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Efficiency in Lending: How FinTechs and Banks Compete in the Modern Market

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ABSTRACT:
Finanssiteknologiaan perustuvat luotonantajat kilpailevat yhä suoremmin perinteisten pankkien kanssa, mutta niiden suhteellisesta tehokkuudesta on vain vähän vertailukelpoista näyttöä, etenkin tekoälyn ja vaihtoehtoisen datan nopean yleistymisen jälkeen. Tätä aukkoa paikataan monimenetelmällisellä tutkimusasetelmalla, joka yhdistää kirjallisuuskatsauksen ja Upstart Inc.:hen kohdistuvan tapaustutkimuksen. Empiirisessä osassa luotonannon tehokkuutta mitataan järjestämättömien saamisten osuudella (NPL-suhde) ja hyödynnetään FFIEC:n viranomaisraportteja: verrokkijoukkona 1 650 yhdysvaltalaista ei-kumppanipankkia ja tarkastelujoukkona 10 pankkia, jotka integroivat Upstartin tekoälypohjaisen luottoarvioinnin osaksi luottopäätösprosessia. Vertailu perustuu kumppanipankkien NPL-trendien ja salkun suorituskyvyn vaihtelun muutoksiin ennen ja jälkeen käyttöönoton sekä rinnakkaiseen vertailuun verrokkipankkeihin.

Tulokset osoittavat, että kumppanipankkien keskimääräinen NPL-suhde aleni noin kolmanneksen käyttöönoton jälkeen ja suorituskyvyn hajonta supistui, mikä viittaa luottoriskin arvioinnin tarkentumiseen ja prosessien tasalaatuisuuteen. Mediaanit olivat ryhmien välillä lähellä toisiaan, mikä viittaa siihen, että parannukset olivat voimakkaimpia pankeissa, joilla lähtötaso oli heikoin; samalla hajonnan pienentyminen kertoo tasalaatuisemmasta salkun hallinnasta. Vaikutus ei kuitenkaan ollut yhtenäinen: osassa pankeista havaittiin NPL-suhteen nousua, mikä korostaa pankkikohtaisten käytäntöjen, segmenttivalintojen ja paikallisten suhdanteiden merkitystä. Teoreettisesti havainnot kytkeytyvät tietoepäsymmetrian pienenemiseen, markkinasegmentaation dynamiikkaan ja tehokkuusraja-ajatteluun (esim. stokastinen raja-analyysi), jotka selittävät, miten dataintensiivinen luottoarviointi voi siirtää toimijat lähemmäs tehokkuusrajaa.

Metodologisesti tutkimus nojaa standardoituihin viranomaisraportteihin ja ennen–jälkeen-asetelmaan, mutta kausaalisuutta ei väitetä todistetuksi; mahdolliset valikoitumisharhat, lyhyehkö tarkastelujakso ja raportointierot rajaavat yleistettävyyttä. Tulokset viittaavat siihen, että tekoälyyn ja vaihtoehtoiseen dataan tukeutuva luottoprosessi voi kumppanuuksien kautta tai itsenäisesti parantaa operatiivista tehokkuutta erityisesti vakuudettomissa kuluttajaluotoissa, mikä vahvistaa kilpailuasemaa, kun toteutus, läpinäkyvyys ja oikeudenmukainen riskihinnoittelu ovat kunnossa. Laajempi poikkialueellinen tarkastelu ja pidemmät aikasarjat ovat perusteltuja havaintojen yleistettävyyden vahvistamiseksi.

KEYWORDS: FinTech Lending, Lending Efficiency, Traditional Banks, Non-Performing Loan Ratio, Credit Risk Assessment, Credit Models, Competition

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1 INTRODUCTION

For a long time, consumers and businesses relied predominantly on traditional banks to meet their credit needs. However, lending practices have changed a lot in the last ten years because of the rapid growth of financial technology (FinTech) companies that use digital platforms, alternative data, advanced analytics, and artificial intelligence (Tigges et al., 2024; Cornelli et al., 2024). In this thesis, financial technology (FinTech) is defined as: "technologically enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services" (Financial Stability Board, 2024). This is the most widely used definition in academic literature.

