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DeFi Lending Stress Meets Duration Risk: Modeling the Link Between Aave Health-Factor Regimes and Treasury Rate Conditions

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Keywords

Decentralized finance; DeFi lending; Aave; health factor; Uniswap; FRED-QD; Treasury rates; duration risk; regime modeling; forecasting.

Abstract

This paper tests whether measured DeFi lending stress co-moves with U.S. Treasury duration conditions. The empirical design uses fixed-release datasets: the Aave V2 Health Factor Dataset released in 2022, the Uniswap Daily Transaction Indices by Network released in 2023, and the FRED-QD 2022m12 quarterly macroeconomic vintage. The final aligned panel contains 54 weekly Aave observations from 4 June 2021 through 25 June 2022. Aave account-level data are aggregated into weekly collateral, debt, health-factor, risky-borrower, and liquidation-zone measures. Uniswap Ethereum daily volume and concentration measures are converted into rolling seven-day controls, and FRED-QD Treasury variables are matched by calendar quarter. A standardized Aave stress score is built from the risky borrower share, liquidation-zone share, debt-collateral ratio, and inverse borrower median health factor, then split into low-, medium-, and high-stress terciles. In the aligned panel, the Aave stress score correlates 0.677 with the 10-year Treasury rate and 0.616 with the quarter-over-quarter 10-year rate change. The risky borrower share correlates 0.736 with the 10-year rate. Regime contrasts show that high-stress Aave weeks have an average risky-borrower share of 20.95%, compared with 7.07% in low-stress weeks. The same high-stress weeks have an average 10-year Treasury rate of 2.42%, compared with 1.57% in low-stress weeks. HAC-adjusted regressions estimate that a one-percentage-point higher 10-year Treasury rate is associated with 12.95 percentage points more risky borrowers and 10.37 percentage points more liquidation-zone borrowers. In expanding-window forecasts, a duration-market ridge model lowers one-week-ahead Aave stress-score RMSE from 3.45 for the historical mean and 1.34 for AR(1) to 1.06. The results identify an empirical association, not a causal proof, between DeFi lending stress and Treasury duration conditions.

Introduction

Decentralized finance has become a measurable venue for lending, collateralized borrowing, automated market making, and liquidation risk. Its economic logic depends on public smart contracts, market-clearing collateral rules, and continuous balance-sheet adjustment rather than session-based intermediation [1]-[8]. A central feature of lending protocols is that borrower safety is observable at the position level. In Aave, the health factor summarizes whether collateral value, liquidation thresholds, and debt value leave a borrower comfortably above or dangerously close to liquidation. When the distribution of health factors deteriorates, DeFi lending conditions are not merely weaker in an accounting sense; they reflect tighter collateral capacity and greater liquidation risk.

The research question is whether those DeFi lending-stress regimes move with Treasury duration conditions. Duration-sensitive assets are affected by changes in discount rates, term-structure level, slope, and risk premia [14]-[18]. DeFi lending stress is affected by collateral values, leverage demand, stablecoin funding conditions, and on-chain market activity. These mechanisms are not identical, but they can be linked through broad liquidity and risk-appetite states. Rising rates, a flatter curve, and tighter dollar conditions can coincide with weaker collateral markets and more fragile DeFi borrower positions.

The study is built around three fixed-release sources to keep the measurement close to lending risk and to avoid dependence on live data pulls. Protocol revenue is not a direct account-level lending-risk or yield variable, and one protocol series gives limited cross-sectional information. The Aave V2 Health Factor Dataset supplies account-level collateral, debt, liquidation-threshold, and health-factor information [9], [10]. The Uniswap daily index dataset supplies DeFi market activity and concentration controls [11], [12]. FRED-QD supplies a standard quarterly macroeconomic and Treasury-rate database [13].

The contribution is empirical and methodological. Empirically, the paper shows that Aave lending stress is higher in weeks associated with elevated long-term Treasury rates and larger quarterly rate increases. Methodologically, it shows how to convert account-level DeFi health-factor data, daily DEX activity controls, and quarterly macro rate data into one aligned weekly panel without relying on proprietary signals or live downloads. The final sample contains 54 weekly observations from 4 June 2021 through 25 June 2022 and measures borrower-level DeFi lending risk directly rather than through protocol revenue.

