Credit Allocation and Lending Decisions Across Monetary Policy Regimes: Evidence from Fintech Lending

통화정책 체제에 따른 신용 배정 및 대출 결정: 핀테크 대출의 증거

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Motivation

- Fintech lending is an increasingly important part of consumer credit markets (e.g., Berg et al.,g et al. 2020; Balyuk, 2023).

- Fintech lending provides
  - faster access to credit (Beaumont et al, 2022)
  - financing to underserved borrowers (Fuster et al. 2019).

- Fintech lending functions as either a substitute for, or a complement to, traditional banks (Tang, 2019)
  - ➢ Substitute on borrower quality → P2P serves infra-marginal bank borrowers
  - ➢ Complement on loan size → P2P specializes in smaller loans

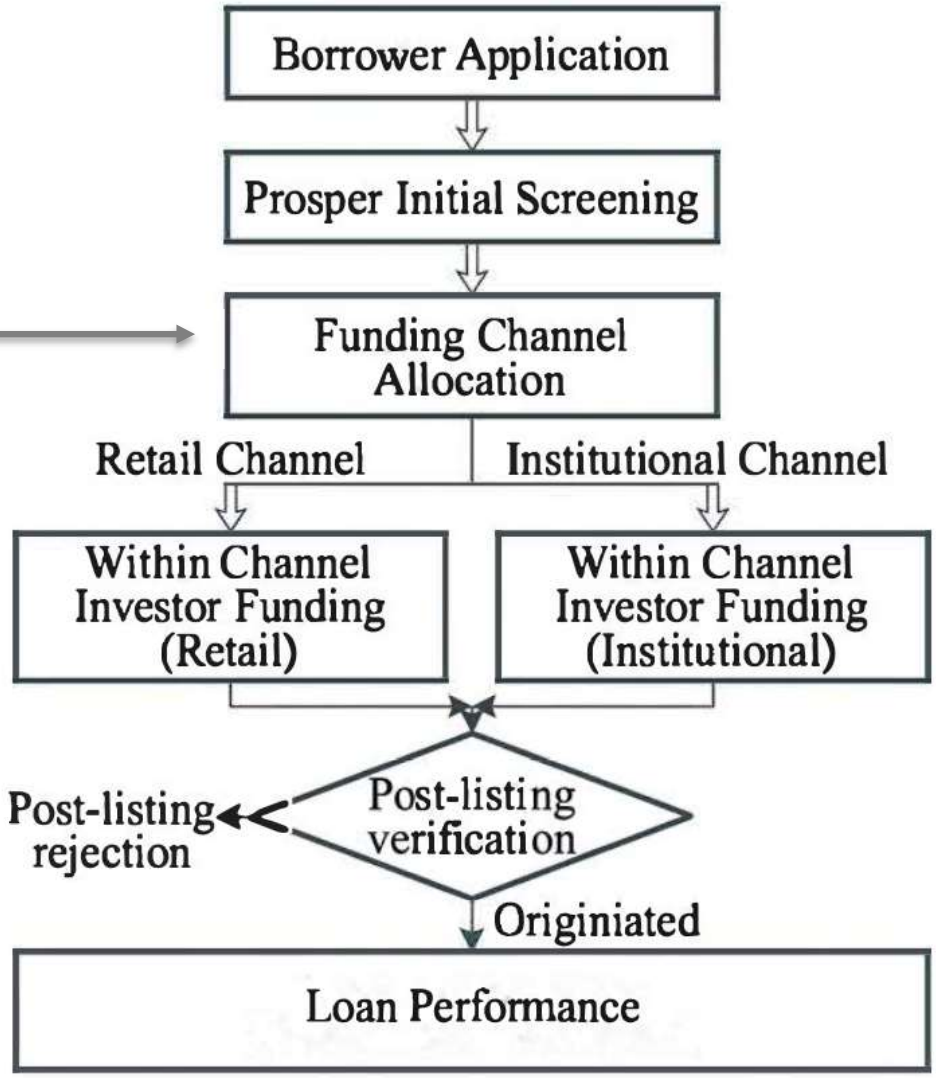
- Fintech lending plays an important role in providing liquidity to the public, especially during crises. (e.g., Buchak et al., 2018; Allen et al., 2023)

RQ1: How do borrower credit quality and contractual exposure affect assignment to retail versus institutional funding channels across monetary policy regimes?