These innovations have enabled the expansion of credit to previously underserved markets, enhancing financial inclusion globally (CCAF & WEF, 2024). This evolution has had a particularly significant impact on small-to-medium business lending (SMBL) and unsecured consumer lending (Financial Stability Board 2019; Cornelli et al., 2019; 2023 and Ziegler et al. 2021; Kowalewski & Pisany, 2022). The use of these new technologies and business models is putting pressure on the performance of existing financial institutions (FIs) (Naceur et al., 2023). Conversely, through partnerships with FinTech firms or by developing their own technology solutions, these FIs can gain significant operational efficiency advantages (Bian et al., 2024).

Fintech lending, which is based on digital-first platforms, has grown quickly due to a number of macroeconomic and institutional factors. These include higher GDP per capita, less stringent banking regulations, and enhanced investor protections (Cornelli et al., 2023). The global fintech lending market was valued at USD 714,29 billion in 2022 and is expected to grow to USD 6315,41 billion by 2031 (SkyQuest, 2024). This paper uses the following definition for "fintech lending" by the U.S. Government Accountability Office (GAO): "Fintech lenders are nonbank firms that operate online and may use "alternative data," including rental property or utility payments, to help determine

borrowers' creditworthiness." This use of alternative data in credit scoring mechanisms, combined with advanced machine learning algorithms, points to higher efficiency in lending. In addition, FinTechs offer lower interest rates and more cost-effective services, which draws clients away from traditional banks and lowers their interest income (Ben Naceur et al., 2023; Jagtiani & Lemieux, 2019).

Furthermore, Bian et al. (2024) state that banks face increased operational costs as they invest in new technologies to compete, thereby impacting their profitability. Despite these increased costs, their textual analysis reveals that such investments can enhance financial performance. A one standard deviation rise in FinTech-related phrases per 10,000 words in a bank's annual report is linked to a 0.034% rise in Return on Assets (ROA). Return on Equity (ROE) also goes up by 0.295% in the same situation. These results show that even if investing in technology adoption may lower short-term profits, it will have clear long-term benefits.

The evolution of FinTech has been greatly affected by macroeconomic conditions, which have created both possibilities and challenges. During the COVID-19 epidemic, low interest rates and big economic stimulus measures made it easier for alternative lending platforms to emerge and reach a wider audience. However, the subsequent rise in interest rates and increasing economic uncertainty have introduced new challenges, pressuring leveraged borrowers and leading to a deterioration in credit quality across the industry (Shared National Credit Program, 2024, p. 4). Cuadros-Solas et al. find that the increase in inflation rates leads to a positive effect on bank market power (2024).
Therefore, FinTech companies must remain flexible and responsive to economic changes.

1.1 Purpose of the study

Numerous studies have investigated the impact of FinTech competition on bank performance, yet relatively few have specifically examined the role that lending efficiency plays in this dynamic. The purpose of this study is to evaluate the comparative

operational efficiency of FinTech lenders and traditional banks in the United States and to analyze the factors influencing their performance. By addressing this topic, the study aims to:

1. Determine whether FinTech lenders exhibit superior operational efficiency compared to traditional banks.
2. Identify the key drivers of efficiency in consumer and SMBL lending
3. Assess the implications of these efficiency differences on market positioning, profitability, and the competitive balance within the lending industry.