The paper does not claim that Treasury rates mechanically cause Aave liquidation risk, or that Aave health factors forecast Treasury markets. The interpretation is narrower: in the fixed-release datasets used here, DeFi lending stress and Treasury duration conditions are empirically linked over the shared sample window. The rest of the paper presents the data, variable construction, regime method, regressions, forecast comparison, robustness checks, limitations, and conclusions.

Method

Data and sample construction

The empirical unit is the Aave weekly snapshot. Weekly frequency is chosen because the public Aave V2 health-factor release is a weekly account-level series, while Uniswap activity is daily and FRED-QD is quarterly. Using the Aave observation date as the panel date preserves the measured DeFi lending-risk frequency. Daily Uniswap variables are converted to rolling seven-day controls and matched to the latest value available at each Aave date. FRED-QD Treasury variables are matched by calendar quarter. The final panel begins on 4 June 2021, the first Aave weekly date with matching Uniswap Ethereum controls, and ends on 25 June 2022, the final Aave weekly date in the sample.

Table 1 summarizes the data inventory. The key empirical choice is to observe borrower-level collateral safety directly through Aave health factors rather than treating protocol revenue as a proxy for lending conditions. This makes the DeFi variable closer to the lending-stress mechanism being tested. Figure 1 shows the data and experiment pipeline.

Table 1. Data inventory used in the experiments.

Dataset	Sample used	Fields used	Frequency
Aave V2 Health Factor Dataset	2022 release; sample used 2021-06-04 to 2022-06-25	Account-level collateral, debt, liquidation threshold, health factor, address	Weekly Aave snapshots

Dataset	Sample used	Fields used	Frequency
Uniswap Daily Transaction Indices by Network	2023 release; Ethereum daily controls used over the same sample window	Daily transaction count, volume, Gini, HHI, entropy	Daily, aggregated to 7-day rolling controls
FRED-QD historical vintage	2022m12 vintage; variables matched by calendar quarter	GS10, GS5, TB3MS, term-spread and credit-spread controls	Quarterly, matched to weekly observations
Derived weekly panel	2021-06-04 to 2022-06-25	Aave stress score, Treasury duration variables, Uniswap controls	Weekly

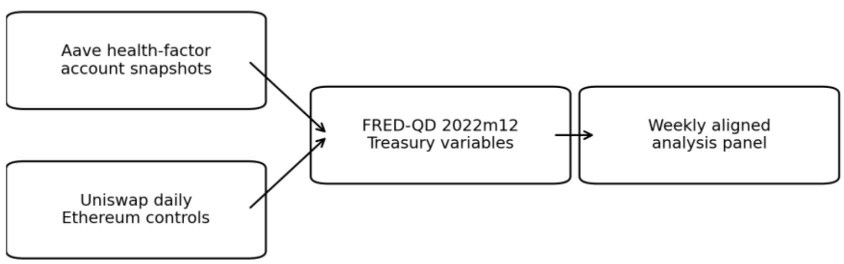

Figure 1. Data and experiment pipeline.

The exact public download links used for the dataset replacement are listed below. Within the FRED-QD historical-vintages archive, the empirical file used in the paper is FRED-QD_2022m12.csv.

- Aave V2 Health Factor Dataset complete CSV ZIP
- Uniswap Daily Transaction Indices release ZIP
- FRED-QD historical vintages ZIP

Variable construction

The first set of variables measures DeFi lending stress. Total collateral and total debt are summed across Aave accounts at each weekly snapshot. The borrower median health factor is computed among accounts with positive debt. The risky borrower share is the share of borrower accounts with health factor below 1.1. The liquidation-zone share is the share with health factor below 1.0. The debt-collateral ratio is total debt divided by total collateral, both measured in ETH units.