통화정책 체제 전반에 걸쳐 차입자의 신용도와 계약상 익스포저(위험 노출액)가 소매 금융 채널과 기관 금융 채널 간의 배정에 어떠한 영향을 미치는가?“

RQ2: How do borrower credit quality and contractual exposure affect Prosper's post-listing rejection (PLR) decisions across monetary policy regimes?

통화정책 체제 전반에 걸쳐 차입자의 신용도와 계약상 익스포저가 프로스퍼(Prosper)의 상장 후 거절 결정에 어떠한 영향을 미치는가



Motivation

- Most fintech papers examine borrower characteristics, platform screening, or credit access (e.g., Wei & Lin, 2017; Buchak et al., 2018; Jagtiani & Lemieux 2018; Fuster et al., 2019; Gopal & Schnabl, 2022).

- *How is credit allocated across investor channels?*
- In fintech lending, investor participation is shaped by platform channel assignment rather than pure investor choice.
- As macro-financial conditions change, platforms reallocate loans across retail and institutional funding channels, altering the distribution of borrower credit quality and contractual exposure.
- Loan allocation does not guarantee origination. Platforms retain discretion to reject funded listings through post-listing verification and screening.
- Yet, we know little about how fintech platforms determine funding channel allocation and post-listing rejection across different monetary policy regimes.

