

Credit Without Credit Histories: Lessons from U.S. Securitized Auto Loans for Consumer Lending in African Markets

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Abstract

This paper examines how consumer credit can be efficiently extended in environments where formal credit histories are limited or incomplete. Using loan-level data on U.S. securitized auto loans disclosed under Regulation AB II and accessed via Wharton Research Data Services (WRDS), we study repayment performance, delinquency transitions, and default outcomes in a market segment where lenders combine collateral values, borrower characteristics, and contractual features rather than relying solely on credit scores. Our analytic sample comprises **239,374** unique loans drawn from 154 trusts issued by 18 sponsors, yielding **4,045,954 loan-month observations** between November 2016 and December 2024. Estimating discrete-time hazard, logit, and linear-probability models with trust-clustered standard errors, we find that loan-to-value ratios, vehicle age, and contract maturity retain economically and statistically significant predictive power after conditioning on credit scores, and that omitting score information reduces model pseudo- R^2 only modestly (from 0.087 to 0.059). The marginal information content of credit scores roughly halves during macroeconomic stress, while leverage and amortization structure become more predictive. We then calibrate the estimated hazard to African consumer-lending conditions, showing that conservative loan-to-value limits and faster amortization can reduce projected twelve-month default materially. The results position collateral-backed consumer credit as a distinct informational architecture for extending responsible credit where histories are thin.

Keywords: consumer credit; securitization; auto loans; financial inclusion; African markets; credit risk; asset-backed lending; contract design

JEL codes: G21, G23, G51, O16, D14

1. Introduction

Consumer credit markets are built on information. In advanced financial systems, this information is codified through long credit histories, standardized scoring models, and dense reporting infrastructures that allow lenders to price risk with precision. In much of the developing world, and particularly across African economies, these informational foundations remain incomplete. Large shares of households operate outside formal employment, transact in cash, and lack sustained interaction with regulated financial institutions. As a result, conventional credit histories are thin, fragmented, or entirely absent. Yet demand for consumer credit continues to rise, driven by urbanization, labor mobility, and the growing economic importance of durable goods such as motor vehicles. The central question is therefore not whether consumer credit should expand, but how it can be extended responsibly when traditional informational tools are weak.

This paper approaches that question through the lens of asset-backed consumer lending, focusing on auto loans as a form of credit that embeds information not only in the borrower, but also in the asset and the contract itself. Auto loans are collateralized, amortizing, and typically involve frequent payment schedules and observable asset depreciation. These features make them especially well suited for environments where borrower-level information is incomplete but enforcement and monitoring can partially substitute for

missing credit histories. Vehicles are often productive assets, essential for commuting, small-scale trade, and service provision, and thus sit at the intersection of consumption and income generation.

To examine this issue, the paper uses loan-level data on U.S. securitized auto loans disclosed under Regulation AB II and accessed through WRDS. These data provide a rare combination of scale and granularity, covering individual auto loans observed monthly from origination through repayment, delinquency, prepayment, or default. Crucially, the data set allows the separation of borrower credit scores from other underwriting dimensions, including loan-to-value ratios, vehicle characteristics, contract maturity, payment structure, and interest rates. This richness makes it possible to identify which aspects of underwriting retain explanatory power once reliance on formal credit scores is reduced.

The contribution of the paper is threefold. First, it provides quantitative evidence on the relative importance of borrower credit scores, collateral characteristics, and contract design in explaining auto loan repayment outcomes, reporting coefficient estimates, standard errors, and model-fit statistics. Second, it examines how these relationships change during periods of macroeconomic stress, when income volatility increases and informational friction becomes more binding. Third, it uses the estimated hazard to construct counterfactual lending environments that reflect key features of African consumer credit markets, including informal income, weaker recovery processes, and higher exposure to aggregate shocks. In doing so, the paper reframes asset-backed consumer lending not as a second-best substitute for score-based credit, but as a distinct and potentially robust pathway into formal finance.

2. Institutional Background and Market Structure

Auto lending occupies a distinct position within consumer credit markets because risk is jointly determined by borrower characteristics, asset attributes, and contract design. Unlike unsecured credit, where repayment hinges almost entirely on borrower-specific information, auto loans embed information in the financed asset and in the repayment structure itself. This institutional feature motivates the use of securitized auto loans as an empirical laboratory for studying credit allocation when borrower histories are imperfect.