The second set of variables captures Treasury duration conditions. GS10 and GS5 are the 10-year and 5-year Treasury constant-maturity rates in the FRED-QD vintage. The quarter-over-quarter 10-year rate change, denoted d_GS10, measures rate pressure at the long end. The 10Y-5Y slope captures the relative long-minus-intermediate maturity structure. These variables serve as the duration measures because the paper uses fixed FRED-QD vintages rather than live market-price downloads.

The third set of variables controls for DeFi market activity. Ethereum Uniswap daily transaction count and dollar volume are converted to rolling seven-day measures. Gini, HHI, and entropy are retained as concentration and decentralization controls. Table 2 defines the variables used in the experiments.

Table 2. Variable construction and empirical role.

Variable	Formula or construction	Empirical role
Risky borrower share	Share of borrower accounts with HF < 1.1	Primary DeFi lending-stress outcome
Liquidation-zone share	Share of borrower accounts with HF < 1.0	Severe DeFi stress check
Borrower median HF	Median health factor among accounts with debt	Collateral-safety measure; lower values imply more stress
Debt-collateral ratio	Total Aave debt in ETH / total Aave collateral in ETH	Aggregate leverage intensity
Aave stress score	z(risky share)+z(liquidation share)+z(debt-collateral ratio)-z(borrower median HF)	Tercile sorting variable
GS10 and GS5	10-year and 5-year Treasury constant-maturity rates	Long and intermediate duration conditions
d_GS10 and d_GS5	Quarter-over-quarter change in GS10 and GS5	Rate-shock proxies
10Y-5Y slope	GS10 - GS5	Long-minus-intermediate duration condition
Uniswap log volume	ln(1 + 7-day Ethereum Uniswap dollar volume)	DeFi market activity control

Regime, regression, forecast, and robustness design

The regime model is intentionally transparent. Four Aave lending-stress inputs are winsorized at the 5th and 95th percentiles: risky borrower share, liquidation-zone share, debt-collateral ratio, and borrower median health factor. The first three enter the score positively. Borrower median health factor enters with a negative sign because lower health factors imply greater stress. The standardized components are summed into an Aave stress score, and the score is split into terciles labeled low stress, medium stress, and high stress.

The regression experiment estimates Aave stress outcomes as a function of Treasury duration conditions and Uniswap activity. For each dependent variable, the common specification includes the 10-year Treasury rate, the 10Y-5Y slope, and the log of rolling seven-day Uniswap Ethereum volume. Heteroskedasticity-and-autocorrelation-consistent standard errors with four weekly lags are used because the panel is weekly and the dependent variables are persistent [19]-[21]. The dependent variables are the risky borrower share, the liquidation-zone share, and the Aave stress score.

The forecasting experiment uses an expanding-window design. The target is the next-week Aave stress score. Three models are compared: a historical mean forecast, an AR(1) forecast using the current stress score, and a duration-market ridge forecast using the current stress score, GS10, the 10Y-5Y slope, and Uniswap log volume. Predictors are standardized inside each expanding training window. Forecast accuracy is evaluated by RMSE, MAE, directional accuracy, and the number of forecast points. The robustness experiment reports Pearson and Spearman correlations, an exclusion check that removes the May-June 2022 stress period, a deterministic 13-week shifted-rate placebo, and a cross-check between risky borrower share and liquidation-zone share.

Results and Discussion

Sample description

Table 3 reports descriptive statistics for the aligned weekly panel. The final sample contains 54 weekly observations. Aave active accounts average 11,503 per weekly snapshot, and borrower accounts average 9,564. Total Aave debt averages 1.91 million ETH, while total collateral averages 3.91 million ETH. The average debt-collateral ratio is 0.485. The borrower median health factor averages 1.906, but it falls to 1.108 at the minimum. The average risky borrower share is 12.57%, and the average liquidation-zone share is 7.73%. These statistics show that the sample contains both ordinary collateralized borrowing states and severe stress states.