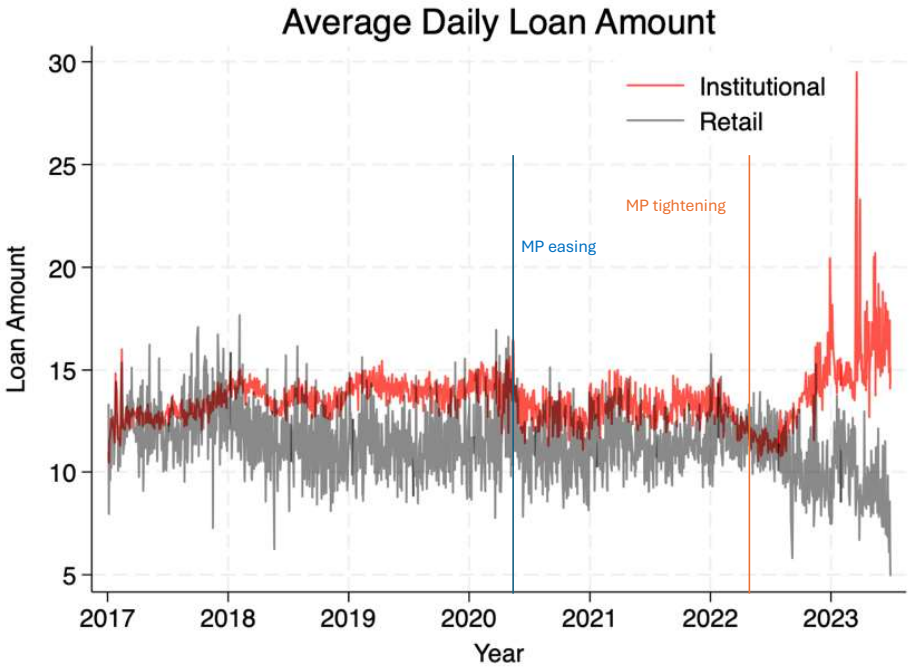
Data

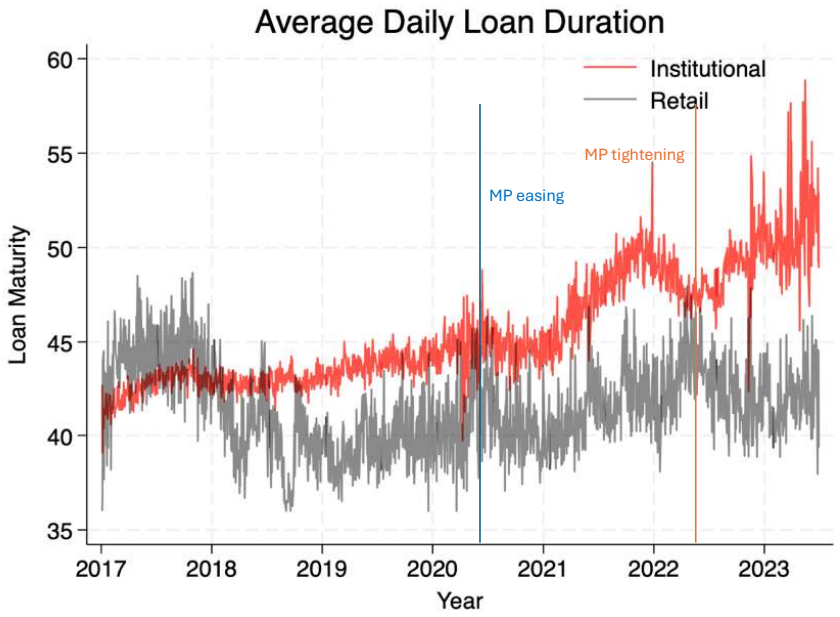
- Data Source: Prosper Marketplace (Leading US Fintech P2P lending platform)

- Covers over 500 variables per loan application at the listing and loan level – including borrower demographics, loan purposes, interest rates, amounts, and durations.

- Sample period: May 1, 2017 – December 31, 2023.
  - Pre-Covid (**보통시기**)
  - MP easing (통화완화, Mar 15, 2020 – Mar 15, 2022): Monetary easing; Massive QE; Liquidity surge. 위험 선호도 (위험 성향) ↑
  - MP tightening (통화긴축, Mar 16, 2022 – Dec 31, 2023): Monetary tightening; Inflation shock. 위험 선호도 (위험 성향)↓

Data


Average Daily Loan Amount
Institutional
Retail
MP easing
MP tightening
Loan Amount
30
25
20
15
10
5
2017
2018
2019
2020
2021
2022
2023
Year


Average Daily Loan Duration
Institutional
Retail
MP tightening
MP easing
Loan Maturity
60
55
50
45
40
35
2017
2018
2019
2020
2021
2022
2023
Year

This Paper:

➢ Setting:

- Prosper Marketplace: ≈2 million unsecured consumer loans (2017–2023).
- Two crises with opposite macro-financial regimes that create a natural contrast:
  - MP easing (Mar 15, 2020 – Mar 15, 2022): near-zero rates, abundant liquidity
  - MP tightening (Mar 16, 2022 – Dec 31, 2023): rising rates, tighter financial conditions

➢ Research Focus:

- Platform-based allocation: retail vs institutional funding channels
- Credit allocation: borrower risk (FICO) & loan contract exposure (loan size, duration).
- Post-listing rejection: platform lending decisions after funding has been secured.
- Monetary policy regimes: how allocation and rejection decisions vary across macro-financial conditions

RQ1: How do Prosper's loan allocations across investor channels vary with borrower risk and contractual exposure?