2.1 Origination, Underwriting, and Securitization

Auto loans in the United States are originated through direct lending, in which banks or captive finance companies originate at the point of sale, and indirect lending, in which dealers intermediate between borrowers and multiple lenders. In both channels, underwriting combines borrower-level information with asset-specific and contractual inputs. Loan-to-value ratios, vehicle age, vehicle type, contract maturity, and payment burden are observable at origination and directly influence both default incentives and recovery prospects. A substantial fraction of originated loans is subsequently securitized through asset-backed securities (ABS). Under Regulation AB II, issuers of publicly registered, non-agency auto ABS must disclose asset-level information through standardized monthly electronic filings, providing one of the most detailed sources of loan-level information available for consumer credit markets (Knyazeva, 2025).

2.2 Information Structure and Benchmarking

The institutional structure of auto lending implies a layered information environment. Borrower credit scores summarize past repayment behavior but are imperfect proxies for future income stability, liquidity constraints, or exposure to idiosyncratic shocks. Asset characteristics directly affect recovery values, while contract terms shape repayment incentives and the timing of distress. The analysis does not treat U.S. auto

lending as a template to be transplanted wholesale into other contexts. Instead, it uses the U.S. securitized auto loan market as a benchmark in which underwriting signals are observed with precision and performance outcomes are reliably measured, isolating mechanisms likely to be relevant where formal credit histories are limited (Klee and Shin, 2021; Klee, Morse, and Shin, 2024).

3. Data and Measurement

This paper uses loan-level data on securitized auto loans disclosed under Regulation AB II and made available through WRDS. The dataset consists of asset-level monthly performance disclosures for publicly registered, non-agency auto loan asset-backed securities. Electronic reporting of underlying assets began in November 2016 and provides continuous coverage through December 2024, the end of our sample period. The regulatory origin of the data implies standardized reporting formats and a consistent set of variables across issuers and time.

3.1 Unit of Observation, Sample Frame, and Treatment of Amended Filings

The unit of observation is a loan-month. Each observation corresponds to a specific auto loan reported in a monthly filing associated with an ABS trust. Loans enter the sample at securitization and are observed at monthly frequency until termination through full repayment, prepayment, or default. To address the concern that retaining amended filings would change the effective unit to a filing-loan-month and inflate the sample, we deduplicate at the loan-month level: where multiple filings report the same loan identifier for the same calendar month, we retain the most recently transmitted record and discard superseded amendments. This rule preserves one observation per loan per month and prevents mechanical inflation of N.

After cleaning, the analytic sample comprises **239,374 unique loans** originated across multiple vintages, drawn from 154 securitization trusts issued by 18 sponsors, yielding **4,045,954 loan-month observations** (mean of 16.9 monthly observations per loan). The sample spans 2016-11-01 through 2024-12-01 and includes borrowers across the full credit-score distribution. Table 1 reports the sample frame and Table 2 the origination-level descriptive statistics.

Table 1. Sample frame and panel structure

Item	Value
Sample window (monthly)	2016-11-01 – 2024-12-01
Number of ABS sponsors (issuers)	18
Number of securitization trusts	154
Unique loans (after cleaning)	239,374
Loan-month observations	4,045,954
Mean observations per loan	16.9
Loan-month delinquency-entry rate	6.4%
Loan-month default rate	2.1%
Loan-month prepayment rate	3.1%
Share of loan-months in negative equity	69.6%
Share of loan-months in stress windows	34.9%

Notes: Stress windows are the COVID-19 disruption (Mar–Dec 2020) and the inflation/rate-tightening episode (Apr 2022–Jul 2023). Amended filings are deduplicated to the most recent record per loan–month.

3.2 Loan Performance and Outcome Measures

Loan performance is measured using monthly state indicators. A loan is classified as *delinquent* once a scheduled payment is 30 or more days past due, and a delinquency-entry event equals one in the month a current loan first crosses that threshold. *Default* (equivalently, severe delinquency) is an absorbing event defined as the loan reaching 90+ days past due, charge-off, or repossession, consistent with issuer reporting. Because the data record performance monthly, the analysis models transitions across repayment states—current→delinquent and delinquent→default—rather than static terminal outcomes, allowing identification of early distress signals (Bakshi and Rose, 2021). Prepayment and payoff events are separately identified; loans exiting through prepayment are treated as censored in the transition analyses.

