DeFi leverage

RiskLab/BoF/ESRB Conference on AI and Systemic Risk Analytics

6 June, 2024

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Disclaimer: The views are our own and not necessarily those of the BIS

Motivation

- Decentralised finance (DeFi) has experienced rapid growth from 2020
  - Lending takes a prominent role: $35 bln deposit and $25 bln debt at its peak
  - User behavior and pool dynamics on lending protocols remain largely unstudied
- Collateralised borrowing is not new in traditional finance
  - Data availability of DeFi lending could shed light on leverage taking behaviour
  - DeFi lending could provide an innovative design for repo and securities lending
  - Note: market design could be completely orthogonal to underlying technology

Main results

- We document DeFi leverage for wallets interacting with lending platforms
  - Actual leverage $<<$ implied leverage by loan-to-value requirement (LTV)
  - The largest users and the most active ones take higher leverage
  - The majority of the users pledge VC as collateral and borrow SC $\rightarrow$ similar to repo

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- We identify the factors associated with high leverage
  - Leverage decreases in more stringent LTV requirements and borrow rate, and increases in market sentiment
  - The gap between the actual leverage and the LTV-implied leverage is driven by (i) the looming threat of automatic liquidation and (ii) the reach-for-yield motive

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  - The gap between the actual leverage and the LTV-implied leverage is driven by (i) the looming threat of automatic liquidation and (ii) the reach-for-yield motive
- High borrower leverage could affect lending resilience and market liquidity
  - When borrower leverage is high, a larger share of lending pools are put at risk
  - Conditional on the occurrence of collateral selection, borrowers with high leverage tend to tilt towards volatile collateral more aggressively
  - High leverage increases liquidity provision in decentralised exchanges

Literature

- **DeFi and crypto in general**: Cornelli et al (2024), Rivera, Saleh and Vandeweyer (2023), Chaudhary, Kozhan and Viswanath-Natraj (2023), Park and Stinner (2023), Chiu et al (2022), Lehar and Parlour (2022), Liu et al (2022), Capponi and Jia (2022)
  - We document DeFi leverage and its impact on resilience and liquidity
- **Leverage**: Adrian and Shin (2010, 2014), Geanakoplos (2001, 2010), Fostel and Geanakoplos (2014), Ang et al (2011), Kaharaman and Tookes (2017)
  - Given the granular transaction data, we study the driving factors behind leverage
- **Repo markets**: Duffie et al (2002), Gorton and Metrick (2009, 2012), Krishnamurthy et al (2014), Copeland et al (2014), Infante (2019), Julliard et al (2022)
  - The supply-demand dynamics in DeFi lending could shed light on repo market design

Roadmap

- The mechanics of DeFi lending
- DeFi leverage: overall trend and group differences
- Factors associated with high leverage
- The impact of high leverage on lending resilience and market liquidity
- Conclusion: lessons for traditional finance

The mechanics of DeFi lending

- In this paper, we document wallet-level leverage in DeFi: wallets $\equiv$ users
- Two concepts of leverage
- Implied leverage from the loan-to-value ratio requirement $\rightarrow$ Leverage^I

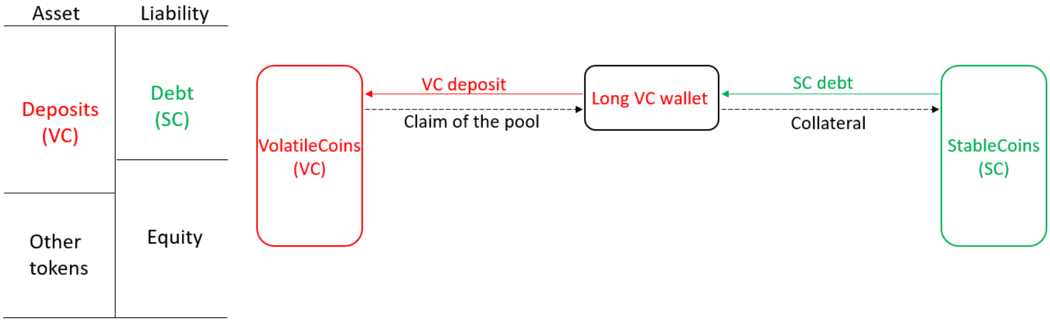
Table: **Loan-to-value (LTV) ratio and implied leverage.**