1. Baseline model of investor composition

$$Logit[Pr(Retail\ Channel_i = 1)] = a + \beta_1 \cdot LoanChar_i + \beta_2 \cdot BorrowerChar_i + \beta_3 \cdot Macro_i + FEs + \varepsilon_i$$

$BorrowerChar_i = FICOL\ (Bottom\ 25\%\ of\ FICO\ score)$ 저신용대출자

$LoanChar_i = LAH\ (top\ 25\%\ of\ loan\ amount), LDH(top\ 25\%\ of\ loan\ duration)$
대출 특성

Table 3: Borrower quality and funding channel allocation

Table 3: Borrower credit quality and funding channel allocation across monetary policy regimes

차입자 특성

	Dependent variable: Retail channel		
	Pre-COVID	MP easing	MP tightening
	(1)	(2)	(3)
Pre-COVID × FICOL	0.1578***		
	(0.024)		
MP easing × FICOL		0.2319***	
		(0.024)	
MP tightening × FICOL			-0.3390***
			(0.018)
Observations	1,178,422	1,178,422	1,178,422
Pseudo R-Squared	0.1087	0.1090	0.1096
Constant	YES	YES	YES
Controls	YES	YES	YES
Loan purposes FE	YES	YES	YES
State FE	YES	YES	YES
Year-Qtr FE	YES	YES	YES
Cluster	State	State	State

Table 4: Loan contractual exposure and funding channel allocation

대출 특성

Table 4: Loan contractual exposure and funding channel allocation across monetary policy regimes

	Dependent variable: Retail channel					
	LAH			LDH		
	Pre-COVID	MP easing	MP tightening	Pre-COVID	MP easing	MP tightening
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-COVID × LAH	0.1569***					
	(0.028)					
MP easing × LAH		0.3095***				
		(0.030)				
MP tightening × LAH			-0.4765***			
			(0.021)			
Pre-COVID × LDH				0.8228***		
				(0.027)		
MP easing × LDH					-0.1235***	
					(0.041)	
MP tightening × LDH						-0.6528***
						(0.018)
Observations	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422
Pseudo R-Squared	0.1086	0.1090	0.1096	0.1119	0.1088	0.1110
Constant	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Loan purposes FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

대출금액

대출기간

Table 5: Borrower quality, Loan contractual exposure and funding channel allocation

Table 5: Borrower credit quality, loan contractual exposure and funding channel allocation across monetary policy regimes

	Dependent variable: Retail channel					
	LAH			LDH		
	Pre-COVID	MP easing	MP tightening	Pre-COVID	MP easing	MP tightening
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-COVID × FICOL × LAH	-0.3603***					
	(0.035)					
MP easing × FICOL × LAH		-0.0522				
		(0.041)				
MP tightening × FICOL × LAH			0.4603***			
			(0.037)			
Pre-COVID × FICOL × LDH				0.1143***		
				(0.035)		
MP easing × FICOL × LDH					0.0697	
					(0.052)	
MP tightening × FICOL × LDH						-0.0633*
						(0.036)
Observations	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422
Pseudo R-Squared	0.1090	0.1095	0.1108	0.1124	0.1092	0.1121
Constant	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Loan purposes FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

?

Table 6: Borrower fundamentals for low FICO loans

Table 6: Borrower fundamentals for low-quality large loans across monetary policy regimes

	Dependent variables								
	Borrower income			Borrower credit history			Homeowner		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-COVID × FICOL × LAH	-0.0113**			-0.0333***			-0.0203***		
	(0.004)			(0.010)			(0.006)		
MP easing × FICOL × LAH		0.0069			0.0180**			0.0020	
		(0.006)			(0.007)			(0.009)	
MP tightening × FICOL × LAH			0.0536***			0.0261**			0.0198***
			(0.005)			(0.010)			(0.005)
Observations	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422
R-Squared	0.4440	0.4436	0.3653	0.2687	0.2685	0.2687	0.1741	0.1741	0.1743
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Loan purposes FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Findings for RQ1

Selection within Risk Segments during MP tightening (Tables 5 & 6):

- ➢ Credit allocation depends on both borrower risk and contract exposure.
- ▪ Low-FICO + large loans are more likely to be allocated to the retail channel.

