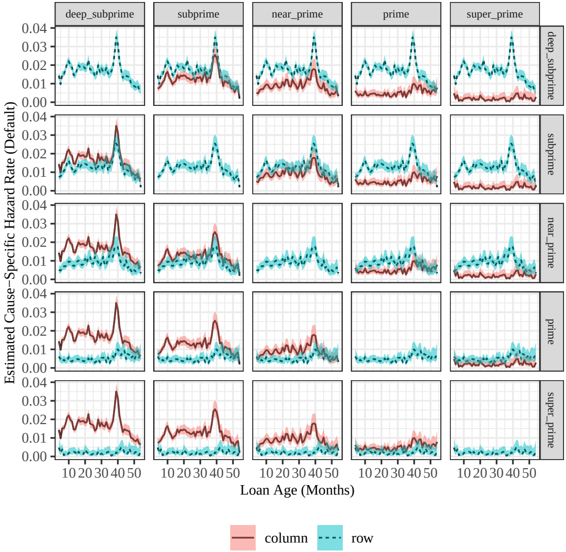

Figure: Spike in hazard rates around month 40 is approximately May-June 2020 (i.e., COVID economic shutdown $\Longrightarrow$ defaults)

COVID-19 discussion

Concern: the shock of the COVID-19 economic shutdown was so severe it "filtered" all the bad risks.

- We see evidence of convergence prior to May 2020.
- We repeated the analysis for the same bonds issued in summer 2019 (SDART 2019-3, DRIVE 2019-4, CARMX 2019-4, AART 2019-3). We see loan age also plays a role (next slide).
- Difficult to find a stretch of 72 consecutive months in the last 20 years without an economic shock (e.g., 9/11, global financial crisis, European sovereign debt crisis, COVID-19) $\Longrightarrow$ credit risk convergence perpetually present, even if partially driven by filtering effects of economic crisis.

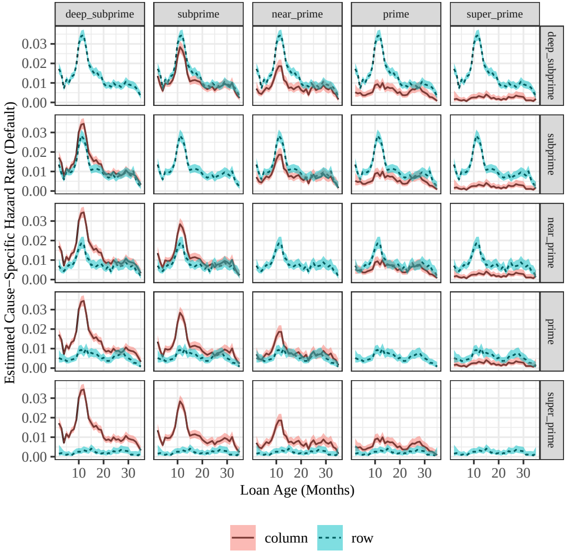

Figure: Repeat of Slide 25 for 2019 issuance; loan age also plays a role (recovery range: $2 \leq X \leq 35$)

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Risk band definition

Concern: lenders possess sophisticated credit scoring models and using credit score is too crude (i.e., payment-to-income, collateral value, down payment amount, etc. also matter).

- Assume lenders can better assign risk $\implies$ repeat 2017 issuance analysis but instead assign risk-band by APR:

Risk Band	APR
deep subprime	20%+
subprime	15-20%
near prime	10-15%
prime	5-10%
super-prime	0-5%

- We see consistent results with assigning credit risk bands by credit score (next slide).