	Aave v2			Compound		
	LTV	Haircut	Leverage^I	LTV	Haircut	Leverage^I
USDC	0.800	0.200	5.000	0.855	0.145	6.897
USDT	0.000	1.000	1.000	0.000	1.000	1.000
DAI	0.750	0.250	4.000	0.835	0.165	6.061
ETH	0.825	0.175	5.714	0.825	0.175	5.714
BTC	0.720	0.280	3.571	0.700	0.300	3.333

- Actual leverage: asset-to-equity ratio $\rightarrow$ Leverage

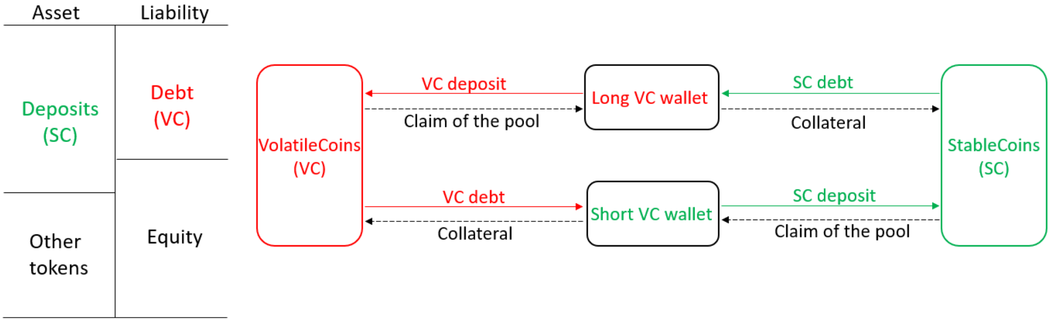
The mechanics of DeFi lending

- Similar to a repo transaction, a user can deposit volatile coins (VC) and use them as collateral to borrow stablecoins (SC)
- The user can lever up by using the borrowed SC to buy more VC



The mechanics of DeFi lending

- Similar to securities lending, a user can deposit SC and borrow the desired VC
- The user could short sell the borrowed VC, or use them for voting purpose



DeFi lending vs repo

- Although DeFi lending is a type of collateralised borrowing, it has unique features

Table: **Key differences between DeFi lending and repo/securities borrowing.**

	DeFi lending	Repo/securities lending
Counterparty	pseudo-anonymous	identifiable
Collateral	pooled across borrowers	segregated
Borrow rate	pre-defined function of utilisation	flexible
Haircuts	pre-defined	flexible
Maturity	perpetual, borrower's option to repay early	short-term
Close-out process	automatically done by liquidators	non-defaulting party starts the process

- DeFi lending also allows users to only deposit without borrowing

Data

- We collect on-chain data of all wallets that took out debt from major DeFi lending platforms on Ethereum network
- Sample period: Jan 2021 - March 2023
- Debt: a user's outstanding debt across platforms
- Asset: a user's total assets including coins not in lending platforms
- Equity: Asset - Debt

Panel A: Overall sample

Platform	#Wallets (Unit)	#Obs (Unit)	Ratio (Unit)	Debt ($)	Asset ($)	Equity ($)
AAVEV1	4,629	1,358,940	294	224,498	607,759	383,261
AAVEV2	42,123	9,625,813	229	340,479	685,142	344,662
CompoundV2	16,836	5,862,197	348	985,870	1,752,627	766,757
Total	57,555	13,094,094	228	580,497	1,168,491	587,995

