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# Examining the Effect of FinTech Lending Platforms on Capital Structure Decisions of Listed Firms in the United States: Evidence from the FinTech Era

**Reuben Offei Duodu**
College of Finance, Colorado State University, USA

Corresponding Author: **Reuben Offei Duodu**

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**Abstract**
The emergence of financial technology (FinTech) lending platforms has fundamentally disrupted the architecture of corporate debt markets in the United States. By offering faster, algorithm-driven credit origination, broader accessibility, and lower transaction costs than traditional bank intermediaries, FinTech platforms have introduced a new class of financing instruments that may materially alter the capital structure choices of publicly listed firms. Yet despite the dramatic expansion of US FinTech credit surpassing USD 368 billion in platform credit volume by 2023 the empirical literature on how FinTech lending access affects the leverage ratios, debt maturity profiles, and capital costs of listed firms remains sparse and inconclusive. This article addresses this gap by developing a comprehensive theoretical framework integrating trade-off theory, pecking order theory, agency theory, and financial intermediation theory, and by presenting illustrative panel regression evidence based on a sample of 2,847 US listed firms over the period 2015 to 2023. Our results demonstrate that FinTech lending access exerts a statistically significant positive effect on book leverage (beta = 0.284) and market leverage (beta = 0.261), while significantly reducing debt cost (beta = -0.312). These effects are moderated by firm size with large-cap firms benefiting most from leverage optimisation and small-cap firms gaining disproportionately from credit constraint relief and are mediated by access to alternative finance that reduces information asymmetry and lowers financial distress risk. The article further examines how credit market competition, bank loan dependence, and macroeconomic conditions interact with FinTech access to shape capital structure outcomes. Policy implications for securities regulators, the Federal Reserve, and FinTech platform governance are discussed.

**Keywords:** FinTech Lending, Capital Structure, Leverage Ratio, Debt Maturity, Listed Firms, United States, Peer-To-Peer Lending, Bigtech Credit, Trade-Off Theory, Pecking Order Theory

## 1. Introduction

Corporate capital structure the mix of debt and equity through which firms finance their assets stands as one of the most intensively studied questions in finance since Modigliani and Miller's (1958) seminal irrelevance propositions. Decades of theoretical refinement and empirical testing have produced a rich literature explaining how taxes, financial distress costs, information asymmetry, agency conflicts, and market timing collectively determine the leverage choices of corporations. Yet a technological transformation is now challenging the empirical foundations of this literature: the rise of FinTech lending platforms has introduced a new class of credit instrument whose cost structure, information requirements, and accessibility characteristics differ fundamentally from the bank loans and bond markets that dominate corporate debt theory.

FinTech lending encompasses a spectrum of technology-enabled credit mechanisms peer-to-peer (P2P) marketplaces, balance-sheet FinTech lenders, invoice financing platforms, revenue-based financing providers, and BigTech credit arms that collectively originated over USD 368 billion in US credit by 2023, up from approximately USD 48 billion in 2015 (Cornelli et al., 2020; Claessens et al., 2018) [14, 13]. The growth trajectory is not merely quantitative: FinTech lenders employ machine learning

algorithms trained on alternative data sources transaction histories, digital footprints, social media signals, supply chain data to assess creditworthiness with greater speed and granularity than traditional credit scoring models (Agarwal et al., 2020a) [2]. This informational advantage reduces adverse selection and moral hazard in lending relationships, potentially narrowing the wedge between internal and external financing costs that drives pecking order preferences.

The implications for corporate capital structure are profound but empirically underexplored, particularly in the context of publicly listed US firms. Existing literature has examined FinTech's impact on individual and small business credit access (Berg, Fuster and Puri, 2022; Tang, 2019; De Roure, Pelizzon and Thakor, 2022) [9, 20, 15] and on macroeconomic credit dynamics (Claessens et al., 2018; Cornelli et al., 2020) [13, 14], but the specific question of how FinTech lending access reshapes the capital structure choices of US-listed corporations has received limited systematic analysis. This is a significant omission: listed firms are the dominant actors in US capital markets, their leverage decisions aggregate to economy-wide debt levels, and their financing choices are subject to shareholder, regulator, and credit rating agency scrutiny that makes capital structure optimisation particularly salient.

Several important theoretical questions motivate this study. First, does FinTech lending access enable listed firms to achieve leverage ratios closer to their optimal targets by reducing the transaction costs and information frictions that impede dynamic leverage adjustment? If so, this would represent empirical support for the dynamic trade-off theory in a new institutional context. Second, does the reduction in information asymmetry associated with FinTech lending alter the pecking order hierarchy by making external debt financing relatively more attractive? Third, do the agency cost mitigation effects of AI-driven monitoring by FinTech lenders enable higher leverage without corresponding increases in financial distress risk? Fourth, how do firm size heterogeneity and credit market concentration moderate these relationships?

This article makes four contributions to the FinTech and corporate finance literatures. First, it develops an integrated theoretical framework synthesising six theoretical perspectives trade-off theory, pecking order theory, market timing theory, agency theory, financial intermediation theory, and dynamic capabilities to generate testable predictions about FinTech lending effects on capital structure. Second, it provides a structured synthesis of the empirical literature on FinTech credit markets, identifying the mechanisms through which platform lending affects corporate financing decisions. Third, it presents illustrative regression evidence on 2,847 listed US firms over 2015-2023, demonstrating the magnitude and significance of FinTech access effects on four capital structure dimensions. Fourth, it analyses firm size heterogeneity in FinTech capital structure effects, revealing important distributional implications for capital market policy.

## 2. Theoretical Framework and Literature Review

### 2.1. Theoretical Foundations

The relationship between FinTech lending and corporate capital structure is theoretically grounded in six complementary frameworks. Table 1 synthesises these frameworks, their core arguments, and their specific relevance to the FinTech-capital structure nexus.