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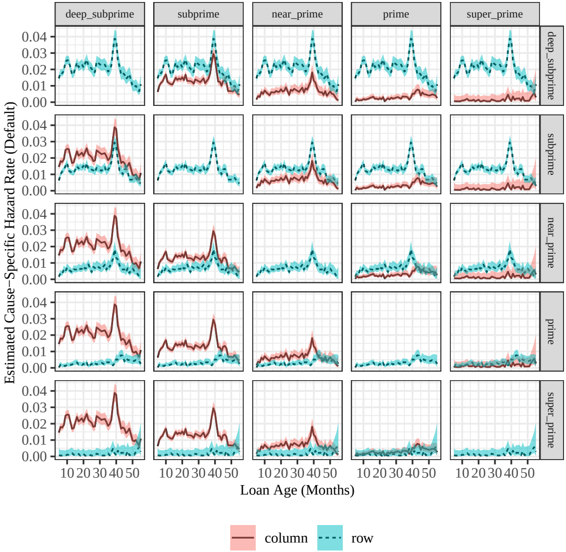

Figure: Repeat of Slide 25 with risk bands defined by APR ranges rather than credit score

COVID-19 Sensitivity Analysis

	deep sub.	subprime	near-prime	prime	sup.-prime
deep sub.	10	18	20	25	NA
subprime		10	14	15	NA
near-prime			10	13	26
prime				10	10
sup.-prime					10

Risk Band Definition Sensitivity Analysis

	deep sub.	subprime	near-prime	prime	sup.-prime
deep sub.	11	36	50	50	51
subprime		11	41	48	48
near-prime			11	13	43
prime				11	11
sup.-prime					11

Recoverable range: top ($2 \leq X \leq 35$); bottom ($4 \leq X \leq 54$)
$\Longrightarrow$ "NA" $=$ no convergence bef. recovery window endpoint

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Influence of assumptions

The market-implied credit spread analysis (Slide 35) relied on two important assumptions; (1) assuming a constant hazard after month 54 (common in survival analysis (Section 12.1 Klugman et al., 2012)) and (2) the constant hazard was the same for two disparate risk bands after convergence (i.e., strong assumptions of *ceteris paribus*).

Concern: These are reasonable assumptions, but we don't have the data to know for sure.

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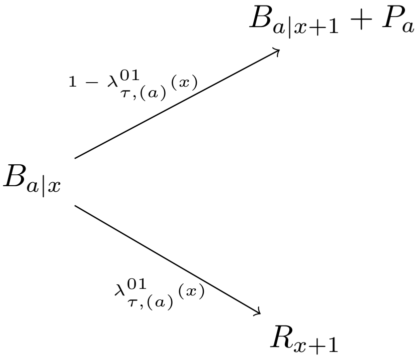
We repeat the analysis but on a rolling one-month return basis. We assume an investor purchased a one-month risky fixed income asset for B_x at month x that pays $B_{x+1} + P$ with probability $1 - \lambda^{01}(x)$ and pays R_{x+1} (defaults) with probability $\lambda^{01}(x)$.



Hence, we find the rolling one-month risk-adjusted rate of return, $\tilde{r}_{a|x}$, such that

$$\mathrm{EPV}^1_{a|x} = \lambda^{01}_a(x)\frac{R_{x+1}}{1+\tilde{r}_{a|x}} + (1-\lambda^{01}_a(x))\left[\frac{B_{a|x+1}+P_a}{1+\tilde{r}_{a|x}}\right] = B_{a|x}.$$

For simplicity, assume a common loan of \$100 amortized over 72 months with a payment that depends on the average APR of risk-band a.

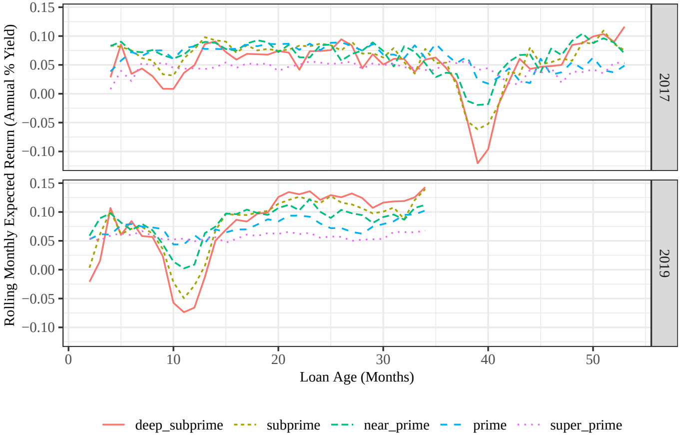


Figure: Expected monthly rate of return (annualized) given survival, 2017 and 2019 issuance

Loan type

Concern: These results for secured auto loans will not extend to other types of loans (e.g., credit-cards, peer-to-peer, unsecured, mortgages, etc.).