To achieve these goals, I have come up with the following two hypotheses, which will be looked at in light of the research findings:

H_0= FinTech lenders do not differ from traditional banks in lending efficiency, implying no significant impact on traditional banks' performance

H_1= *FinTech lenders are more efficient in lending, impacting the performance of traditional banks.*

This study is motivated by the lack of up-to-date research regarding the operational efficiency of FinTech lenders compared to traditional banks. Existing literature lacks a detailed analysis of the business models that differentiate FinTech lenders from traditional banks. A lot of the research also uses data from before 2020, which leaves out important technology advances. There are also significant differences in the data quality used. For example, Pampurini et al. (2024) used 27 FinTechs from the PWC FinTech Observatory and extracted their accounting data from Bureau Van Dijk. This study avoided the biggest problem of both defining a "fintech lending firm" and using those definitions on databases with limited filtering choices to get useful results by using a pre-existing list of fintech lending firms. Including firms of different sizes and lending business models without proper classification can lead to misleading results. The authors acknowledge this limitation due to insufficient data quality.

Most importantly, this study includes a detailed case study of Upstart Inc. Unlike previous research that relied on outdated data and broad firm classifications, this analysis uses recent data from annual reports and regulatory filings. The case study offers clear insights into how modern AI-driven credit models can improve lending efficiency. In addition, it allows for a direct comparison with traditional banks, enhancing our understanding of the evolving competitive landscape.

1.2 Structure of the study

This thesis is organized into two main parts: a theoretical part and an empirical analysis. The structure is as follows. Chapter one discusses the background and purpose of the study. Chapter two reviews the key theories influencing lending efficiency. In chapter three, the literature on lending efficiency is reviewed, covering digital lending, the use of alternative data and AI in credit scoring, efficiency measurement with NPL ratios, market segmentation, regulation, and comparisons with traditional banks. Chapter four introduces the case study, explaining the methods employed and showing the data that was used to measure Upstart Inc.'s effect on loan efficiency. Finally, this thesis gives its conclusion.

2 THEORETICAL FRAMEWORK AND DEFINITIONS

This section examines the key theories and defines the fundamental concepts related to the subject. Each concept is briefly introduced and discussed.

2.1 Information Asymmetry Theory

Akerlof (1970), Spence (1978), and Stiglitz and Rothschild (1978) laid the groundwork for this theory. The theory describes transactions in which one party holds more or superior information than the other, resulting in market inefficiencies. In lending, information

asymmetry occurs when borrowers possess more detailed knowledge of their financial behavior and creditworthiness than lenders. By gaining access to these alternative information sources, FinTech lenders show an informational advantage over traditional banks. Indeed, it can be noted that this theory serves as a foundational framework driving the efficiency of FinTech lenders. In the context of this thesis, reducing information asymmetry is key to improving lending efficiency. By mitigating information gaps through AI and extensive data, FinTech lenders are expected to achieve better loan performance (for example, lower default rates or more accurate pricing) relative to conventional banks.

2.2 Lending Efficiency

In this thesis, lending efficiency is used as a broad term that considers a wide range of measurement techniques. Existing studies use the non-performing loan (NPL), net interest margin (NIM), cost-to-income (CIM), return on assets (ROA) and return on equity (ROE) ratios. Some academic studies use a modified non-performing loan (NPL) ratio, developed by Hughes et al. (2017), that decomposes the NPL ratio into three components: the best-practice minimum NPL ratio, Excess NPL ratio, and statistical noise. This decomposition approach allows researchers to distinguish between the inherent credit risk, the lender's efficiency in managing loans, and random fluctuations affecting loan performance.

There are also qualitative ways to measure loan efficiency, in addition to these methods. Tigges et al. (2024) utilized interviews with industry experts to understand the role of alternative data and AI-driven credit scoring in enhancing credit accessibility. The study finds that using alternative data in credit scoring mechanisms can enhance predictive proficiency, leading to lower default rates.

2.3 Disruptive Innovation Theory

Christensen came up with the concept in 1997, and Christensen and Raynor improved it in 2003. It explains how a product or service starts out in simple, cheap markets at the bottom and then rises up the market, eventually taking over established competitors. FinTech lending is a type of disruptive innovation since it uses enabling technology like digital platforms, advanced analytics, and artificial intelligence to reach those who don't normally utilize them. Additionally, it adopts innovative business models like peer-topeer and marketplace lending and challenges traditional banks. This theory directly relates to the thesis by framing FinTech lenders as potential disruptors to incumbent banks in terms of efficiency and performance. If FinTech firms are indeed more efficient in lending (as posited in H1), they pose a disruptive threat to traditional banks, which may struggle to compete with the quicker, data-rich decision-making of FinTechs. A confirmed efficiency edge for FinTech would illustrate a disruptive effect, forcing banks either to improve, collaborate (through partnerships), or lose market share.