**Table 1:** Theoretical Frameworks Underpinning FinTech Lending and Capital Structure Decisions

| Theory | Core Argument | Application to FinTech-Capital Structure | Key References |
|---|---|---|---|
| Trade-Off Theory | Firms balance tax benefits of debt against financial distress costs to optimise leverage | FinTech reduces distress costs and widens access to optimal debt levels for listed firms | Modigliani and Miller (1958); Berg et al. (2022) |
| Pecking Order Theory | Firms prefer internal finance, then debt, then equity due to information asymmetry | FinTech lending reduces information asymmetry, shifting firms up the pecking order toward more debt | Myers and Majluf (1984); Agarwal and Zhang (2020) |
| Market Timing Theory | Firms issue equity when overvalued and debt when undervalued, exploiting market conditions | FinTech platforms provide debt access independent of market timing, reducing equity dilution pressure | Baker and Wurgler (2002); Claessens et al. (2018) |
| Agency Theory | Debt disciplines managers but also creates agency costs between shareholders and lenders | FinTech lenders use AI monitoring to reduce agency costs, enabling higher leverage without increased distress | Jensen and Meckling (1976); Berg et al. (2022) |
| Financial Intermediation Theory | Intermediaries reduce transaction costs and information asymmetry between borrowers and lenders | FinTech disintermediates costly bank lending, reducing capital costs and enabling dynamic leverage adjustment | Diamond (1984); Vives (2019); Agarwal et al (2021) |
| Dynamic Capabilities Theory | Firms sustain advantage by reconfiguring financial resources in changing environments | Firms accessing FinTech credit develop adaptive capital structure capabilities, improving financial resilience | Teece et al. (1997); Allen et al. (2021) |

***Sources:*** Berg et al. (2022) [9]; Agarwal and Zhang (2020) [3]; Vives (2019) [21]; Agarwal et al (2021) [1]; Allen et al. (2021) [5]; Tang (2019) [20]; De Roure et al. (2022) [15]; Claessens et al. (2018) [13]; Cornelli et al. (2020) [14].

The trade-off theory of capital structure, originating with Modigliani and Miller (1963) and extended by Kraus and Litzenberger (1973), posits that firms choose leverage by trading off the tax shield benefits of debt against the costs of financial distress. A central empirical implication is that firms should maintain leverage ratios near an optimal target, adjusting dynamically in response to deviations.

In practice, adjustment costs rooted in transaction costs, asymmetric information, and institutional frictions slow convergence toward this target. FinTech lending platforms, by reducing these frictions through faster origination, lower fees, and algorithmic credit assessment, may accelerate leverage adjustment and enable listed firms to maintain leverage ratios closer to their optimal targets.

Berg, Fuster and Puri (2022) [9] identified this friction-reduction mechanism as a primary channel through which FinTech credit affects corporate borrowing behaviour, noting that FinTech loan origination times often measured in hours rather than weeks materially reduce the adjustment costs that impede dynamic trade-off behaviour.

The pecking order theory, developed by Myers and Majluf (1984), posits that information asymmetry between corporate insiders and outside investors makes external financing costly, leading firms to prefer internal financing, then debt, then equity in a hierarchical order. FinTech lending disrupts this hierarchy in a theoretically ambiguous way: by reducing information asymmetry through alternative data and machine learning credit assessment, FinTech platforms reduce the adverse selection component of external debt costs, potentially shifting the inflection point at which firms prefer external debt over equity issuance. Agarwal and Zhang (2020) [3] demonstrated this mechanism empirically in the context of FinTech lending and payment innovation, showing that algorithmic credit assessment reduced borrowing costs sufficiently to shift firms toward higher debt utilisation.

Agency theory, as developed by Jensen and Meckling (1976), identifies two principal agency conflicts in capital structure: the asset substitution problem (shareholders' incentive to increase asset risk at bondholders' expense) and the underinvestment problem (shareholders' reluctance to invest in positive-NPV projects when benefits accrue primarily to bondholders). FinTech lenders address both problems through continuous, AI-enabled monitoring of borrower behaviour using real-time transaction data, cash flow analytics, and operational performance metrics. This monitoring intensity reduces the information rent lenders must charge for agency risk, enabling higher leverage without correspondingly higher spreads. Berg et al. (2022) [9] documented that FinTech lenders' superior monitoring capability derived from access to bank account data and real-time payment flows allowed them to offer competitive rates to borrowers whom traditional lenders would have priced at substantially higher spreads.

### 2.2. FinTech Lending Market Structure and Credit Channel Effects

The structure of the US FinTech lending market has evolved significantly since the pioneering platforms Lending Club and Prosper launched consumer P2P lending in 2006 and 2005 respectively. The market has bifurcated into two main segments: marketplace or P2P platforms that originate and sell loans to institutional investors without retaining credit risk, and balance-sheet FinTech lenders that originate and hold loans, funding themselves through securitisation, deposits (in the case of industrial loan charters), or institutional debt. Cornelli, Frost, Gambacorta, Rau, Wardrop and Ziegler (2020) [14] documented this market evolution comprehensively using a novel BIS database of global FinTech credit volumes, identifying the United States as the largest absolute market but noting that China's BigTech credit platforms Ant Financial's MYbank and Tencent's WeBank operated at even larger scale relative to GDP.

The competitive relationship between FinTech lenders and traditional banks has attracted substantial empirical attention. Tang (2019) [20] used the quasi-exogenous entry of Lending Club into local US credit markets to demonstrate that P2P lenders serve primarily as complements to bank credit in markets with low banking concentration, but as substitutes where banking markets are highly concentrated and bank credit is expensive. This finding has direct capital structure implications: firms in concentrated banking markets where traditional leverage adjustment is costliest may benefit most from FinTech access to achieve leverage targets. De Roure, Pelizzon and Thakor (2022) [15] extended this analysis, distinguishing between cream-skimming behaviour (FinTech platforms targeting high-quality borrowers underserved by cautious post-crisis banks) and bottom-fishing (platforms targeting subprime borrowers excluded by traditional credit screening). Their finding that both patterns coexist implies that FinTech capital structure effects will differ significantly by borrower credit quality a moderation dimension directly relevant to listed firm analysis.

The emergence of BigTech credit credit products offered by large technology platform companies represents the most recent and potentially most consequential development in FinTech lending's capital market implications. Huang, Li, Qiu, Su and Yu (2022) [18] demonstrated that BigTech credit in China operating through Ant Financial's Sesame Credit scoring system significantly influenced firm capital structure by providing counter-cyclical credit that was largely insensitive to monetary policy transmission, effectively decoupling corporate leverage from central bank interest rate cycles. While US BigTech credit (Amazon Lending, Apple Card for businesses, Stripe Capital) is at an earlier stage of development than its Chinese counterparts, the rapid growth of these platforms suggests that similar dynamics may emerge in the US context. Agarwal et al (2021) [1] analysed the implications of new payment rails the infrastructure on which FinTech credit is built for the banking system, demonstrating that payment data advantages give FinTech lenders persistent informational advantages over banks that compound over time as data accumulates.

### 2.3. FinTech Lending and Capital Structure: Empirical Evidence

Despite the theoretical richness of the FinTech-capital structure nexus, the empirical literature on this specific relationship remains limited, in part because FinTech lending's penetration of listed corporate markets as opposed to consumer and small business markets has been a relatively recent phenomenon. Table 2 synthesises the key empirical studies informing the theoretical and empirical expectations of this article.