Data – Heterogeneity across wallets

- Very skew sample

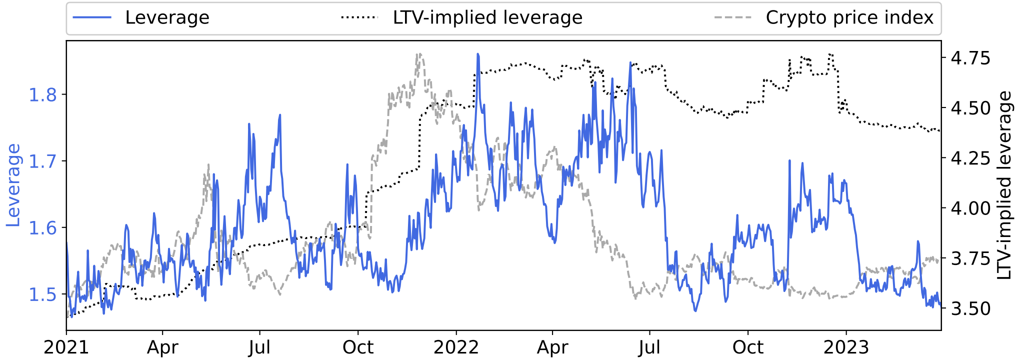
Panel B: Heterogeneity across users

Variable	Mean	Std	25%	Median	75%	Max
Debt ($)	580,497	13,258,569	72	4,038	36,644	1,123,007,715
Assets ($)	1,168,492	22,937,139	1,080	15,824	121,712	2,828,857,418
Equity ($)	587,995	11,825,693	793	10,069	76,905	1,833,842,618
Leverage (Unit)	1.644	0.731	1.140	1.431	1.861	7.554
Leverage^{I} (Unit)	4.229	1.130	3.428	4.000	5.068	7.692

- We classify the following three groups of users:
  - The largest: 1000 users with largest mean outstanding debt users on their active days
  - The most active: 1000 users with highest number of loans taken out
  - The earliest: first 1000 users that took out debt on each protocol

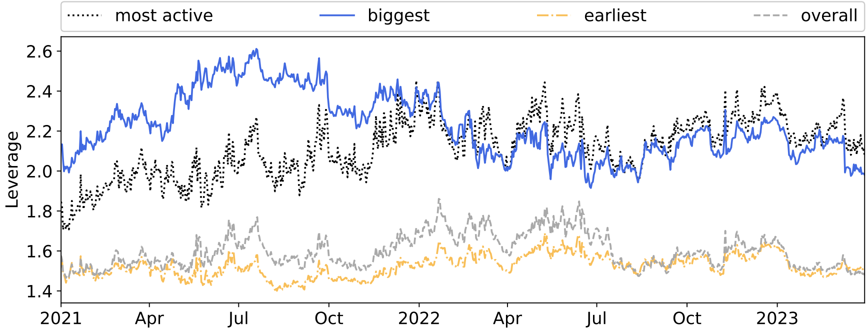
Leverage

Figure: **Leverage vs LTV-implied leverage.**



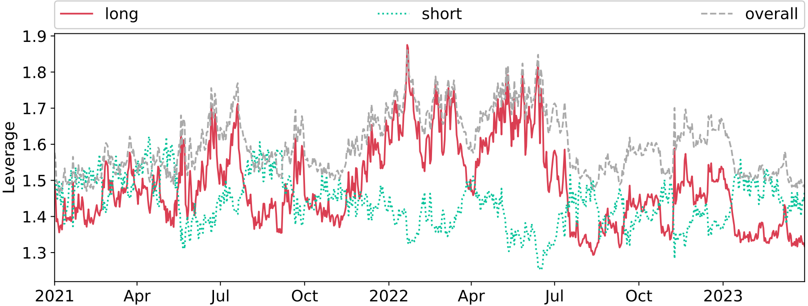
- Leverage ranges from 1.4 to 1.9, similar to hedge fund leverage after GFC (≈ 1.5)
- Actual leverage is materially lower than the LTV-implied leverage (different scales)
- Leverage tracks crypto price index, with a roughly 3-month lag

Group differences



- The largest/most active users appear to take higher leverage compared to others (often exceeding 2)
- The earliest users, however, tend to have low leverage (potential testing wallets)

Long and short users



	Mean	Std	25%	50%	75%	#Wallets	#Obs	Ratio
Long	1.511	0.516	1.119	1.380	1.730	42,647	8,615,139	202
Short	1.725	0.736	1.190	1.532	2.015	4,554	526,361	116

- Leverage of the long and short users are negatively correlated
- VC price movements have opposite effects on long and short positions
- The majority are long users, but short users have higher leverage