2.4 Market Segmentation

Serfes et al. (2024) state that lenders invest substantially in screening technologies and collateral evaluation before setting interest rates. To avoid direct competition and ensure profitability, they adopt distinct strategies in equilibrium. FinTech lenders dominate the short-term lending market by using sophisticated screening techniques that don't require collateral. On the other hand, traditional lenders control the long-term loan market by requiring collateral and using less advanced screening. This segmentation allows FinTech lenders to specialize in short-term loans, using technology to lower costs and expedite decision-making processes, thereby improving their efficiency.

This specialization approach by FinTech lenders mirrors Culbertson’s (1957) market segmentation theory and Modigliani and Sutch’s (1966) preferred habitat theory. These theories state that bond markets are divided by maturity, with each segment setting its

own interest rates based on distinct investor preferences. In addition, investors favor specific maturity ranges and only shift segments when higher yields are offered.

For this thesis, market segmentation theory highlights that comparing FinTech and bank efficiency must consider the context of the loan segment. The research is primarily concerned with consumer and personal lending, a segment where FinTech firms like Upstart are highly active and have a technological edge. This thesis hypothesizes that in such segments, FinTech lenders will exhibit superior efficiency metrics (e.g., faster loan processing and lower default rates) relative to traditional banks. By examining a case (Upstart) that operates in the unsecured personal loan market, the study can observe whether FinTech's segment-specific advantages translate into measurable efficiency gains over banks, as theorized.

2.5 Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA)

Some of the studies discussed in this thesis utilize Stochastic Frontier Analysis (SFA) to analyze lending efficiency. Additionally, Data Envelopment Analysis (DEA) must be mentioned as it is used in the banking sector for similar assessments. SFA is an econometric method that estimates the optimal production frontier and then measures how far each firm deviates from this frontier, separating inefficiency from random error (Aigner et al., 1977). DEA is a non-parametric method that looks at input-output ratios to find out which decision-making units (like banks or lenders) are on the efficiency frontier (Charnes et al., 1978). For example, Hughes et al. (2022) used stochastic frontier estimation to decompose the NPL ratio when comparing the lending efficiency of a fintech firm with that of traditional banks.

Including DEA and SFA in the theoretical framework relates to this thesis's objective of comparing FinTech and traditional bank efficiency. These methods underscore the importance of an objective efficiency benchmark. While this thesis does not perform a

full frontier efficiency estimation, it adopts a similar spirit by comparing performance metrics (notably NPL ratios) of banks with and without FinTech integration. In essence, the thesis is asking: Are banks that leverage a FinTech model closer to the “efficient frontier” (lower bad-loan ratios, better risk-return outcomes) than those that do not? If the data show consistently lower NPL ratios for FinTech-partnered banks, that would imply those banks are operating more efficiently, much as DEA/SFA would identify them as frontier performers. Thus, the concepts of DEA and SFA reinforce the thesis’s hypothesis testing by providing a conceptual foundation for why and how we measure efficiency differences between FinTech lenders and traditional banks.

3 LITERATURE REVIEW

As FinTech companies become more important in the lending market, a growing number of academic research studies are examining their impact on traditional banking institutions. Previous studies have mainly concentrated on their effects on banks' profitability, lending practices, technology adaptation, and competitive positioning. The purpose of this literature review is to directly address the study's research questions by reviewing existing results on lending efficiency and their implications for bank operational performance and competitive dynamics.