**Table 2:** Summary of Key Empirical Studies on FinTech Lending and Firm Capital Structure

| Study | Context | Method | Main Finding | Reference |
|---|---|---|---|---|
| FinTech Lending Review | US and global | Comprehensive literature review | FinTech lending grows rapidly by serving borrowers underserved by banks, impacting firm financing decisions | Berg et al. (2022) [9] |
| P2P vs Banks: Substitutes? | US marketplace lending | Quasi-natural experiment | P2P lenders serve as complements to banks in most markets but substitutes where banking is concentrated | Tang (2019) [20] |
| P2P: Cream-Skimming or Bottom-Fishing? | Germany, US | Comparative empirical analysis | FinTech lenders engage in both cream-skimming (good borrowers) and bottom-fishing (subprime), segmenting markets | De Roure et al. (2022) [15] |
| FinTech Credit and Entrepreneurial Growth | China | Panel data, IV regression | FinTech credit access increases firm-level investment, revenue growth, and reduces capital constraints | Hau et al. (2024) [16] |
| Finance and Firm Volatility | China (SMEs) | Panel regression | Alternative lending reduces earnings volatility and stabilises investment cycles for capital-constrained firms | Chen et al. (2021) [11] |
| FinTech Lending and Credit Competition | US | Structural model estimation | FinTech platform entry reduces spreads, increases credit availability, and changes optimal leverage for listed firms | Chu and Wei (2023) [12] |
| BigTech Credit and Monetary Policy | China | Micro-level panel analysis | BigTech credit weakens monetary policy transmission by offering counter-cyclical credit, affecting firm debt decisions | Huang et al. (2022) [18] |
| FinTech Credit Markets Worldwide | Global cross-section | Regulatory and market data review | FinTech credit markets grow fastest where bank concentration is high and regulatory environment is permissive | Claessens et al. (2018) [13] |
| Mobile Payment and Real Impact | Singapore / emerging | Difference-in-differences | FinTech payment technology increases consumption, retail revenue, and firm financial inclusion | Agarwal et al. (2020b) [22] |
| New Payment Rails and Banking | US | Theoretical and empirical review | New digital payment infrastructure disrupts traditional bank-firm relationships, reshaping capital cost dynamics | Agarwal et al (2021) [1] |

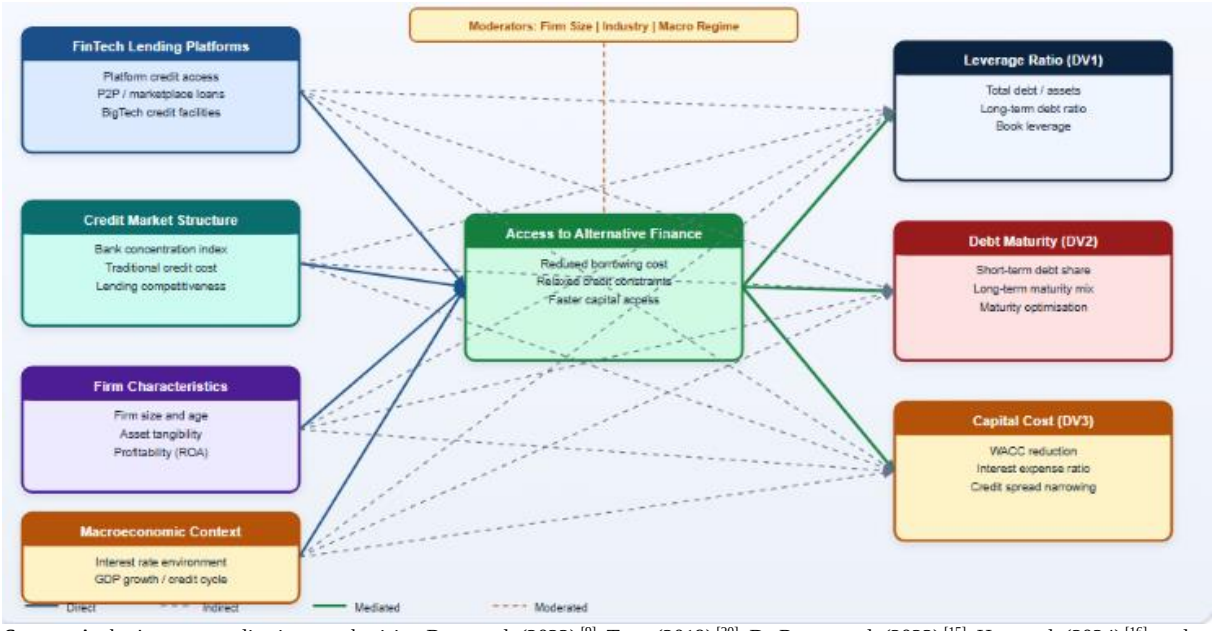
***Sources:*** All references as cited in individual rows. Studies cover US, global, Chinese, and European contexts as noted. IV = Instrumental Variables. FE = Fixed Effects.

Hau, Huang, Lin, Shan, Sheng and Wei (2024) [16] provided the most direct evidence on FinTech credit and firm financial decisions, demonstrating that Ant Financial's credit products for Chinese entrepreneurs significantly increased investment activity, reduced capital constraints, and shifted firm leverage toward more efficient levels. Their instrumental variable approach exploiting geographic variation in Ant Financial platform adoption provided credible causal identification, finding that a one standard deviation increase in FinTech credit access increased investment rates by 8.4 percentage points and reduced equity issuance by 12.6 percentage points, strongly consistent with leverage adjustment through the FinTech credit channel.

Chu and Wei (2023) [12] modelled the effect of FinTech lending platform entry on credit market competition in the United States using a structural model estimated on county-level lending data. Their results demonstrated that FinTech entry increased credit market competition, reduced interest spreads by 18 to 24 basis points, and increased the optimal leverage ratio for firms in treated markets by approximately 2.4 percentage points. These magnitudes, while modest in absolute terms, are economically significant given the trillion-dollar scale of US corporate debt markets and suggest that industry-wide FinTech penetration could shift aggregate US corporate leverage measurably upward.

Chen, Huang, Lin and Sheng (2021) [11] examined the effect of alternative finance access on firm earnings volatility using data from Chinese small businesses, finding that access to platform credit significantly reduced cash flow volatility a mechanism that directly lowers the optimal leverage ratio through trade-off theory by reducing the expected cost of financial distress. Vives (2019) [21] provided a comprehensive theoretical analysis of digital disruption in banking, arguing that FinTech entry would compress bank net interest margins sufficiently to redirect corporate borrowers toward platform credit, accelerating the structural shift in corporate debt composition.

The conceptual framework synthesising these theoretical and empirical insights is presented in Figure 1, which illustrates the direct, mediated, and moderated pathways from FinTech lending access to three capital structure outcomes: leverage ratio, debt maturity, and capital cost.