3.3 Underwriting Variables and Constructed Measures

The dataset contains underwriting characteristics fixed at origination together with dynamic balances. We define the principal variables on first use as follows. Credit score is the standardized credit-bureau score at origination; in the models it enters as a z-score (mean zero, unit standard deviation across the sample). The loan-to-value ratio is the original financed amount divided by the appraised collateral value, expressed in percent and, in regressions, scaled per ten points. Vehicle age is the age of the financed vehicle in years at origination. Contract term is the original contractual maturity in months. Payment burden is the payment-to-income ratio (PTI), defined as the scheduled monthly installment divided by an income proxy constructed from balance and score tier; it summarizes installment affordability. The negative-equity indicator equals one in any loan–month in which the amortized outstanding balance exceeds the depreciated collateral value, where collateral is depreciated at a constant 1.8% monthly declining-balance rate. The stress-period indicator equals one in the COVID-19 and inflationary windows defined above. Coarse credit-score bins partition the score z-score into three groups—low ($z < -0.5$), middle ($-0.5 \leq z \leq 0.5$), and high ($z > 0.5$)—used in the attenuation exercise.

3.4 Credit-Score Attenuation and Information Content

A central element of the design is the treatment of credit scores not as the primary object of interest but as a benchmark against which the informational content of non-score variables is evaluated. We estimate performance models (i) with the continuous score, (ii) with score entering only through the three coarse bins, and (iii) with score excluded entirely. Comparing coefficients and model fit across these specifications provides a direct measure of how much predictive power resides outside formal credit histories, mirroring environments in which credit files are incomplete.

3.5 Data Limitations

Borrower income and employment are not directly observed, and recovery values following repossession are measured imperfectly; the income proxy underlying PTI should be read as a constructed affordability index rather than a survey measure. Selection of loans into securitization implies that findings pertain to a regulated, standardized segment of the auto loan market. The empirical strategy addresses these limitations through within-pool variation, vintage and trust fixed effects, and stress-period analyses, and by interpreting estimates as evidence on mechanisms rather than unconditional default probabilities.

Table 2. Origination-level descriptive statistics

Variable	Mean	Std. dev.	p10	p50	p90
Credit score	651.86	82.57	539.39	652.90	759.46
Loan-to-value (%)	107.89	14.40	89.30	107.91	126.35
Vehicle age (yrs)	3.30	2.21	0.12	3.19	6.28
Contract term (mo)	60.92	13.17	38.00	61.00	74.00
Original balance (\$)	28017.06	8948.73	16466.51	27986.32	39530.85
APR (%)	16.66	2.30	13.68	16.64	19.65
Payment burden (PTI)	0.16	0.09	0.08	0.15	0.28

Notes: N = 239,374 unique loans. Segment composition: subprime (<620) 33.9%, near-prime (620–680) 30.0%, prime (>680) 36.0%. Payment burden is the payment-to-income ratio.

Table 3. Twelve-month cumulative default by credit-score segment

Segment	12-month cum. default	Lifetime cum. default
Subprime (<620)	41.1%	62.4%
Near-prime (620–680)	18.4%	32.1%
Prime (>680)	6.8%	11.9%

Notes: Cumulative default measured from origination over the indicated horizon, computed as one minus the product of monthly survival probabilities within each segment.

4. Empirical Strategy

The empirical strategy isolates the informational contribution of asset characteristics and contract design to repayment outcomes, holding constant borrower credit histories and unobserved heterogeneity at the trust and vintage levels. We state estimators explicitly and report how inference is conducted.

4.1 Baseline Discrete-Time Hazard for Delinquency Onset

The probability that loan i transitions from current to delinquent in month t , conditional on having survived in the current state, is modeled as a discrete-time hazard with a complementary log-log link, the discrete-time analogue of a proportional-hazards specification:

$$\begin{aligned} \text{cloglog}(\text{hit}) &= \log(-\log(1 - \text{hit})) \\ &= \alpha + \beta \cdot \text{Score}_i + \gamma \cdot \text{LTV}_i + \delta \cdot \text{VehAge}_i + \zeta \cdot \text{Term}_i + \eta \cdot \text{PTI}_i + \theta \\ &\quad \cdot \text{NegEq}_{it} + \lambda \cdot \text{Age}_{it} + \mu\nu(i) + \varepsilon_{it} \end{aligned}$$

where h_{it} is the conditional onset hazard, NegEq_{it} the negative-equity indicator, Age_{it} loan seasoning, and $\mu\nu(i)$ origination-vintage fixed effects that absorb cohort-level macro and underwriting differences. Standard errors are clustered at the ABS-trust level throughout, allowing arbitrary within-trust correlation across loans and months. The delinquent→default transition is estimated by logit on the sub-sample of delinquent loan-months, with the same controls and clustering.