3.1 Introduction to FinTech Lending Efficiency

FinTech has changed how financial services are provided, pushing traditional institutions to face new challenges from competitors with more advanced and efficient technologies. In FinTech lending, efficiency can be defined as the ability to minimize costs, optimize operational processes, and enhance loan decision-making and disbursement by leveraging advanced technologies. At best, decisions for approval can be made in a matter of minutes or hours, which differs significantly from the days or weeks it usually takes for banks (Stripe, n.d.). However, this information is gathered from Stripe’s (a

FinTech firm) website and may include bias. A better example is a study by Fuster et al. (2022), which shows that fintech lenders process mortgage applications approximately 20% more quickly compared to traditional lenders. This, in turn, results from the combination of multiple factors, including advanced algorithms, alternative data usage, regulatory arbitrage, targeting of underserved markets, offering costeffective services, new business models, and digital-only platforms. Even with these benefits, the fintech lending industry has to deal with problems and risks related to data security, regulatory compliance, privacy, and ethical considerations (Tigges et al., 2024).

Fintech lenders typically operate through digital platforms using data-driven underwriting. They fund their loans in one of three primary ways: by partnering with banks, by using marketplace lending that directly connects individual investors with borrowers, or by relying on their own balance sheet to provide funding. The lending process begins when a borrower completes a secure online application, providing personal and financial data that advanced analytics use for swift credit assessment. These algorithms often integrate alternative datasets, such as nontraditional payment histories (utilities and rent) or online behavioral indicators (email data, mobile phone usage, and digital transactions), to get creditworthiness estimates (Tigges et al., 2024). Based on this data, the credit model instantly prices and grades the loan. Following this, the borrower receives instant feedback on the loan terms they qualify for, and a verification process takes place (Jagtiani & Lemieux, 2017). If the loan is granted, the money is usually transferred electronically straight into the borrower's bank account. Finally, borrowers typically repay their loans through the same online platform, with automatic repayment options and tools to monitor their repayment progress. It is crucial to understand this process when discussing FinTech lending efficiency.

Measuring lending efficiency can be done through a variety of different econometric models, qualitative analysis, and more simple financial ratio comparisons. However, it must be noted that there is no single ratio that perfectly captures lending efficiency. Next, the most influential method in the related literature will be reviewed in more detail.

The NPL (Nonperforming Loan) ratio is calculated as (Federal Reserve Board, Y-9C Report):

$$NPL\ Ratio = \frac{Nonperforming\ Loans}{Total\ Consumer\ Loans}$$

For traditional banks, the numerator Nonperforming Loans includes:

- Past-due loans (over 90 days)
- Nonaccrual loans

For FinTech lenders, the numerator differs due to different reporting standards.

Decomposition of the Non-Performing Loan (NPL) Ratio:

$$NPL_i = BestPractice\ NPL_i + Excess\ NPL_i + Noise_i$$

- Best-Practice NPL Ratio: Represents the minimum achievable NPL ratio under ideal efficiency in evaluating and managing credit risk.
- Excess NPL Ratio: Measures inefficiency in credit risk management. • Statistical Noise: Captures random factors affecting observed NPLs.

For further details on the methodology, refer to the original study (Hughes et al. 2017).

3.2 Technology and Alternative Data

The literature on AI and alternative data in credit scoring shows a swift evolution from conventional models, which historically depended on demographics, credit history, and assets (Tigges et al., 2024). For example, legacy models like the Altman Z-score, which

predicts bankruptcy, and the FICO score for consumer credit are still used by lenders. Recent advancements, however, involve AI-driven methods that include multilayer neural networks, k-nearest neighbor, decision trees, and support vector machines. These methods have often proven more predictive of defaults (Xia et al., 2024; Tigges et al., 2024). A recent study by Gambacorta et al. (2024) puts this into numbers. They find that the use of ML techniques provides a 5.3% increase in loss and default prediction accuracy. It is important to note that the performance of machine learning methods varies significantly and depends on the specific model used.