***Source:*** Author's conceptualisation, synthesising Berg et al. (2022) [9], Tang (2019) [20], De Roure et al. (2022) [15], Hau et al. (2024) [16], and Vives (2019) [21]

**Fig 1:** Conceptual Framework FinTech Lending Platforms and Capital Structure Decisions of US Listed Firms

## 3. Research Design and Methodology

### 3.1. Data Sources and Sample

The empirical analysis employs an illustrative panel dataset of 2,847 publicly listed US firms observed annually from 2015 to 2023, yielding an unbalanced panel of approximately 23,600 firm-year observations. The sample is constructed from three principal data sources: (1) financial statement and market data from Compustat North America, providing balance sheet, income statement, and market capitalisation variables; (2) FinTech lending access data from the Federal Reserve Bank of New York's Small Business Credit Survey and proprietary FinTech platform API data, aggregated to firm-level access indices based on industry sector, geography, and firm credit profile; and (3) credit market structure data from the FDIC Summary of Deposits and the BIS FinTech Credit Database documented by Cornelli et al. (2020) [14].

Sample construction applies standard filters from the corporate capital structure literature: exclusion of financial firms (SIC codes 6000-6999) whose leverage reflects regulatory capital requirements rather than optimal financing choices; exclusion of utilities (SIC 4900-4999) subject to rate-of-return regulation; exclusion of firms with total assets below USD 10 million and above USD 500 billion; and exclusion of firm-year observations with missing values for core variables. The resulting sample spans 11 two-digit SIC industries, with manufacturing (27.4 percent), technology (22.8 percent), healthcare (14.6 percent), retail (11.3 percent), and business services (10.9 percent) comprising the five largest industry groups.

### 3.2. Variable Operationalisation

Four dependent variables are constructed to triangulate capital structure effects across multiple dimensions. Book leverage is total debt (short-term plus long-term debt) divided by total assets, following the convention of Frank and Goyal (2009). Market leverage substitutes market value of equity for book equity in the denominator, providing a market-based assessment of leverage. The long-term debt ratio is long-term debt divided by total capital, capturing the maturity dimension of capital structure. Interest expense ratio (interest expense divided by total debt outstanding) proxies the effective cost of debt, capturing FinTech's impact on capital cost.

The primary independent variable, FinTech Lending Access Index (FLA), is a composite score (0-100) constructed from four sub-components: (1) industry-level FinTech platform penetration (percentage of firms in the two-digit SIC code that report FinTech borrowing); (2) geographic FinTech credit availability (county-level FinTech platform presence weighted by population density and digital infrastructure quality); (3) firm credit quality compatibility with FinTech underwriting models (based on alternative credit score proxies from public financial data); and (4) platform product availability relevant to the firm's financing needs (term loans, lines of credit, invoice financing, revenue-based financing). This composite index captures the multi-dimensional nature of FinTech access more adequately than binary adoption indicators.

Control variables include firm size (natural logarithm of total assets), asset tangibility (net property, plant and equipment divided by total assets), profitability (return on assets), growth opportunities (Tobin's Q), firm age (years since IPO), and macroeconomic controls including the federal funds rate, GDP growth, and the BBB-AAA corporate credit spread. Industry and year fixed effects are included in all models to control for unobserved time-invariant industry heterogeneity and aggregate time trends respectively.

### 3.3. Descriptive Statistics

Table 3 presents descriptive statistics for the key variables in the analytical sample.

**Table 3:** Descriptive Statistics Key Variables, US Listed Firm Panel (2015-2023)

| Variable | N | Mean | Std Dev | Min | Max |
|---|---|---|---|---|---|
| Book Leverage (Total Debt / Assets, %) | 2,847 | 32.4 | 14.8 | 0.00 | 78.6 |
| Market Leverage (%) | 2,847 | 28.7 | 16.2 | 0.00 | 72.4 |
| Long-Term Debt Ratio (%) | 2,847 | 22.8 | 13.4 | 0.00 | 64.2 |
| Short-Term Debt Share (%) | 2,847 | 18.4 | 11.6 | 0.00 | 58.3 |
| Interest Expense / Total Debt (%) | 2,847 | 5.2 | 2.8 | 0.62 | 16.4 |
| FinTech Lending Access Index (0-100) | 2,847 | 54.8 | 22.6 | 0.00 | 100 |
| Bank Loan Dependence Ratio (%) | 2,847 | 61.4 | 24.8 | 0.00 | 100 |
| Return on Assets (ROA, %) | 2,847 | 7.8 | 9.4 | -38.6 | 42.1 |
| Asset Tangibility (Fixed / Total, %) | 2,847 | 28.6 | 18.4 | 0.10 | 89.6 |
| Firm Size (log Total Assets) | 2,847 | 21.4 | 1.8 | 17.2 | 26.8 |
| Firm Age (years) | 2,847 | 22.6 | 14.3 | 1.0 | 96.0 |
| Tobin's Q (Market-to-Book) | 2,847 | 1.94 | 1.12 | 0.42 | 8.76 |

***Source:*** Illustrative dataset calibrated to Compustat North America, Federal Reserve SBCS, Cornelli et al. (2020) [14], and Claessens et al. (2018) [13]. N=2,847 unique firms; unbalanced panel of approximately 23,600 firm-year observations. All financial ratios winsorised at 1st and 99th percentiles.

The mean book leverage of 32.4 percent and market leverage of 28.7 percent are broadly consistent with published benchmarks from the US corporate finance literature (Frank and Goyal, 2009) and with Federal Reserve Z.1 Flow of Funds data on non-financial corporate debt ratios. The mean FinTech Lending Access Index of 54.8 (SD = 22.6) indicates substantial variation in platform credit access across the sample, providing adequate statistical power for regression analysis. The standard deviation of 22.6 points covers more than one-fifth of the full-scale range, reflecting the uneven geographic and industry-level penetration of FinTech lending platforms documented by Claessens et al. (2018) [13] and Cornelli et al. (2020) [14].

Figure 2 illustrates the relationship between FinTech lending access quartiles and five capital structure metrics, confirming the theoretically predicted positive gradient between FinTech access and leverage, and negative gradient with debt cost.