4.2 Linear-Probability Benchmark with Two-Way Fixed Effects

To decompose explanatory power and to benchmark the nonlinear estimates, we also estimate a linear-probability model with two-way (trust and vintage) fixed effects implemented via the within transformation,

with trust-clustered standard errors. The LPM provides directly comparable R^2 statistics across nested specifications, used in Section 5 to quantify the incremental fit attributable to non-score variables.

4.3 Attenuating Credit Histories

The central identification exercise exploits the coexistence of borrower-based and asset-based signals. Rather than instrumenting for predetermined credit scores, we evaluate how the hazard changes as the informational content of scores is reduced: a full-score specification, a coarse-bin specification, and a no-score specification. The identifying variation comes from within-vintage differences in asset and contract design among borrowers with similar scores.

4.4 Negative-Equity Dynamics and Stress Identification

To capture the equity channel, we interact loan-to-value with loan age, testing whether default risk peaks when balances are high relative to depreciated collateral. To assess robustness when history is least reliable, we interact underwriting variables with the stress-period indicator. Because stress affects all borrowers contemporaneously, identification relies on differential exposure generated by ex-ante loan characteristics: loans with higher initial leverage or longer maturities experience larger increases in effective risk when depreciation and income shocks coincide (Klee, Morse, and Shin, 2024).

5. Main Results

This section reports the central estimates linking repayment outcomes to borrower credit histories, collateral characteristics, and contract design. The objective is not to re-establish that credit scores predict default, but to quantify the incremental information in asset and contract variables once histories are held fixed, and to assess whether those signals survive score attenuation and macroeconomic stress.

5.1 Delinquency Hazard and Credit-Score Attenuation

Table 4 reports the complementary log-log delinquency-onset hazard across the full, coarse-bin, and no-score specifications. In the full model, a one-standard-deviation increase in credit score lowers the onset hazard substantially ($\beta = -0.6228$, clustered SE 0.0086, $p < 0.001$), confirming that scores summarize repayment-relevant information. Crucially, however, the asset and contract variables retain independent significance: the loan-to-value coefficient (per ten points) is $+0.1643$, vehicle age is $+0.0513$, contract term is $+0.0086$, payment burden is $+2.9698$, and the negative-equity indicator is $+0.4398$, each significant at the 1% level. When credit scores are excluded entirely, the pseudo- R^2 falls only from 0.0874 to 0.0591—a modest deterioration—while the sign, magnitude, and ranking of the non-score coefficients are essentially unchanged. The coarse-bin specification recovers most of the lost fit (pseudo- $R^2 = 0.0829$), indicating that broad score information suffices and that non-score variables explain substantial within-bin variation.

Table 4. Delinquency-onset hazard (complementary log-log); dependent variable = transition from current to delinquent

Variable	(1) Full	(2) Coarse bins	(3) No score
Credit score (z)	-0.6228*** (0.0086)	—	—
Score bin: low	—	0.5687*** (0.0133)	—
Score bin: high	—	-0.5773***	—

		(0.0170)	
LTV (per 10 pts)	0.1643*** (0.0051)	0.1733*** (0.0050)	0.2157*** (0.0053)
Vehicle age (yrs)	0.0513*** (0.0027)	0.0507*** (0.0028)	0.0532*** (0.0031)
Contract term (mo)	0.0086*** (0.0005)	0.0090*** (0.0005)	0.0108*** (0.0005)
Payment burden (PTI)	2.9698*** (0.0616)	3.1604*** (0.0628)	4.2951*** (0.0664)
Negative equity	0.4398*** (0.0232)	0.4366*** (0.0232)	0.4479*** (0.0236)
Loan age (per 10 mo)	-0.0698*** (0.0060)	-0.0775*** (0.0060)	-0.0986*** (0.0060)
Vintage FE	Yes	Yes	Yes
Observations	444,100	444,100	444,100
Pseudo-R ²	0.0874	0.0829	0.0591
AIC	206,658	207,679	213,070

Notes: Complementary log-log discrete-time hazard. Clustered (trust-level) standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Pseudo-R² is McFadden's. Credit score enters continuously in (1), as coarse bins (middle omitted) in (2), and is excluded in (3).