Figure 2 plots the risky borrower share and aggregate Aave debt. The risky share rises sharply in the final part of the sample, indicating a deterioration in borrower safety. Figure 3 presents the Treasury rate environment. The 10-year and 5-year Treasury rates both rise over the sample window, with the 5-year rate catching up to the 10-year rate as the curve flattens. Figure 4 shows that Uniswap Ethereum activity varies substantially, providing a useful DeFi market-activity control rather than relying on Aave alone.

Table 3. Descriptive statistics for the aligned weekly panel.

Variable	N	Mean	Std.	Min	Median	Max
Active accounts	54	11,503.1	3,053.7	7,314.0	10,620.0	19,761.0
Borrower accounts	54	9,563.9	2,741.2	6,055.0	8,684.0	17,050.0
Total collateral (ETH)	54	3.907m	872,169.5	2.729m	3.967m	6.210m
Total debt (ETH)	54	1.910m	527,933.4	1.157m	1.806m	3.364m
Debt/collateral	54	0.485	0.043	0.353	0.491	0.562
Borrower median HF	54	1.906	0.326	1.108	1.880	2.617
Risky share HF<1.1	54	0.126	0.094	0.060	0.091	0.493
Liquidation share HF<1	54	0.077	0.087	0.027	0.042	0.433
10-year rate	54	1.889	0.601	1.323	1.593	2.930
5-year rate	54	1.597	0.817	0.797	1.180	2.947
Change in 10-year rate	54	0.316	0.438	-0.270	0.277	0.990
10Y-5Y slope	54	0.291	0.243	-0.017	0.357	0.753
Uniswap 7-day volume	54	11.961bn	5.723bn	4.428bn	10.378bn	30.964bn
Uniswap 7-day tx	54	293,706.4	77,238.4	148,100.0	270,291.5	556,448.0

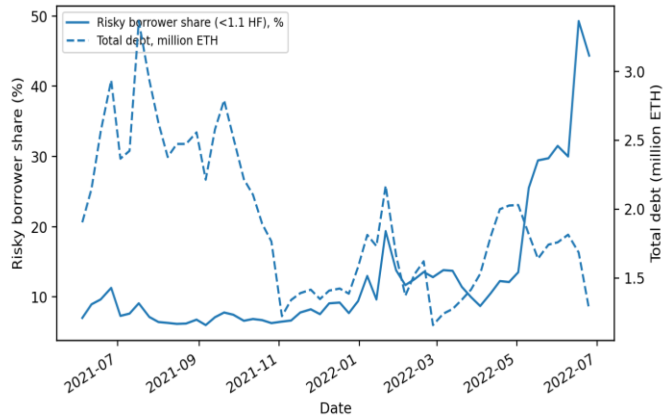

Figure 2. Aave risky borrower share and aggregate debt.

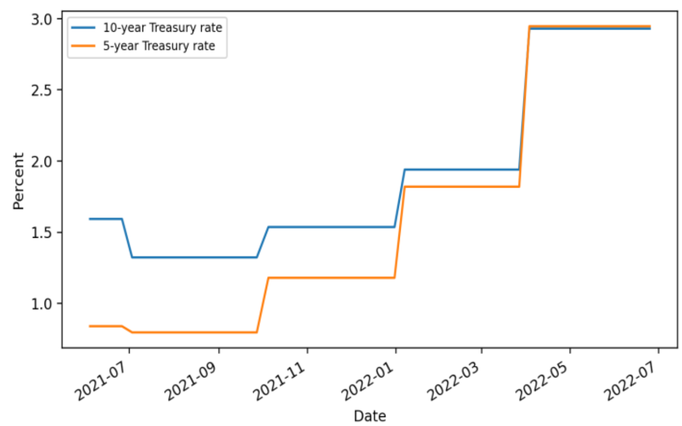

Figure 3. Treasury duration-rate conditions from FRED-QD.