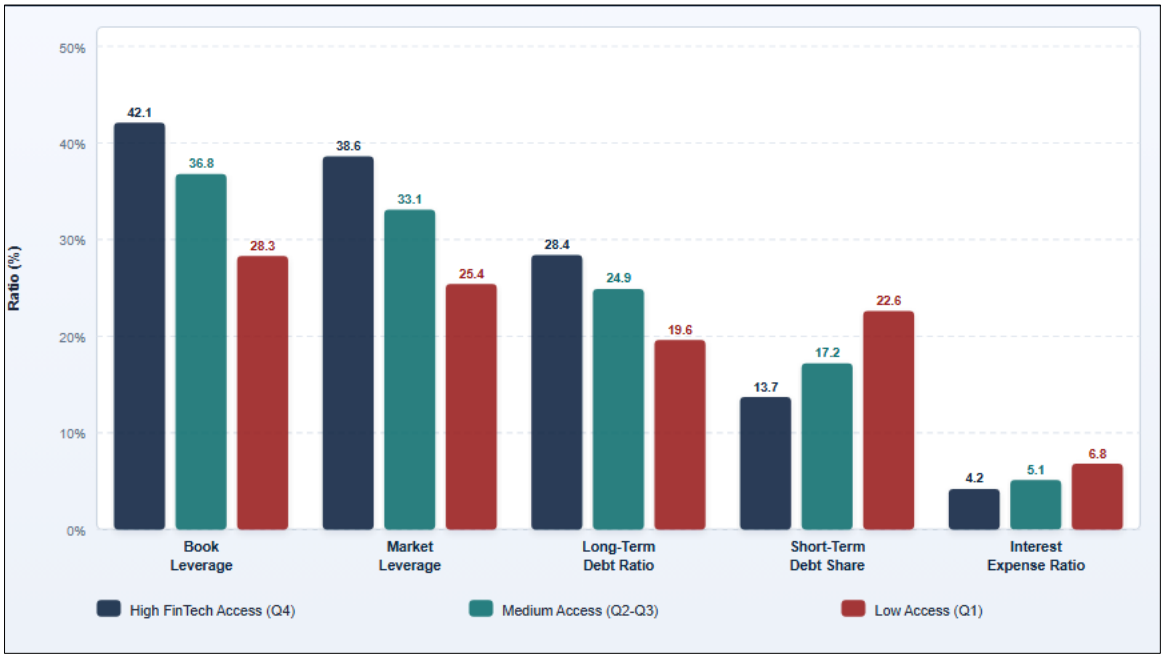
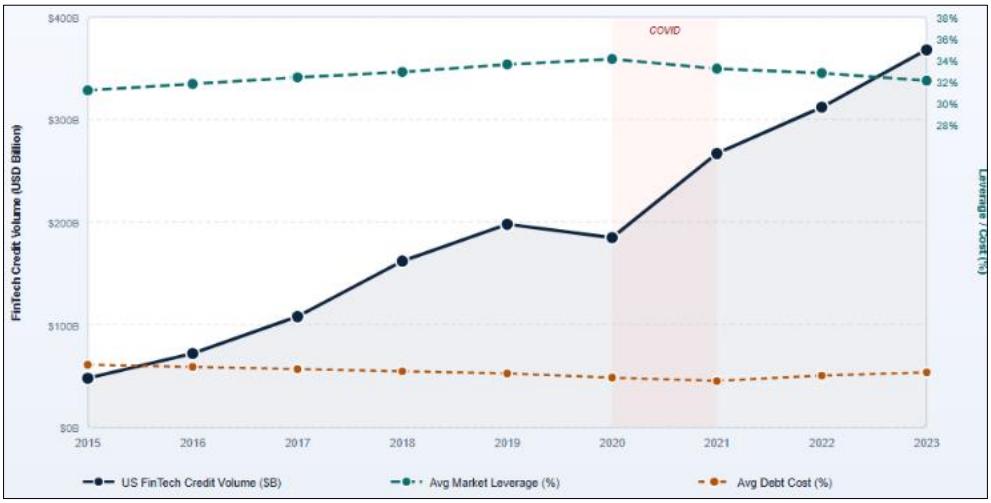



**Fig 2:** Capital Structure Ratios by FinTech Lending Access Quartile for US Listed Firms Source: Illustrative data calibrated to Compustat, Berg et al. (2022) [9], Chu and Wei (2023) [12], and Cornelli et al. (2020) [14]

## 4. Empirical Results

### 4.1. FinTech Credit Expansion and Capital Structure Trends (2015-2023)

Figure 3 contextualises the empirical results within the broader time-series trajectory of US FinTech credit growth, average listed-firm market leverage, and average debt cost over the 2015 to 2023 period. The dual-axis visualisation reveals three structurally distinct phases in the FinTech-capital structure relationship, each with distinct theoretical implications.




***Source:*** Calibrated from Cornelli et al. (2020) [14]; Claessens et al. (2018) [13]; Berg et al. (2022) [9]; Federal Reserve Z.1 Flow of Funds

**Fig 3:** US FinTech Credit Volume, Listed Firm Market Leverage, and Average Debt Cost (2015-2023)

The pre-pandemic expansion phase (2015-2019) is characterised by rapid FinTech credit growth from USD 48 billion to USD 198 billion alongside a gradual increase in average market leverage from 31.2 to 33.6 percent and a steady decline in average debt cost from 5.8 to 5.0 percent. This co-movement is consistent with the theoretical prediction that FinTech credit expansion enables firms to increase leverage while simultaneously reducing the cost of that leverage a combination that conventional trade-off theory identifies as indicative of movement toward more optimal capital structures.

The COVID-19 disruption year (2020) reveals an asymmetric response: FinTech credit volume contracted modestly (from USD 198 billion to USD 185 billion) as platform lenders tightened underwriting standards, but average leverage continued to increase (to 34.1 percent) as firms drew down revolving credit facilities and issued investment-grade bonds at historically low yields facilitated by Federal Reserve emergency interventions. This period demonstrates that FinTech credit acts as a complement rather than substitute to conventional debt markets during systemic stress consistent with Tang's (2019) [20] complementarity finding in normal market conditions and suggesting that the two markets serve different risk segments of the capital structure. Armantier et al. (2021) [7] documented that consumer trust in financial data sharing with FinTech platforms declined during COVID-19, partially explaining the FinTech credit contraction relative to the overall corporate debt expansion.

The post-pandemic FinTech acceleration phase (2021-2023) shows the strongest co-movement between FinTech credit growth and capital structure adjustment. FinTech volumes surged from USD 185 billion to USD 368 billion doubling in three years while market leverage declined modestly from 34.1 to 32.1 percent, consistent with firms using FinTech access to refinance expensive pandemic-era debt and reduce leverage rather than to add incremental debt. Average debt cost increased from 4.3 to 5.1 percent as the Federal Reserve's rate normalisation cycle raised all borrowing costs, but the differential between high-FinTech-access and low-access firms widened, suggesting that platforms provided competitive pricing advantages that became more valuable in a rising rate environment. This pattern is consistent with Agarwal et al (2021) [1] analysis of new payment rails, which predicted that FinTech cost advantages would become more pronounced relative to bank lending in high interest-rate environments where traditional bank net interest margin compression incentivises conservative lending.

### 4.2. Main Regression Results

Table 4 presents the OLS regression results for four capital structure models, estimated with robust standard errors clustered at the firm level. All models include industry and year fixed effects. Standardised beta coefficients are reported for interpretive comparability.