- Borrowers are slowing building an equity position, which likely acts as an incentive to keep making payments to own the vehicle outright (good sign for mortgages).
- Auto loans are a high priority of payment ("You can live in your car..."); may not hold for residential mortgages or vacation/income properties.
- We suggest caution before accepting these results for unsecured loan types, especially, and we leave this open as an area of further study.

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Table of Contents

1. Introduction
2. Data
3. The Probabilistic Model
4. Financial Implications
5. Sensitivity Analysis
6. Conclusion

Concluding remarks

Credit risk convergence: Regardless of a borrower's credit profile at contract signing, the longer a borrower remains active and paying, the lower the risk of default (intuitive: we contribute the method to measure, the when, and the economic implications).

Money on the table: Deep subprime, subprime, and near prime borrowers that don't refinance eventually overpay by amounts ranging from 285-1,391 basis points of APR.

Not alternative financing: We analyze secured auto loans from major financial institutions in a core economic lending space; such large market inefficiencies are troubling.

Residential mortgages(?): We find convergence between 2-5 years for 72-month auto loans. If convergence for traditional 30-year mortgages happens at a similar rate, the potential savings could be substantial.

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Regressive taxation?

Lender POV: the loans that don't default pay for the loans that do.

Risk Band	Min	Q1	Med	Mean	Q3	Max
deep sub.	9.76	29.20	37.91	46.31	51.84	3,727.34
subprime	9.78	30.30	39.50	48.14	53.38	2,392.74
near-prime	10.16	30.61	41.14	52.41	57.61	3,784.60
prime	8.78	31.79	44.32	57.60	64.56	3,479.45
sup.-prime	8.93	36.55	55.03	76.78	88.42	1,448.391

Note: Est. annual income by risk band (risk band defined by credit score, all 50,107 loans, in thousands)

The risk bands that eventually overpay the most (deep subprime, subprime, etc.) are also lower income $\Longrightarrow$ exacerbating economic inequality. This is a cost-sharing that runs counter to most standard progressive taxation schemes.

What can be done?

- *Consumerus Ignoramus?*: Consumers have a poor reputation in making financial decisions (e.g. Gross and Souleles, 2002; Stango and Zinman, 2011; Lusardi and de Bassa Scheresberg, 2013; Campbell, 2016; Heidhues and Kőszegi, 2016; Dobbie et al., 2021), but prepayments do accelerate as loans mature (next slide). Encourage borrowers to self-correct (questionable effectiveness (e.g., Keys et al., 2016; Agarwal et al., 2017)).
- *Financial innovation*: Lenders offer loans structured with a reducing payment based on good performance (may also act as an incentive to keep borrowers current).
- *Competition*: Competing lenders seek out these mature loans to offer refinancing (similar to SOFI with student loans).
- *Regulation*: Require ongoing loans to be "re-underwritten" after a sustained period of good performance.

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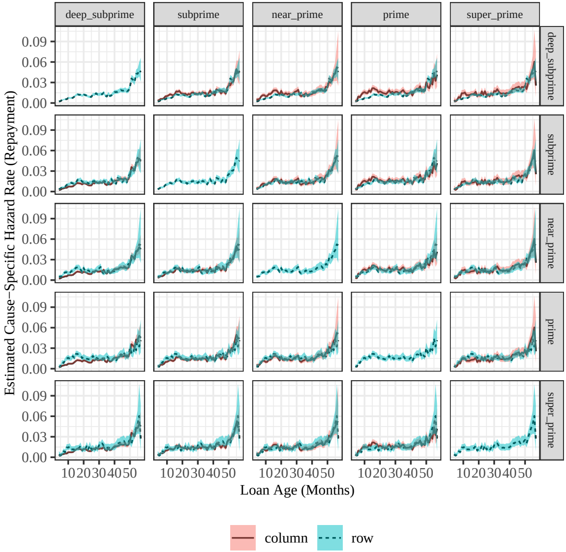

Figure: Prepayment behavior by risk band, 2017 issuance

Thank you!

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