Factors that are associated with high leverage

$$
\begin{aligned}
Leverage_{i,t} = {} & \beta_0 + \beta_1 Leverage^{I}_{i,t-1} + \beta_2 NetBorrowCost_{i,t-1} + \beta_3 Utilisation_{i,t-1} \qquad (1) \\
& + \beta_4 SignedVCPrice_{i,t-1} + \beta_5 Volatility_{i,t-1} + \beta_6 CollateralReturn_{i,t-1} + \gamma_i + \mu_t +
\end{aligned}
$$

- Leverage^{I}: LTV-implied leverage, weighted by a user's outstanding debt $\rightarrow \beta_1 > 0$
- NetBorrowCost: a user's debt-weighted net borrow cost $\rightarrow \beta_2 < 0$
- Utilisation: a user's debt-weighted pool utilisation rate $\rightarrow \beta_3 > 0$

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- CollateralReturn: a user's collateral-weighted past-30-day return $\rightarrow \beta 6 < 0$

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Leverage_{i,t} = \beta_0 + \beta_1 Leverage^{l}_{i,t-1} + \beta_2 NetBorrowCost_{i,t-1} + \beta_3 Utilisation_{i,t-1} \qquad (1) \\
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- Standard errors: double-clustered (Peterson (2009))

Wallet-level regression results

	All	Winsorised	Largest	MostActive	Earliest
Leverage^l	0.074***	0.074***	0.082	0.181***	0.093***
	(16.030)	(15.989)	(1.609)	(6.293)	(4.204)
NetBorrowCost	-0.021***	-0.021***	-0.232**	-0.124***	-0.056**
	(-3.300)	(-3.200)	(-1.965)	(-4.230)	(-2.395)
Utilization	0.031**	0.028**	0.436***	0.367***	0.010
	(2.456)	(2.159)	(2.692)	(3.494)	(0.224)
SignedVCPrice	-0.043***	-0.042***	-0.103***	-0.056***	-0.014
	(-17.108)	(-16.394)	(-4.678)	(-3.819)	(-1.438)
Volatility	-3.697**	-3.8882**	14.439	0.176	7.347***
	(-2.418)	(-2.426)	(1.144)	(0.029)	(3.124)
CollateralReturn	-0.154***	-0.155***	-0.269***	-0.172***	-0.049***
	(-20.658)	(-20.794)	(-7.012)	(-5.076)	(-3.435)
Time FE	✓	✓	✓	✓	✓
User FE	✓	✓	✓	✓	✓
No. Observations	12345871	12026304	173034	327793	435770
R-squared	0.0181	0.0175	0.0429	0.0459	0.0205

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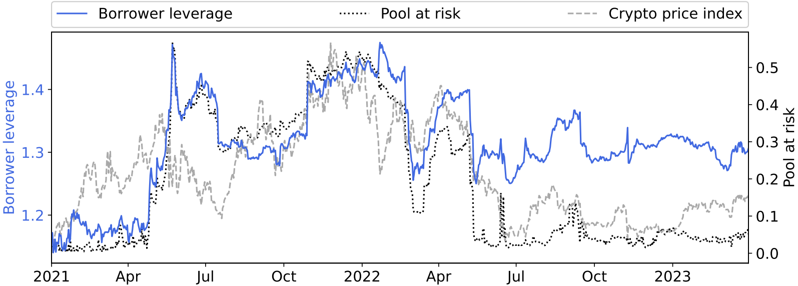
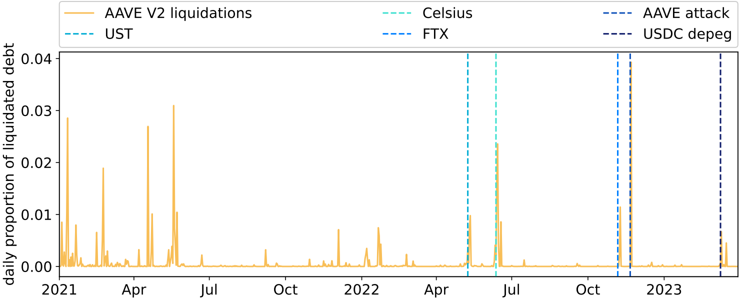
The impact of high borrower leverage on lending resilience

- DeFi loans are secured by overcollateralisation
- When collateral depreciates, lenders could be exposed to default risk
- To manage such risk, DeFi platforms allow anyone to liquidate a loan when the loan-to-value ratio rises above a certain threshold
- Are lending pools more risky when their borrowers have higher leverage?