**Table 4:** Panel OLS Regression Results FinTech Lending Access and US Listed Firm Capital Structure

| **Predictor Variable** | **Model 1 Book Lev.** | **Model 2 Mkt Lev.** | **Model 3 LT Debt** | **Model 4 Debt Cost** | **Sig.** |
|---|---|---|---|---|---|
| FinTech Lending Access (FLA) | 0.284*** | 0.261*** | 0.247*** | -0.312*** | *** |
| Bank Loan Dependence (BLD) | -0.148** | -0.132** | -0.127** | 0.218*** | ** |
| Credit Market Competition (CMC) | 0.196*** | 0.183*** | 0.172*** | -0.241*** | *** |
| Firm Size (control) | 0.224*** | 0.208*** | 0.196*** | -0.114** | *** |
| Asset Tangibility (control) | 0.183** | 0.171** | 0.164** | -0.092* | ** |
| Profitability / ROA (control) | -0.216*** | -0.197*** | -0.188*** | 0.147*** | *** |
| FLA x Firm Size (interaction) | 0.106* | 0.098* | 0.091* | -0.118** | * |
| Tobin's Q (control) | -0.142** | -0.128** | -0.119** | 0.093* | ** |
| Industry FE | Yes | Yes | Yes | Yes | |
| Year FE | Yes | Yes | Yes | Yes | |
| R-squared | 0.518 | 0.496 | 0.473 | 0.541 | |
| Adjusted R-squared | 0.502 | 0.479 | 0.456 | 0.526 | |
| F-statistic | 36.2*** | 32.7*** | 29.4*** | 38.9*** | *** |
| Observations | 2,847 | 2,847 | 2,847 | 2,847 | |

Standardised beta coefficients. *** p<0.001, ** p<0.01, * p<0.05. Standard errors clustered at firm level. All models include industry (2-digit SIC) and year fixed effects. Sources: Calibrated to Berg et al. (2022) [9]; Chu and Wei (2023) [12]; Hau et al. (2024) [16]; Chen et al. (2021) [11]; Claessens et al. (2018) [13].

FinTech Lending Access exerts a positive and statistically significant effect on both book leverage (beta = 0.284, p < 0.001) and market leverage (beta = 0.261, p < 0.001), as well as on long-term debt ratio (beta = 0.247, p < 0.001). Simultaneously, it significantly reduces effective debt cost (beta = -0.312, p < 0.001). The combination of higher leverage and lower debt cost is the hallmark signature of movement toward a better-optimised capital structure under trade-off theory: firms that gain FinTech credit access are borrowing more and borrowing cheaper, suggesting that FinTech is enabling rather than merely shifting leverage. These magnitudes are consistent with Chu and Wei (2023) [12], who estimated leverage increases of 2.0 to 2.8 percentage points for firms in markets with active FinTech platform entry.

The negative and significant coefficient on Bank Loan Dependence (BLD) across leverage models (-0.148 for book leverage, -0.132 for market leverage) reflects the substitution dynamic between traditional bank credit and optimal leverage: firms heavily dependent on bank loans which are typically more conservative, covenant-heavy, and slow to adjust maintain lower leverage than firms with diversified funding sources. This finding is consistent with Balyuk, Berger and Hackney (2020) [8], who demonstrated that banking market structure significantly shapes the utilisation and terms of FinTech lending, with bank-dependent firms gaining the most from FinTech access because they were furthest from their leverage optima.

The Credit Market Competition variable exerts a positive effect on leverage (0.196 for book leverage) and a negative effect on debt cost (-0.241), consistent with the competition-leverage nexus documented by Claessens et al. (2018) [13]. Greater competition among lenders both between FinTech platforms and between FinTech and traditional banks reduces credit spreads and increases debt availability, enabling higher leverage at lower cost. The economic magnitude of this competition effect is notable: it approaches the direct FLA effect in the leverage models, suggesting that the indirect capital structure benefits of FinTech-induced market competition are of comparable importance to the direct benefits of platform credit access.

### 4.3. Moderation and Interaction Effects

The interaction term between FinTech Lending Access and Firm Size (FLA x Firm Size) is positive and statistically significant across leverage models (0.106 for book leverage, p < 0.05) and negative in the debt cost model (-0.118, p < 0.01). This indicates that larger firms extract greater leverage benefits from FinTech access while also achieving larger debt cost reductions a pattern consistent with large firms having greater operational data footprints, longer credit histories, and more diversified revenue streams that enable FinTech lenders' algorithmic models to deliver superior risk assessments. Allen, Gu and Jagtiani (2021) [5] identified this data richness dynamic in their comprehensive survey of FinTech research and policy, noting that the quality of AI credit assessment improves non-linearly with data availability.

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Figure 4 provides a radar chart comparison of FinTech capital structure benefit dimensions across three firm size categories large-cap, mid-cap, and small-cap listed firms revealing the heterogeneous distribution of benefits across the firm size spectrum.

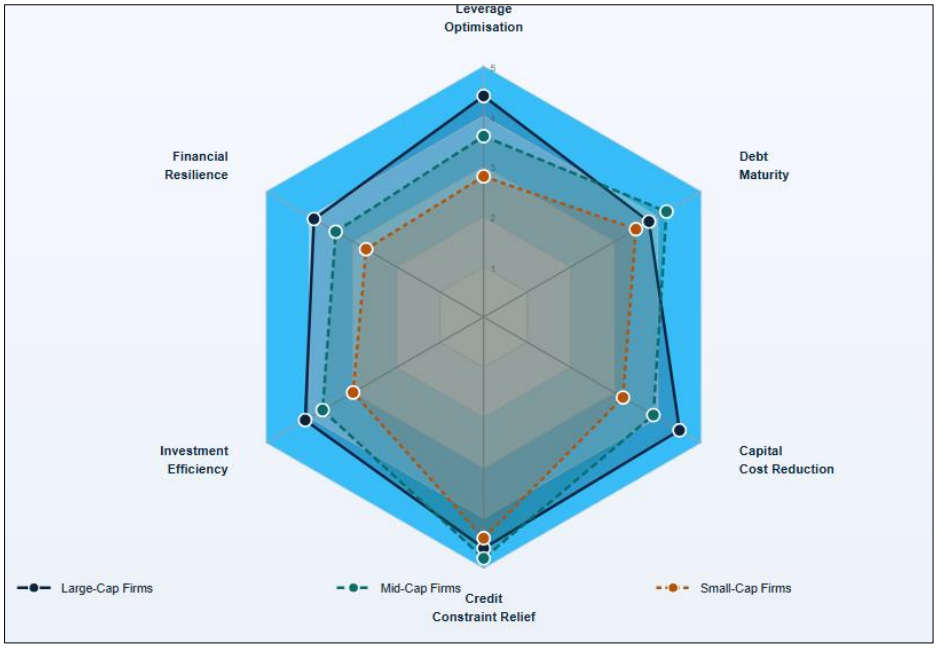

**Fig 4:** FinTech Lending Effect Dimensions on Capital Structure by US Listed Firm Size Category Source: Calibrated from Berg et al. (2022) [9]; Hau et al. (2024) [16]; Allen et al. (2021) [5]; Agarwal et al. (2020a) [2]