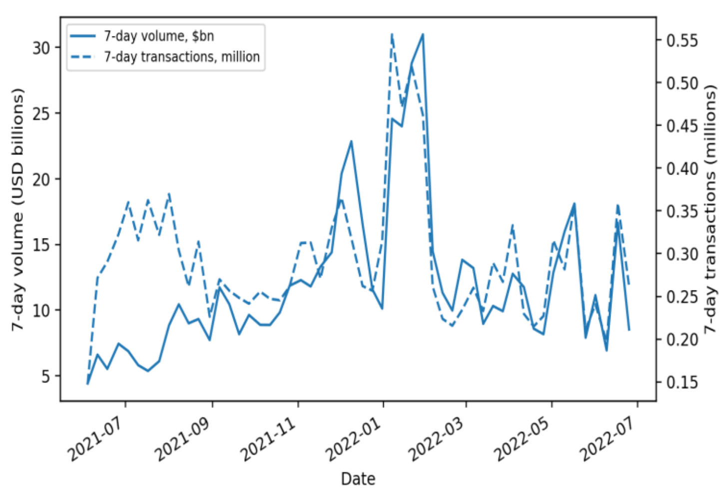

Figure 4. Uniswap Ethereum activity controls.

Correlation evidence

Table 4 and Figure 5 provide the first direct comparison between DeFi lending stress and Treasury duration conditions. The Aave stress score has a Pearson correlation of 0.677 with the 10-year Treasury rate and 0.616 with the quarter-over-quarter 10-year rate change. The risky borrower share has an even stronger correlation of 0.736 with the 10-year rate. Borrower median health factor is negatively correlated with GS10 at -0.700, which is consistent with the interpretation that borrower safety declines when duration conditions tighten. Uniswap log volume has a smaller correlation with the stress score at 0.105, so the main relationship is not simply a Uniswap activity proxy.

Table 4. Correlation matrix of Aave stress, Treasury, and Uniswap variables.

Variable	Stress score	Risky share	Debt/collat.	Borrower HF	GS10	dGS10	10Y-5Y	Uni volume
Stress score	1	0.847	-0.084	-0.932	0.677	0.616	-0.508	0.105
Risky share	0.847	1	-0.495	-0.802	0.736	0.682	-0.607	0.16
Debt/collat.	-0.084	-0.495	1	0.182	-0.486	-0.489	0.568	-0.106
Borrower HF	-0.932	-0.802	0.182	1	-0.7	-0.666	0.586	-0.109
GS10	0.677	0.736	-0.486	-0.7	1	0.954	-0.844	0.186
dGS10	0.616	0.682	-0.489	-0.666	0.954	1	-0.822	0.257
10Y-5Y	-0.508	-0.607	0.568	0.586	-0.844	-0.822	1	-0.479
Uni volume	0.105	0.16	-0.106	-0.109	0.186	0.257	-0.479	1

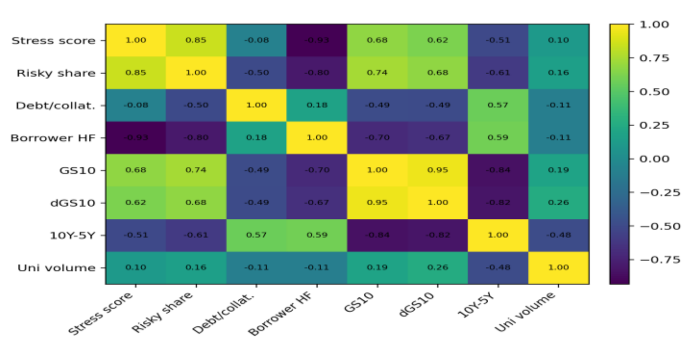

Figure 5. Correlation heatmap of Aave, Treasury, and Uniswap variables.

Aave stress regimes

Table 5 reports the stress-regime centroids, and Figure 6 plots the weekly stress score. The tercile split produces 18 low-stress, 18 medium-stress, and 18 high-stress weeks. Low-stress weeks have an average risky borrower share of 7.07% and an average liquidation-zone share of 3.42%. High-stress weeks have an average risky borrower share of 20.95% and an average liquidation-zone share of 14.58%. The borrower median health factor declines from 2.256 in the low-stress regime to 1.582 in the high-stress regime. The regime labels therefore capture economically meaningful differences in account-level collateral safety, not merely small variations in a noisy score.

Table 5. Aave stress-regime centroids.