5.2 Default Transition

Table 5 reports the logit for the delinquent→default transition. Conditional on delinquency, higher leverage and older collateral raise default odds, and the negative-equity indicator carries an odds ratio of **1.843**: a delinquent loan in negative equity is roughly 1.84 times as likely to roll to default as an otherwise comparable loan with positive equity. A one-standard-deviation higher score reduces default odds (OR = 0.578), but the asset and equity terms remain economically large, reinforcing that recovery-relevant collateral dynamics operate independently of borrower history.

Table 5. Default transition (logit); dependent variable = transition from delinquent to default

Variable	Coefficient (SE)	Odds ratio
Credit score (z)	-0.5480*** (0.0177)	0.578
LTV (per 10 pts)	0.0941*** (0.0093)	1.099
Vehicle age (yrs)	0.0305*** (0.0055)	1.031
Negative equity	0.6114*** (0.0437)	1.843
Loan age (per 10 mo)	-0.0145 (0.0128)	0.986
Vintage FE	Yes	
Observations	44,181	
Pseudo-R ²	0.0431	

Notes: Logit on delinquent loan–months. Clustered (trust-level) SE in parentheses. *** p<0.001, ** p<0.01, * p<0.05.

5.3 Linear-Probability Decomposition

The two-way fixed-effects LPM corroborates the hazard results and quantifies fit. The full model attains $R^2 = 0.0292$; dropping credit score lowers R^2 only to 0.0191, whereas a score-only specification reaches just 0.0202. Non-score underwriting variables thus account for the larger share of explained delinquency variation within trust and vintage cells, consistent with the view that borrower histories do not saturate repayment risk in asset-backed lending (Klee and Shin, 2021; Momeni, 2024).

Table 6. Linear-probability decomposition (two-way fixed effects)

	(1) Full	(2) No score	(3) Score only
Credit score (z)	-0.0336*** (0.0005)	—	-0.0336*** (0.0005)
LTV (per 10 pts)	0.0100*** (0.0003)	incl.	—
Vehicle age (yrs)	0.0027*** (0.0002)	incl.	—
Contract term (mo)	0.0006*** (0.0000)	incl.	—
Payment burden (PTI)	0.1833*** (0.0044)	incl.	—
Negative equity	0.0123*** (0.0010)	incl.	—
Trust & vintage FE	Yes	Yes	Yes
R^2	0.0292	0.0191	0.0202

Notes: Within (two-way demeaned) OLS with trust-clustered SE in parentheses. Column 2 omits credit score; column 3 retains score and loan age only. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

6. Mechanisms, Stress Tests, and External Relevance

6.1 The Negative-Equity Channel and the Timing of Distress

Table 7 reports the equity-path interaction. The loan-to-value \times loan-age term is positive and significant (+0.0149), and the standalone loan-age coefficient is negative (-0.2225). Together these imply that the marginal effect of leverage on delinquency is largest early in the loan's life, when balances are high relative to depreciated collateral, and attenuates as equity accumulates. This temporal signature is difficult to reconcile with a pure borrower-type story and is instead consistent with default incentives responding to the option value of walking away from depreciated collateral (Mian and Sufi, 2014). The pattern persists within narrow score groups, indicating it is not driven by unobserved borrower quality correlated with contract terms.

Table 7. Negative-equity interaction (delinquency-onset hazard, complementary log-log)

Variable	Coefficient (SE)
LTV (per 10 pts)	0.1300*** (0.0064)
Loan age (per 10 mo)	-0.2225*** (0.0409)
LTV \times Loan age	0.0149***

	(0.0037)
Negative equity	0.5545*** (0.0213)
Score, vehicle age, PTI, vintage FE	Included

Notes: Clustered (trust-level) SE in parentheses. *** p<0.001, ** p<0.01, * p<0.05.

6.2 Performance Under Macroeconomic Stress

Table 8 reports the stress-interaction hazard. Two findings stand out. First, the stress \times LTV interaction is positive (+0.0588), so leverage becomes more dangerous when aggregate shocks compress liquidity. Second, the stress \times score interaction is positive (+0.3223), meaning the protective effect of a high score weakens during stress. Consistent with this, the marginal explanatory power of credit score—measured as the increment to pseudo-R² from adding score to the non-score model—falls from **0.0416 in normal periods to 0.0236 during stress**, roughly a halving. Asset-based underwriting dimensions continue to sort outcomes under stress, whereas borrower histories lose precision precisely when they are needed most (Bakshi and Rose, 2021; Klee, Morse, and Shin, 2024).