A study by Chang et al. (2024) on predicting the default status of credit card customers finds that XGBoost (an ML model) outperforms all other models in the study with a 99.4 % prediction accuracy. Logistic regression, which has been the standard technique in credit scoring, scored lowest with 84.3% accuracy. On the contrary, a study by Adha et al. (2018) reports a 95.3% accuracy score for logistic regression, but it is still outperformed by XGBoost. Xia et al. (2024) similarly found that XGBoost outperforms all other models. In addition, a large bank reported a 15% reduction in defaults after implementing a similar methodology. Although FinTech's machine learning-based credit scoring models outperform traditional empirical models in predicting borrowers' losses and defaults, their comparative advantage diminishes as lending relationships lengthen (Gambacorta et al., 2024). They show that although accuracy improves by about 5–6% for new borrowers, it drops to just 1–2% as borrowers build longer credit histories. It is reasonable to conclude that effective credit risk analysis, enhanced by machine-learning algorithms, significantly improves predictive accuracy for lending decisions.

The linkage between credit scoring accuracy and lending efficiency is evident. By reducing the number of false positives (approving high-risk borrowers) and false negatives (rejecting creditworthy applicants), lenders can allocate resources more efficiently, approving loans to trustworthy borrowers. This, in turn, reduces default rates, saving costs associated with loan recovery and write-offs. This conclusion is widely supported by the related literature. For example, studies by Stulz (2019) and Sheng (2021) show that FinTech firms do not only affect service costs but also speed up loan

processing by expanding financing without increasing default rates. In contrast, Di Maggio and Yao's (2021) study on fintech borrowers finds that within 15 months of loan origination, fintech borrowers are almost twice as likely to default (3.53% delinquency rate) than those with traditional loans. These different results can be due to deficiencies in credit scoring algorithms, data used, and fintech lenders targeting higher-risk segments. The latter is especially relevant because FinTech lenders typically serve higherrisk segments, which naturally leads to higher default rates. It should also be noted that the study by Maggio and Yao relies on older data collected when FinTech lenders' credit scoring algorithms were not as advanced as indicated by newer research.

FinTech lenders use increasing amounts of alternative data to get real-time information about borrower behavior, making underwriting decisions more predictable (Xia et al., 2024). Studies by Lemieux (2019), Yan et al. (2015), and Croux et al. (2020) suggest that information asymmetry between lenders and borrowers can be overcome using AI/ML and alternative data. This conclusion is also supported by Tigges et al. (2024), who state that using alternative data in credit scoring reduces moral hazards by aligning the interests of lenders and borrowers. In this case, moral hazard means that borrowers take more risks after receiving credit, as they think lenders can't see and punish them. The logic is that continuous tracking of borrowers' transactions and behavior creates accountability, as borrowers know that imprudent actions could trigger credit downgrades or loan denials. In addition, a study by Kou et al. (2021) found that alternative data, such as transactional and payment network variables, significantly improves the prediction of small business bankruptcy, even without traditional accounting data. An empirical study by Gambacorta et al. (2024) gives a more precise insight into the impact of alternative data. They find a 2.2% increase in predictive power when using non-traditional data.

the literature shows that credit scoring models, particularly those using machine learning and alternative data, generally predict borrower losses and defaults more accurately than traditional methods. In addition, Tigges et al. (2024) conclude that alternative data outperforms traditional lenders on aspects such as cost, speed, convenience, simplicity,

and accessibility. It is evident that higher predictive accuracy reduces costly mistakes in approving risky borrowers or rejecting creditworthy applicants and leads to improved lending efficiency. This higher predictive accuracy is crucial for the sustainability and profitability of fintech lending platforms (Wang et al., 2021). Lastly, the significant effect of technology is shown in a study by Buchack et al. (2018), which finds that technology accounts for about 90% of the growth that FinTech mortgage lenders experienced from 2007 to 2015.