Regime	N	Risky share (%)	Liquidation share (%)	Borrower median HF	Debt/collateral	Stress score
low stress	18	7.067	3.421	2.256	0.475	-2.652
medium stress	18	9.691	5.198	1.879	0.493	-0.308
high stress	18	20.946	14.576	1.582	0.487	2.96

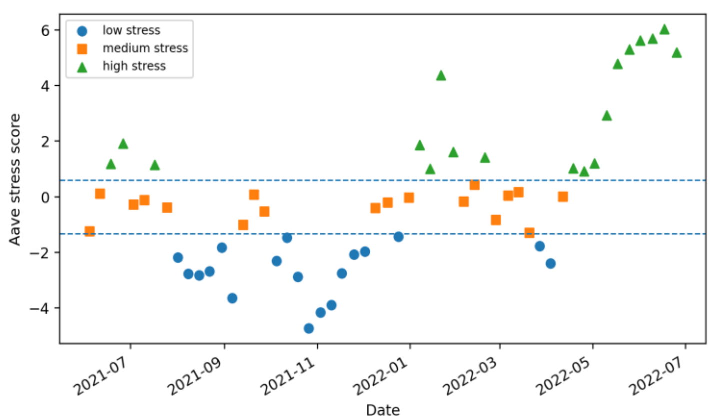

Figure 6. Aave stress score and tercile regimes.

Table 6 compares Treasury and Uniswap conditions across the same Aave regimes. High-stress weeks have an average 10-year Treasury rate of 2.42%, compared with 1.57% in low-stress weeks. The average quarterly change in the 10-year rate is 0.678 percentage points in high-stress weeks and 0.106 percentage points in low-stress weeks. The 10Y-5Y slope is lower in high-stress weeks, which is consistent with the curve-flattening environment that accompanied the 2022 rate repricing. Uniswap Ethereum volume is also higher in high-stress weeks, but the regime pattern is strongest in the Treasury rate variables and the Aave risk variables.

Table 6. Treasury and Uniswap conditions by Aave stress regime.

Regime	N	GS10	Change in 10Y	GS5	10Y-5Y slope	Uni 7-day volume ($m)	Uni 7-day tx
low stress	18	1.565	0.106	1.186	0.379	11,274.2	289,041.6
medium stress	18	1.684	0.166	1.326	0.358	10,637.9	266,086.7
high stress	18	2.417	0.678	2.28	0.137	13,969.5	325,991.1

HAC regression evidence

Table 7 reports HAC-adjusted regressions using a common specification for all three dependent variables. For the risky borrower share, the GS10 coefficient is 12.955, meaning that a one-percentage-point higher 10-year Treasury rate is associated with 12.96 percentage points more borrowers below the 1.1 health-factor threshold, conditional on the 10Y-5Y slope and Uniswap log volume. The HAC p-value is 0.0136. For the liquidation-zone share, the GS10 coefficient is 10.366 with a p-value of 0.0499. For the composite stress score, the GS10 coefficient is 4.095 with a p-value of 0.0005, and the 10Y-5Y slope coefficient is 3.464 with a p-value of 0.0289.

The coefficients should be read as conditional associations, not causal estimates. The FRED-QD variables are quarterly and are matched to weekly Aave observations, so the regressions are best interpreted as a compact description of stress differences across Treasury-rate environments. Even with that caution, the direction and consistency of the coefficients support the main result: Aave lending stress is higher in weeks attached to more restrictive long-rate conditions.

Table 7. HAC-adjusted regressions of Aave stress on Treasury and Uniswap variables.