Lending resilience measures





How leverage affects pool resilience

$$PoolResilience_{j,t} = \alpha + \beta BorrowerLeverage_{j,t} + \theta Control_{j,t} + \gamma_j + \mu_t + \varepsilon_{j,t} \quad (2)$$

	Pool Value-at-Risk			Liquidation share		
	All	**Volatile coins**	**Stablecoins**	**All**	**Volatile coins**	**Stablecoins**
			Panel A: Aave v2			
BorrowLeverage	0.9178***	0.6265***	1.0833***	0.0055*	0.0074	0.0034
	(6.0587)	(2.6351)	(7.4830)	(1.9227)	(1.6242)	(0.9485)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Pool FE	✓	✓	✓	✓	✓	✓
No. Observations	21157	13952	7205	22816	15568	7248
R-squared	0.3473	0.1435	0.6554	0.0018	0.0028	0.0015
			Panel B: Compound			
BorrowLeverage	1.2050***	1.1563***	0.4677*	0.0035*	0.0037*	0.0004
	(4.1348)	(2.8542)	(1.7666)	(1.7078)	(1.7215)	(0.2164)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Pool FE	✓	✓	✓	✓	✓	✓
No. Observations	11137	7286	3851	11848	7928	3920
R-squared	0.2685	0.3371	0.5272	0.0003	0.0011	0.0013

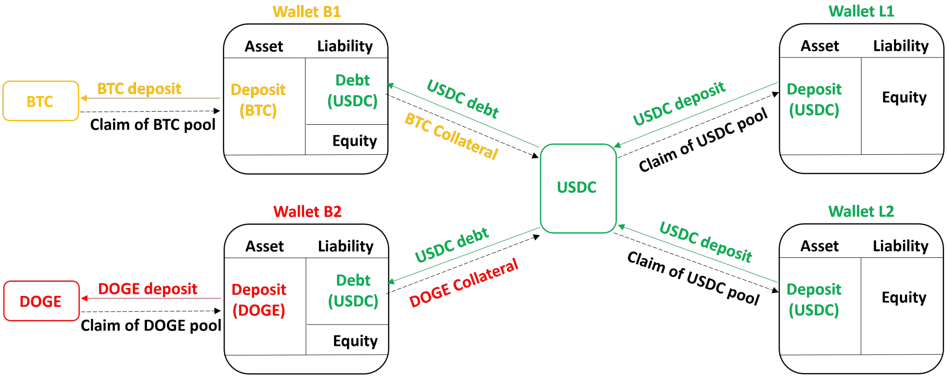
Policy relevance: repo market design

- Can we replace market-makers/dealer banks with smart contracts/lending pools?
  - Nothing related to crypto or Blockchain
  - Just similar to algo traders (HFTs) replacing dealer banks in limit order book
  - Can algo replace dealers in less liquid segments?
- Smart contracts could potentially alleviate pressures on dealers' b/s capacity
- Our analysis unveils the importance of several key design variables
  - Haircuts and rates
  - Liquidation procedures
  - Pooling or segregation of collateral across users
  - Link between leverage and liquidity

Appendix

Ambiguity of collateral that backs debt positions

- One unique feature of DeFi lending is the pooling of collateral *across users*
  - Case 1: Only B2 is liquidated → Lenders can redeem subject to availability
  - Case 2: Both B1 and B2 are liquidated → Lenders can redeem fully
  - Case 3: B1 is liquidated but B2 ends up with bad debt → The lender that redeem late suffer the loss



Strategic collateral selection right ahead of liquidation

- Due to the pooling of collateral across borrowers, **borrowers have information advantage over lenders** on the quality of the collateral
- Borrowers can substitute **low** quality collateral for **high** quality one when they expect their debt positions to be liquidated (Chiu et al (2022))