Table 8. Stress-period interactions (delinquency-onset hazard, complementary log-log)

Variable	Coefficient (SE)
Credit score (z)	-0.8297*** (0.0138)
LTV (per 10 pts)	0.1347*** (0.0068)
Stress period	0.7458*** (0.0901)
Stress \times LTV	0.0588*** (0.0082)
Stress \times Score	0.3223*** (0.0145)
Negative equity	0.4713*** (0.0222)
Other controls + vintage FE	Included

Notes: Stress = COVID-19 (Mar–Dec 2020) and inflation/rate-tightening (Apr 2022–Jul 2023) windows. Clustered (trust-level) SE in parentheses. *** p<0.001, ** p<0.01, * p<0.05.

6.3 Robustness: Competing Risk of Prepayment

A concern is that the contract-structure effects reflect differential prepayment rather than repayment distress. Re-estimating the delinquency-onset hazard after removing loans that ever prepay (treating prepayment as a competing exit) leaves the non-score coefficients essentially unchanged: LTV remains +0.1470, vehicle age +0.0477, term +0.0077, and negative equity +0.4623. The stability confirms that the documented relationships capture genuine credit risk rather than the selection of low-risk borrowers into early payoff.

6.4 African Counterfactual Calibration

To operationalize external relevance, we hold the estimated full-model hazard coefficients fixed and shift the covariate distribution and environment to reflect African consumer-lending conditions: thinner files (a lower score percentile), higher payment burden, older collateral, and an environment shifter capturing

weaker recovery and higher idiosyncratic income volatility. We then compute projected twelve-month cumulative default under each scenario. The exercise is explicitly a calibration, not an out-of-sample fit to African data; it isolates which design margins lenders can act on. Table 9 reports the results.

Table 9. Calibrated twelve-month cumulative default under alternative lending environments

Scenario	12-month cumulative default
US benchmark (prime)	13.9%
US benchmark (subprime)	77.9%
African base (thin file)	83.8%
African + conservative LTV	49.8%
African + income volatility	93.0%
African + faster amortization	56.6%

Notes: Projections apply the Table 4 (column 1) full-model hazard coefficients to scenario covariate profiles. African scenarios add an environment shifter for weaker recovery and elevated income volatility. Figures are relative calibrations, not forecasts; the policy-relevant content is the gradient across design choices, not the level.

The calibration delivers a clear, design-relevant message. Relative to the African base case (83.8% projected twelve-month default), imposing a conservative loan-to-value limit and shorter term reduces projected default to **49.8%**, and faster amortization alone brings it to 56.6%, whereas heightened income volatility pushes it to 93.0%. The actionable margins are therefore leverage at origination, amortization speed, and exposure to depreciation—precisely the dimensions lenders can design even when borrower histories are unavailable.

6.5 Synthesis

Taken together, the estimates support the paper's central claim. Asset-backed consumer lending does not merely substitute collateral for missing histories; it embeds information through contract design that shapes borrower incentives over time. The persistence of the effects under score attenuation, the competing-risk treatment of prepayment, and macroeconomic stress supports an incentive-based interpretation rather than one driven by unobserved heterogeneity.

7. Conclusion

This paper studies how consumer credit can be extended and monitored when formal credit histories are incomplete, using loan-level evidence from 239,374 U.S. securitized auto loans observed over 4,045,954 loan-months. Exploiting detailed asset- and contract-level disclosures, the analysis isolates underwriting mechanisms that operate alongside, and partly independently of, borrower credit histories. The central finding is that asset characteristics and contract design embed economically meaningful, statistically significant information about repayment risk that credit scores do not subsume, and that this information becomes relatively more salient under heightened income volatility.

The results contribute to the literature in three ways. First, borrower histories do not saturate repayment risk even in a market with deep bureau coverage: omitting credit score reduces hazard pseudo- R^2 only from 0.0874 to 0.0591. Second, non-score signals retain their sign, magnitude, and significance when score reliance is attenuated, supporting the interpretation that collateral and contract structure capture risk dimensions orthogonal to histories. Third, the importance of asset-based underwriting intensifies under

stress, with the marginal information in scores roughly halving while leverage and amortization become more predictive.

While conducted in the U.S. auto ABS market, the contribution is not institutional transposition. The calibration exercise shows that the design margins lenders can act on—leverage discipline, amortization speed, and exposure to depreciation—materially move projected default in African-calibrated environments. Future work could extend the analysis to other collateralized consumer products and to settings with explicit data on enforcement and recovery frictions. In highlighting these mechanisms, the paper reframes asset-backed consumer lending as a distinct informational architecture for credit allocation under uncertainty.

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