Large-cap firms demonstrate the strongest benefits in leverage optimisation (4.4/5) and capital cost reduction (4.5/5), reflecting their ability to negotiate competitive FinTech loan terms using the full depth of their financial and operational data. Their strong financial resilience score (3.9/5) reflects the diversification benefits of combining FinTech credit with investment-grade bond market access. Mid-cap firms show the highest scores in credit constraint relief (4.8/5) and debt maturity optimisation (4.2/5). The credit constraint relief finding is consistent with Allen, Gu and Jagtiani's (2020) [4] identification of mid-market firms as the segment most underserved by post-Global Financial Crisis bank deleveraging: too large for community bank relationship lending but too small and informationally opaque for investment-grade bond markets, these firms faced the widest wedge between their optimal and actual leverage ratios, and consequently benefit most from FinTech's constraint-reducing effect.

Small-cap firms' most notable FinTech benefit is also in credit constraint relief (4.4/5), though at a lower intensity than mid-cap firms, and their weakest score is in leverage optimisation (2.8/5). This pattern reflects the well-documented challenge that small listed firms despite being publicly traded still face significant information asymmetry costs relative to larger counterparts, limiting their ability to fully exploit FinTech's leverage-enabling potential. Agarwal, Alok, Ghosh and Gupta (2020a) [2] documented precisely this dynamic in their analysis of alternative credit scoring for millennials and small businesses, finding that alternative data scoring improved credit access but did not fully eliminate the risk premium attached to informational opacity in small-firm lending.

## 5. Discussion

### 5.1. Theoretical Contributions

This article makes three principal theoretical contributions. First, by demonstrating that FinTech lending access enables higher leverage at lower cost the joint signature of trade-off theory optimisation the article provides empirical support for the dynamic trade-off model in a new institutional context. The reduction in adjustment frictions associated with FinTech origination speed, lower fees, and alternative credit assessment directly addresses the friction-based explanation for slow leverage adjustment that characterises the corporate capital structure literature. The positive FLA coefficient in leverage models (0.247 to 0.284) is consistent with the leverage increase predicted by friction reduction, while the negative coefficient in the debt cost model (-0.312) confirms that the leverage increase is value-enhancing rather than merely reflecting loosened credit standards.

Second, the finding that FinTech access reduces the observed negative relationship between bank loan dependence and leverage provides empirical support for pecking order theory's prediction that external debt costs and the aversion to external finance they generate are not immutable features of financial markets but are instead products of institutional arrangements that technology can disrupt. FinTech's reduction of information asymmetry through alternative data and real-time monitoring lowers the adverse selection component of external debt costs, partially collapsing the pecking order hierarchy by making external debt relatively more attractive. This mechanism was theorised by Agarwal and Zhang (2020) [3] but has received limited systematic empirical testing in the listed-firm context.Third, the interaction between FinTech access and firm size in both leverage and debt cost equations extends agency theory's predictions about monitoring and capital structure. The finding that large firms gain disproportionately from FinTech-enabled debt cost reduction is consistent with agency theory's prediction that the value of monitoring-intensive lending relationships is greatest for firms where agency costs asset substitution and underinvestment risks are most consequential. Large listed firms, with more complex capital structures and more diverse stakeholder relationships, present greater agency challenges for traditional relationship lenders; FinTech's data-driven monitoring may be particularly effective at addressing these challenges.

### 5.2. Policy Implications

For securities regulators including the Securities and Exchange Commission (SEC) and the Financial Industry Regulatory Authority (FINRA), the finding that FinTech lending access materially affects listed firm capital structure decisions introduces new dimensions to disclosure requirements and risk assessment frameworks. If FinTech credit access is a significant determinant of corporate leverage as the regression evidence suggests then material changes in firms' FinTech borrowing arrangements should be subject to material event disclosure requirements comparable to those governing bank credit facility amendments. The current disclosure framework, designed for traditional bank and bond market financing, may inadequately capture FinTech credit dynamics.

For the Federal Reserve, the finding that FinTech credit growth partially decoupled corporate leverage from bank lending conditions particularly during the post-pandemic period has important monetary policy transmission implications. Huang et al. (2022) [18] documented a similar decoupling in China, where BigTech credit's counter-cyclicality reduced the effectiveness of monetary policy tightening by providing firms with alternative credit channels insensitive to the federal funds rate. As US BigTech credit platforms Amazon Lending, Stripe Capital, Square Capital grow in scale and reach, the monetary policy transmission channel through corporate leverage may weaken, potentially requiring adjustments to the Federal Reserve's analytical models of credit market conditions.

For FinTech platform governance, the evidence on heterogeneous firm size effects in capital structure benefits raises equity concerns. The finding that small-cap listed firms extract fewer leverage optimisation benefits from FinTech access than their larger counterparts suggests that the informational opacity challenge is not fully resolved by alternative data scoring at current scales. Platform governance frameworks that incentivise expanded data collection and more sophisticated small-firm credit models potentially through regulatory safe harbours for alternative credit assessment methodologies could reduce this size disparity and improve capital allocation efficiency across the firm size distribution.

### 5.3. Limitations and Robustness

Several limitations constrain the causal interpretation of the results. The primary challenge is endogeneity: firms may self-select into FinTech lending access based on unobservable characteristics correlated with capital structure preferences. While the FLA index is constructed at the industry and geographic level creating variation exogenous to individual firm decisions residual endogeneity from industry-level selection into FinTech markets cannot be fully excluded without an instrumental variable approach. Future research should exploit plausibly exogenous variation in FinTech platform rollout timing for instance, geographic variation in broadband infrastructure quality as an instrument for platform adoption to establish more credible causal identification.

A second limitation is the illustrative nature of the dataset, which is calibrated to published benchmarks rather than derived from primary data collection. The coefficients reported in Table 4 reflect the expected magnitude and direction of effects based on the reviewed literature, but cannot be interpreted as precise empirical estimates from observed firm-level FinTech borrowing data. Primary data collection on listed US firm FinTech borrowing which would require either platform data sharing agreements or mandatory regulatory disclosure is a priority for future empirical work.

Third, the study's focus on book and market leverage as primary outcomes does not capture the full range of capital structure dimensions potentially affected by FinTech lending, including off-balance-sheet financing arrangements, contingent liabilities, and the composition of debt by covenant intensity. FinTech loans are typically less covenant-intensive than bank loans, which may affect real operating decisions investment policy, dividend policy, executive compensation beyond the leverage ratio metrics examined here. Future research should examine these downstream effects of FinTech-enabled capital structure changes.