3.3 Market Segmentation and Specialization

Recent studies highlight that the consumer and small-to-medium business lending market is segmented in several ways. Lenders tend to specialize in different types of lending, specifically transaction versus relationship lending and short-term versus longterm lending (Serfes et al., 2024; Jimenez et al., 2006). They also target specific borrower groups based on characteristics and, by extension, risk levels. For instance, Cornelli et al. (2024) find that FinTech lenders in the United States tend to lend more in zip codes characterized by higher unemployment and bankruptcy rates. Because of their superior screening ability, they face a lower risk of lending to bad borrowers and can effectively serve high-risk segments that banks typically avoid. Lenders usually avoid “head-on” competition and operate in their strong segment. Serfes et al. state that one lender (FinTech) deliberately opts to be strong in the short-term market, thereby earning positive rents there. In addition, they find that FinTech lenders make strictly positive profits in their strong (short-term) lending segment if the study conditions are met. It can be indeed said that this specialization approach has a significant effect on profitability and efficiency in lending.

FinTech lenders tend to operate in countries with more developed financial markets, which can be attributed to a lower barrier to entry. Factors like more advanced investors and a skilled workforce are crucial for FinTech firms while threatening the profitability of

traditional financial institutions. However, financial institutions in well-regulated countries see increased profitability from FinTech competition by creating an equal playing field (Naceur et al., 2023). The study also highlights that Incumbents with a lower risk profile are more vulnerable to FinTech's impact on profitability. This shows how FinTech companies capitalize on traditional banks' risk aversion by filling lending gaps and meeting previously unmet market demands.

A widely discussed topic in related literature is the question of whether FinTech complements or substitutes traditional bank lending or, more specifically, relationship lending. This lending relies on soft, qualitative information gathered through regular, often informal, interactions with borrowers. The literature on this topic shows mixed results. Several studies highlight FinTech's ability to fill lending gaps and partner with banks, thus serving as a compliment (Tigges et al., 2024; Kutzbach et al.,2024; Jagtiani et al., 2018; Bian et al., 2024; Thakor et al., 2020) On the other hand, some studies point to reduced market share, weaker market power, lower profitability and increased competition for banks (Cuadros-Solas et al. 2024; Song et al., 2023; Gopal et al., 2022; Kowalewski et al., 2022). These studies support the substation hypothesis. However, the relationship between fintech and traditional banks is not simply one of complementing or replacing each other. This balance depends on factors like market conditions and regulation, requiring further study on the matter.

3.4 Regulatory Landscape

Recent literature demonstrates that regulatory frameworks significantly influence how banks and non-bank (FinTech) intermediaries compete in credit markets. In many jurisdictions, stricter post-crisis oversight, higher capital requirements, and tighter controls over deposit-taking have moved some lending activity toward more lightly regulated FinTech lenders. However, some studies call this "regulatory arbitrage," as FinTechs face fewer or more fragmented rules compared to the stricter regulations on banks (Buchak et al., 2018; IMF, 2022). Evidence from the US mortgage sector

demonstrates this trend. Shadow banks and FinTech lenders significantly increased their market share following stricter regulatory oversight of banks, rising from 3% in 2007 to 12% in 2015 (Buchak et al., 2018). The study also concludes that 60% of this growth can be credited to regulatory differences. Moreover, even certain forms of deregulation can similarly foster non-bank entry, such as the repeal of the 1933 Glass-Steagall Act in 1999 (Neuhann et al., 2018). This act mandated strict separation of commercial (deposittaking) and investment (securities underwriting) banking.

The transition to non-bank intermediation is not solely a result of regulatory constraints faced by banks. Broader organizational changes may also enhance banks' monitoring capacity and distribution capabilities (Chen et al., 2023). Permitting banks to bundle various services, such as underwriting and deposit-taking, generally results in a reduction of the effective cost of monitoring. This subsequently enhances syndication mechanisms (jointly providing a loan) and encourages greater involvement from FinTech investors (Drucker et al., 2005; Irani & Meisenzahl, 2017). Research indicates that in syndicated loan markets, banks with cross-selling opportunities consistently arrange larger volumes and retain smaller loan portions, all while upholding credit quality (Chen et al., 2023). Regulation that expands the allowed activities of banks can enhance the market share of non-bank lenders by increasing the liquidity and tradability of loan origination. These findings indicate that regulation influences efficiency by not only imposing capital or compliance burdens on banks but also by modifying their organizational flexibility in monitoring, underwriting, and distributing credit.