However, these borrowers exhibit stronger observable characteristics:

- Higher income
- Longer credit history

→ Indicates selection within risk segments, rather than increased risk-taking.

RQ2: How do borrower credit quality and contractual exposure affect Prosper's post-listing rejection (PLR) decisions?

$$logit[Pr(Post\text{-}listing\ rejection_i = 1] = a + \boldsymbol{\beta_1 \cdot TimePeriod \times FICOL} + \beta_2 \cdot TimePeriod + \beta_3 \cdot FICOL + \delta \cdot X_i + FEs + \varepsilon_i$$

$$logit[Pr(Post\text{-}listing\ rejection_i = 1] = a + \boldsymbol{\beta_1 \cdot TimePeriod \times LoanRisk} + \beta_2 \cdot TimePeriod + \beta_3 \cdot LoanRisk + \delta \cdot X_i + FEs + \varepsilon_i$$

$rejected\ by\ Prosper\ before\ origination\ and\ zero\ otherwise. Post-listing\ Rejection, equals\ one\ if\ a\ funded\ listing\ is\ subsequently$

Table 7: Borrower credit quality and post-listing rejection

Table 7: Borrower credit quality and post-listing rejection across monetary policy regimes

	Dependent variable: Post-listing rejection		
	Pre-COVID	MP easing	MP tightening
	(1)	(2)	(3)
Pre-COVID × FICOL	-0.1703***		
	(0.014)		
MP easing × FICOL		-0.0536***	
		(0.016)	
MP tightening × FICOL			0.3951***
			(0.022)
Observations	1,178,422	1,178,422	1,178,422
Pseudo R-Squared	0.1000	0.0996	0.1001
Constant	YES	YES	YES
Controls	YES	YES	YES
Loan purposes FE	YES	YES	YES
State FE	YES	YES	YES
Year-Qtr FE	YES	YES	YES
Cluster	State	State	State

Table 8: Loan contractual exposure and post-listing rejection

Table 8: Loan contractual exposure and post-listing rejection across monetary policy regimes

	Dependent variable: Post-listing rejection					
	LAH			LDH		
	Pre-COVID	MP easing	MP tightening	Pre-COVID	MP easing	MP tightening
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-COVID × LAH	0.4751***					
	(0.016)					
MP easing × LAH		-0.2993***				
		(0.017)				
MP tightening × LAH			-0.6596***			
			(0.027)			
Pre-COVID × LDH				0.3067***		
				(0.013)		
MP easing × LDH					-0.1358***	
					(0.014)	
MP tightening × LDH						-0.3990***
						(0.021)
Observations	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422
Pseudo R-Squared	0.1014	0.1005	0.1009	0.1004	0.0997	0.1001
Constant	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Loan purposes FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

Table 9: Borrower credit quality, loan contractual exposure and post-listing rejection

Table 9: Borrower credit quality, loan contractual exposure and post-listing rejection across monetary policy regimes

	Dependent variable: Post-listing rejection					
	LAH			LDH		
	Pre-COVID	MP easing	MP tightening	Pre-COVID	MP easing	MP tightening
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-COVID × FICOL × LAH	0.1837***					
	(0.037)					
MP easing × FICOL × LAH		0.1474***				
		(0.047)				
MP tightening × FICOL × LAH			-0.4714***			
			(0.065)			
Pre-COVID × FICOL × LDH				0.1613***		
				(0.029)		
MP easing × FICOL × LDH					-0.0138	
					(0.034)	
MP tightening × FICOL × LDH						0.0004
						(0.014)
Observations	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422	1,178,422
Pseudo R-Squared	0.1015	0.1006	0.1013	0.1006	0.0998	0.1005
Constant	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Loan purposes FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

This Paper:

- Key Findings:

1. Regime dependence
   - •MP easing: greater retail-channel allocation and broader credit allocation
   - •MP tightening: shift toward institutional funding and more stringent post-listing screening.