Dep. var.	Regressor	Coef.	HAC SE	p	R2	N
Risky share (pp)	const	-47.305	35.134	0.1782	0.545	54
Risky share (pp)	GS10	12.955	5.251	0.0136	0.545	54
Risky share (pp)	duration_slope_10y5y	4.883	4.2	0.245	0.545	54
Risky share (pp)	log_uni_eth_volume_7d	1.47	1.498	0.3264	0.545	54
Liquidation share (pp)	const	-7.52	31.756	0.8128	0.489	54
Liquidation share (pp)	GS10	10.366	5.286	0.0499	0.489	54
Liquidation share (pp)	duration_slope_10y5y	0.646	4.567	0.8875	0.489	54
Liquidation share (pp)	log_uni_eth_volume_7d	-0.195	1.326	0.8829	0.489	54
Stress score	const	-20.92	23.223	0.3677	0.477	54
Stress score	GS10	4.095	1.171	0.0005	0.477	54
Stress score	duration_slope_10y5y	3.464	1.586	0.0289	0.477	54
Stress score	log_uni_eth_volume_7d	0.527	1.005	0.6	0.477	54

Forecast and robustness evidence

Table 8 and Figure 7 report the expanding-window forecast comparison. The historical mean model has a stress-score RMSE of 3.447. The AR(1) model lowers RMSE to 1.337, confirming that DeFi lending stress is persistent. The duration-market ridge model lowers RMSE further to 1.059 and raises directional accuracy to 66.67%. The forecast comparison does not imply an exploitable trading rule. It shows that adding duration and market-activity variables to the current stress score improves one-week-ahead stress measurement in this sample.

Table 8. Expanding-window forecast comparison.

Target	Model	RMSE	MAE	Direction (%)	N forecasts
Aave stress score, one-week ahead	Historical mean	3.447	2.732	33.333	21
Aave stress score, one-week ahead	AR(1)	1.337	1.181	33.333	21
Aave stress score, one-week ahead	Duration-market ridge	1.059	0.884	66.667	21

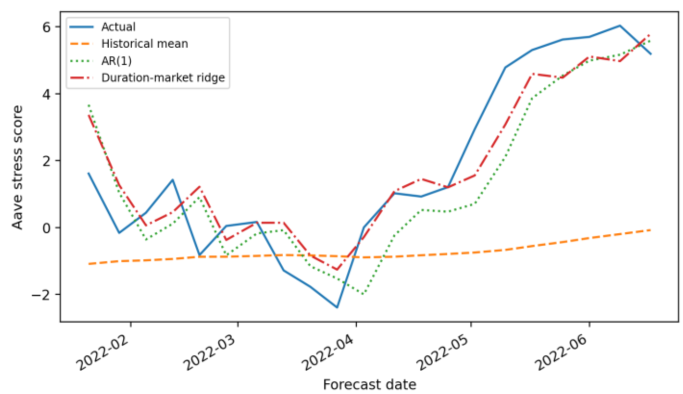

Figure 7. Expanding-window Aave stress forecast comparison.

Table 9 reports robustness and falsification checks. The Spearman correlation between the Aave stress score and GS10 is 0.640, so the result is not confined to linear Pearson correlation. The correlation between risky borrower share and GS10 is 0.565 even when the May-June 2022 stress period is removed, suggesting that the link is not generated solely by the final crisis weeks. The 13-week shifted-rate placebo correlation is 0.223, much smaller than the measured same-time stress-score and d_GS10 correlation of 0.616. Finally, the risky borrower share and liquidation-zone share correlate 0.982, confirming that the two account-level stress measures identify the same underlying deterioration in borrower safety.

Table 9. Robustness and falsification checks.

Check	Statistic
Pearson: stress score vs GS10	0.677

Check	Statistic
Pearson: stress score vs d_GS10	0.616
Spearman: stress score vs GS10	0.64
Spearman: risky share vs GS10	0.837
Excluding May-June 2022: stress score vs GS10	0.328
Excluding May-June 2022: risky share vs GS10	0.565
Placebo: stress score vs 13-week-shifted d_GS10	0.223
Cross-check: risky share vs liquidation share	0.982

Across descriptive statistics, correlations, regime contrasts, regressions, forecasts, and robustness checks, the results are internally coherent. The direct Aave health-factor data show more borrower stress when Treasury duration conditions are more restrictive. The core DeFi variable comes from account-level collateral and debt safety, so the empirical link is measured closer to the borrower-level lending mechanism than a protocol-revenue proxy would allow.