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- Borrowers can substitute **low** quality collateral for **high** quality one when they expect their debt positions to be liquidated (Chiu et al (2022))
- The granular wallet-level data allows us to investigate such strategic behaviours
- In total 1,526 wallets were liquidated in our sample
- For each one of these wallets, we calculate two measures of collateral volatility

$$CollateralVol_{i,t} = \frac{\sum_K (CollateralValue_{k,i,t} \times Vol_{k,t})}{\sum_K CollateralValue_{k,i,t}}, \tag{3}$$

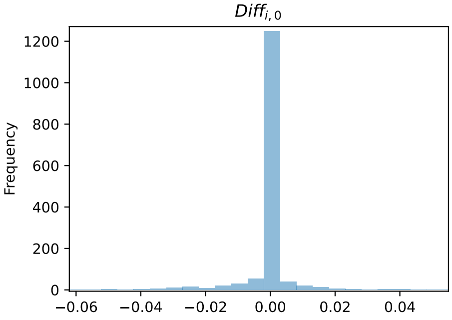
$$SimulatedVol_{i,t} = \frac{\sum_K (CollateralValue_{k,i,-29} \times Vol_{k,t})}{\sum_K CollateralValue_{k,i,-29}}, \tag{4}$$

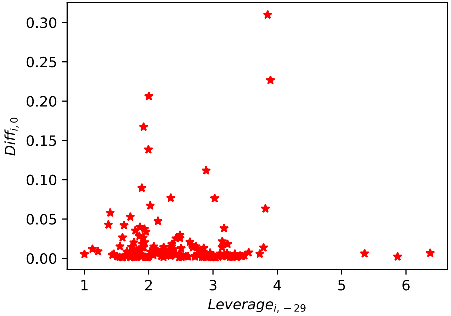
$$Diff_i = CollateralVol_{i,0} - SimulatedVol_{i,0}. \tag{5}$$

- If $Diff_i > 0$ – it means that wallet i tilts towards more volatile collateral

Collateral selection when borrower leverage is high

- Most liquidated wallets did not modify their collateral composition
- Potential reason: LTV requirement of more volatile collateral is more stringent
- If LTV requirements reflect the collateral quality *perfectly*, such strategic behaviour should not take place
- However, some wallets tilted towards to more volatile collateral $\rightarrow$ The aggresiveness is associated with leverage





High leverage is associated with more aggressive collateral selection

$$Diff_i = \beta_0 + \beta_1 Leverage_i + Debt_i + \varepsilon_i \tag{6}$$

- Both higher leverage and higher implied leverage are associated with more aggressive collateral selection
- The higher is the distance between leverage and implied leverage, there is more room for collateral selection

	Diff	**Diff**	**Diff**
Leverage	0.0078***		
	(4.561)		
Leverage^I		0.0050***	
		(5.594)	
Leverage^I - Leverage			0.0100***
			(6.067)
Debt	-0.0001	-0.0002	0.0000
	(-0.595)	(-0.990)	(0.214)
No. Observation	145	145	145
R-squared	0.1754	0.1836	0.1383

The impact of high leverage on liquidity provision

- More than 25% of the borrowers in DeFi lending pools are also liquidity providers in decentralised exchanges (DEX)
- When liquidity providers have lower leverage, they provide less liquidity in DEX
- However, the impact of leverage is limited, as collateral is locked in lending pools

$$LiquidityProvision_{j,t} = \alpha + \beta BorrowerLeverage_{j,t} + \theta Control_{j,t} + \gamma_j + \mu_t + \varepsilon_{j,t} \quad (7)$$

	(1)	**(2)**	**(3)**	**(4)**
Leverage	1.769e+04*			1.837e+04*
	(1.7010)			(1.7052)
Leverage^{l}		-301.45		-1374.6
		(-0.0911)		(-0.3932)
BorrowRate			-4172.3	-3537.0
			(-0.4216)	(-0.3567)
Time FE	✓	✓	✓	✓
UserFE	✓	✓	✓	✓
No. Observations	3026386	3026386	2950970	2950970
R-squared	0.0001	7.339e-08	4.499e-07	0.0001