2. Selection within risk segments
   - •Retail funding declines overall in tightening. But persists for a subset of low-FICO borrowers with stronger observable characteristics → reflects platform-driven selection, not risk-taking

This Paper:

- Key Findings:

3. Interaction of risk and exposure
    - •Borrower credit quality and contractual exposure jointly influence both funding allocation and post-listing rejection.
    - •Large loans to low-FICO borrowers are treated differently across monetary policy regimes.
    - •The effect of contractual exposure depends on the underlying borrower profile.

4. Platform decisions extend beyond traditional credit scores
    - •FICO scores alone do not fully explain allocation and rejection decisions.
    - •Income, credit history, homeownership, and repeat borrowing provide additional information.
    - •Platform screening reflects a holistic assessment of borrower quality.

Summary of findings 주요 결과 요약

MP 완화기	MP 긴축기
• Retail allocation (소매 배분) ↑ ✓ Broader credit allocation (광범위한 신용 배분) ✓ Low-FICO borrowers in retail channel ↑ (저신용(FICO) 차입자의 소매 채널 배정 가능성 ↑) ✓ Tolerance for borrower risk ↑ (차입자 위험에 대한 관용 ↑) • Post-listing rejection (상장 후 거절률 ↓)	• Retail allocation (소매 배분) ↓ ✓ More selective allocation (보다 선택적인 배분) ✓ Low-FICO borrowers in retail channel ↓ (저신용(FICO) 차입자의 소매 채널 배정 가능성 ↓) ✓ Greater emphasis on borrower quality 차입자 신용도에 대한 강조 ↑ • Post-listing rejection ↑ (상장 후 거절률 ↑)

Contribution:

1. Platform-based credit allocation

    - Shows how fintech platforms reallocate credit across investor channels over monetary policy regimes.
    - Documents how monetary policy conditions reshape the allocation of borrower risk and contractual exposure.
    - Highlights systematic shifts between broad allocation (easing) and selective allocation (tightening).

2. Selection within risk segments

    - Shows that allocation is not uniform: even within low-FICO borrowers, funding shifts toward those with stronger observable characteristics.
    - Provides evidence of platform-mediated screening under tightening.

Contribution:

3. Post-listing rejection as a second stage of screening

- Examines how borrower credit quality and contractual exposure affect post-listing rejection decisions.
- Shows that borrower credit quality becomes substantially more important during MP tightening.
- Demonstrates that platform lending decisions rely on information beyond traditional credit scores, including income, credit history, homeownership, and repeat borrowing.

Conclusion

1. Funding allocation is regime-dependent
   - During MP easing, loans are more likely to be allocated to the retail channel, including lower-credit-quality borrowers and loans with greater contractual exposure.
   - During MP tightening, retail allocation declines and funding shifts toward institutional channels.
   - Credit allocation becomes increasingly selective under tighter financial conditions.

2. Allocation within risky borrower segments is selective
   - Retail funding does not disappear entirely during MP tightening.
   - Low-FICO borrowers receiving retail allocation exhibit stronger observable characteristics, including higher income, longer credit history, and homeownership.
   - These patterns suggest platform-mediated screening rather than increased risk-taking.

Conclusion

3. Post-listing rejection represents a second stage of platform screening
   - Borrower credit quality becomes substantially more important during MP tightening.
   - Low-FICO borrowers are significantly more likely to experience post-listing rejection under tighter financial conditions.
   - The importance of contractual exposure varies across monetary policy regimes.

4. Platform decisions extend beyond traditional credit scores
   - Large-loan borrowers during MP tightening often possess stronger observable fundamentals.
   - Lower rejection rates among long-duration loans appear linked to repeat borrowing and borrower familiarity.
   - Platform lending decisions incorporate information beyond FICO scores alone.

Thank you.
감사합니다