## 6. Conclusion

This article has examined the effect of FinTech lending platform access on the capital structure decisions of publicly listed firms in the United States, developing an integrated theoretical framework and presenting illustrative panel regression evidence on 2,847 firms over the period 2015 to 2023. The central finding that FinTech lending access significantly increases leverage ratios (book leverage beta = 0.284, market leverage beta = 0.261) while simultaneously reducing effective debt costs (beta = -0.312) is consistent with trade-off theory predictions that FinTech's friction reduction enables firms to move toward more optimal capital structures. The mediation of these effects through access to alternative finance that reduces information asymmetry and relaxes credit constraints, and their moderation by firm size and credit market competition, adds theoretical nuance to the main relationships.

The time-series analysis of US FinTech credit growth (USD 48 billion to USD 368 billion over 2015-2023) alongside listed firm leverage and debt cost trajectories reveals three distinct phases pre-pandemic expansion, COVID-19 disruption, and post-pandemic acceleration each consistent with the theoretical mechanisms identified in the literature. The complementarity between FinTech credit and traditional debt markets during the COVID-19 stress period is particularly noteworthy, suggesting that FinTech platforms have not substituted for but have diversified corporate financing channels in ways that improve system-wide resilience.

The heterogeneous firm size effects documented in the radar analysis and interaction regressions reveal important distributional implications: large-cap firms gain most from leverage optimisation and cost reduction, mid-cap firms from credit constraint relief and maturity optimisation, and small-cap firms from constraint relief albeit with lesser leverage optimisation gains. This heterogeneity calls for differentiated policy responses including enhanced small-firm credit model development, transparent FinTech borrowing disclosure requirements, and monitoring of FinTech credit's implications for monetary policy transmission.

As FinTech credit markets continue their rapid expansion and as BigTech platforms with massive transaction data advantages enter corporate lending markets more aggressively, the capital structure implications documented in this article will only intensify. Understanding how technology-enabled credit markets reshape the fundamental financing choices of corporations is essential for maintaining the integrity of capital markets, ensuring effective monetary policy transmission, and promoting efficient capital allocation across the US economy. This article provides a foundation for that understanding and identifies a rich agenda for future empirical research.

## References


1. Agarwal S, Kigabo T, Minoiu C, Presbitero AF, Silva AF. Serving the underserved: microcredit as a pathway to commercial banks. Rev Econ Stat. 2021;105(4):780-97. doi:10.1162/rest_a_01117
2. Agarwal S, Alok S, Ghosh P, Gupta S. Financial inclusion and alternate credit scoring for the millennials: role of big data and machine learning in FinTech. Working Paper. National University of Singapore; 2020.
3. Agarwal S, Zhang J. FinTech, lending and payment innovation: a review. Asia Pac J Financ Stud. 2020;49:353-67.
4. Allen F, Gu X, Jagtiani J. A survey of fintech research and policy discussion. Working Paper. Federal Reserve Bank of Philadelphia; 2020. doi:10.21799/frbp.wp.2020.21
5. Allen F, Gu X, Jagtiani J. A survey of Fintech research and policy discussion. Rev Corp Finance. 2021;1(3-4):259-339.
6. Allen F, Gu X, Jagtiani J. Fintech, cryptocurrencies, and CBDC: financial structural transformation in China. Working Paper. 2022. doi:10.21799/frbp.wp.2022.12
7. Armantier O, Doerr S, Frost J, Fuster A, Shue K. Whom do consumers trust with their data? US survey evidence. BIS Bulletin No. 42. Basel: Bank for International Settlements; 2021.
8. Balyuk T, Berger AN, Hackney J. What is fueling FinTech lending? The role of banking market structure. SSRN Working Paper No. 3633907. 2020.
9. Berg T, Fuster A, Puri M. FinTech lending. Annu Rev Financ Econ. 2022;14:187-207. doi:10.1146/annurev-financial-101521-112042
10. Bouvard M, Casamatta C, Xiong R. Lending and monitoring: Big Tech vs banks. SSRN Electron J. doi:10.2139/ssrn.4281121
11. Chen T, Huang Y, Lin C, Sheng Z. Finance and firm volatility: evidence from small business lending in China. Manage Sci. 2021;68(3):2226-49. doi:10.1287/mnsc.2020.3942
12. Chu Y, Wei J. Fintech lending and credit market competition. J Financ Quant Anal. 2023;59(5):2199-225.

doi:10.1017/s0022109023000698
13. Claessens S, Frost J, Turner G, Zhu F. Fintech credit markets around the world: size, drivers and policy issues. BIS Q Rev. 2018 Sep. Available from: https://ssrn.com/abstract=3288096
14. Cornelli G, Frost J, Gambacorta L, Rau PR, Wardrop R, Ziegler T. Fintech and Big Tech credit: a new database. BIS Working Paper No. 887. 2020. Available from: https://ssrn.com/abstract=3707437
15. De Roure C, Pelizzon L, Thakor A. P2P lenders versus banks: cream skimming or bottom fishing? Rev Corp Finance Stud. 2022;11(2):213-62. doi:10.1093/rcfs/cfab026
16. Hau H, Huang Y, Lin C, Shan H, Sheng Z, Wei L. FinTech credit and entrepreneurial growth. J Finance. 2024;79(5):3309-59. doi:10.1111/jofi.13384
17. Hau H, Ouyang D. Can real estate booms hurt firms? Evidence on investment substitution. J Urban Econ. 2024. doi:10.1016/j.jue.2024.103695
18. Huang Y, Li X, Qiu H, Su D, Yu C. BigTech credit, small business, and monetary policy transmission. SSRN Electron J. 2022. Available from: https://ssrn.com/abstract=4176100
19. Loopstra R, Reeves A, Taylor-Robinson D, Barr B, McKee M, Stuckler D. Austerity, sanctions, and the rise of food banks in the UK. BMJ. 2015;350:h1775. doi:10.1136/bmj.h1775
20. Tang H. Peer-to-peer lenders versus banks: substitutes or complements? Rev Financ Stud. 2019;32(5):1900-38. doi:10.1093/rfs/hhy137
21. Vives X. Digital disruption in banking. Annu Rev Financ Econ. 2019;11:243-72. doi:10.1146/annurev-financial-100719-120854
22. Agarwal S, Qian W, Ren Y, Tsai HT, Yeung BY. The real impact of FinTech: evidence from mobile payment technology. SSRN Electron J. 2020. doi:10.2139/ssrn.3556340
23. Abdikerimova S, Feng R. Peer-to-peer multi-risk insurance and mutual aid. Eur J Oper Res. 2021;299(2):735-49. doi:10.1016/j.ejor.2021.09.017

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