The economic interpretation is plausible. Rising long rates and curve flattening reflect a tighter discount-rate environment. In such an environment, risky collateral prices and leverage demand can deteriorate, pushing DeFi borrowers closer to liquidation. Uniswap activity controls show that the relationship is not merely a single-protocol time series. The evidence therefore supports the view that DeFi lending stress and traditional duration conditions are connected through broad liquidity, discount-rate, and risk-appetite states.

Limitations

The first limitation is sample coverage. The fixed Aave V2 Health Factor Dataset used here ends in June 2022, so the sample does not cover later DeFi cycles, later Aave versions, or the full post-2022 Treasury regime. This limitation is the cost of satisfying a fixed-release dataset design. The benefit is that the data are downloadable as a single public release and do not depend on a live API pull.

The second limitation is frequency alignment. Aave is weekly, Uniswap is daily, and FRED-QD is quarterly. Matching quarterly Treasury variables to weekly observations preserves the fixed macro vintage but cannot identify the exact week in which market participants priced a rate shock. A daily or intraday market-rate dataset would be needed for lead-lag trading tests. The present study instead measures whether weekly DeFi lending stress is systematically different across Treasury duration environments.

The third limitation is that health-factor stress is related to DeFi lending risk but is not the same object as a pool-level lending APY. This revision deliberately prioritizes borrower-level collateral safety because it is directly observed in the 2022 Aave dataset. A future extension can combine the present health-factor panel with pool-level supply and borrow APRs when fixed historical APR releases become available.

The fourth limitation is protocol scope. Aave is a major lending protocol, and Uniswap controls broaden the DeFi activity dimension, but the design does not include Compound, MakerDAO/Sky, Morpho, Curve, or liquid-staking protocols. A larger cross-protocol release would allow protocol fixed effects and separation of lending, exchange, and staking channels.

The final limitation is causal interpretation. The evidence documents co-movement and forecasting content inside a fixed-release sample. It does not prove that Treasury rates cause Aave health-factor deterioration or that Aave stress causes changes in

Treasury rates. Causal identification would require exogenous shocks, higher-frequency timing, or instruments that isolate either rate news or DeFi-specific collateral shocks.

Conclusion

This paper studies the link between DeFi lending stress and Treasury duration conditions using fixed 2022 and 2023 dataset releases. The empirical design uses Aave V2 account-level health-factor data, Uniswap daily transaction indices, and a FRED-QD quarterly macro vintage. DeFi lending stress is measured at the borrower-position level, DeFi market activity is controlled with an external DEX dataset, and Treasury conditions are taken from a standard fixed macroeconomic vintage.

The results show a consistent association between Aave lending stress and Treasury duration conditions. The Aave stress score correlates 0.677 with the 10-year Treasury rate, and the risky borrower share correlates 0.736 with the same rate. High-stress Aave weeks have much higher risky and liquidation-zone borrower shares than low-stress weeks, and they also occur in a higher-rate, flatter-curve environment. HAC regressions show positive GS10 coefficients for risky borrower share, liquidation-zone share, and the composite stress score. The expanding-window forecast comparison shows that a duration-market ridge model improves one-week-ahead stress-score RMSE relative to both the historical mean and AR(1) benchmarks.

The conclusion is therefore narrow and empirically grounded. The paper does not depend on protocol revenue as a lending-yield proxy or on live ETF data. It shows, using fixed public datasets released in 2022 and 2023, that DeFi account-level lending stress and Treasury duration conditions are empirically linked over the shared sample window. The result is not a causal law, but it is a coherent and auditable empirical regularity that can be extended to richer fixed-release DeFi datasets as they become available.

Data Availability and Download Links

The empirical analysis uses fixed public data releases. The complete Aave V2 health-factor data file, the Uniswap release archive, and the FRED-QD historical-vintages archive can be downloaded from the links below. Within the FRED-QD archive, the empirical vintage used in the paper is FRED-QD_2022m12.csv.

- Aave V2 Health Factor Dataset complete CSV ZIP
- Uniswap Daily Transaction Indices release ZIP
- FRED-QD historical vintages ZIP

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