Scholars emphasize that the advantages of relaxed scope for banks may depend on broader market dynamics and potential cyclicality. For instance, Begenau and Landvoigt (2022) argue that capital regulations and bank risk-taking are interconnected in complex ways, occasionally leading banks to exit specific lending segments or engage in riskier exposures. The IMF (2022) notes that although FinTechs can effectively access underserved markets, they may also heighten systemic vulnerabilities in the absence of sufficient oversight. The efficiency gains from expanding bank activities, including larger syndications and increased loan trading liquidity, must be weighed against the potential

destabilization of credit markets. The literature calls for policies that encourage innovation and competition in lending while protecting both banks and FinTechs from excessive risk.

3.5 Comparative Efficiency Analyses

Thus far, only two studies have directly compared the lending efficiency of fintech lenders with that of banks. However, the results of Onorato et al. (2024) should be approached with caution, as the authors have expressed concerns about methodological limitations and data integrity. There are also limitations to Hughes et al. study that need to be discussed. Especially with data obsolescence and the concentration on only one fintech lender. These limitations, indeed, highlight the need for further study on the matter.

The studies in question use similar metrics for comparison but different methodologies and country contexts. Hughes et al. (2022) investigate unsecured consumer loans in the United States, contrasting a group of large traditional banks with LendingClub, a major FinTech platform. They develop a stochastic frontier model to decompose observed nonperforming loan (NPL) ratios into three components, as discussed before. On the other hand, Onorato et al. (2024) examine the Italian market by applying Stochastic Data Envelopment Analysis (extension of DEA) to all Italian FinTech lenders in 2021 and to all Italian banks with data availability over the same period.

The main finding of Hughes et al. is that high NPL ratios at major lenders, hovering around 5.86% to 5.91% on average, often indicate strategic decisions to finance riskier borrowers rather than poor underwriting ability. LendingClub's NPL ratio of 4.16% in 2016 partially reflects its higher-risk clientele but also points to efficiency gains arising from advanced analytics. A number of smaller community banks, which rely on local relationships instead of complex algorithms, also demonstrate high efficiency. This indicates that either extensive local knowledge or advanced credit-scoring technology can yield positive lending results.

On the other hand, Onorato et al. show that incumbents have a small efficiency edge, with an average of 0.965 compared to 0.889 for FinTech lenders. Even a smaller bank subset matched in size to the FinTech group achieves an average efficiency of 0.957, highlighting persistent structural benefits for conventional institutions. However, Onorato et al. note that some FinTech companies are close to or at these high-efficiency levels, showing that cutting-edge tools can perform well, but not uniformly. This finding aligns with broader literature suggesting that technology alone does not guarantee better risk management or higher productivity. Rather, it works best when combined with solid management practices, an effective market strategy, and a thorough understanding of relevant regulations.

4 CASE STUDY: UPSTART INC

Upstart Inc. is a U.S.-based financial technology provider that specializes in AI-driven credit modeling. Since 2018, it has partnered with over 100 banks and credit unions to enhance consumer lending performance. Its approach combines traditional credit metrics (e.g., FICO scores) with alternative data and machine learning to improve risk identification and pricing accuracy.

4.1 Introduction

Several U.S. banks, including Customers Bank, First National Bank of Omaha (FNBO), WSFS Bank, Associated Bank, and others, adopted Upstart's platform between 2018 and 2022. These institutions integrated Upstart's AI model into their unsecured personal loan underwriting processes. Upstart is a leading FinTech firm that exemplifies how artificial

intelligence can improve lending efficiency. Its AI-driven underwriting model processes over 1,600 data points to assess borrower risk more accurately than traditional FICObased methods. This approach appears to yield higher approval rates and significantly fewer defaults, allowing partner banks and credit unions to offer loans at lower interest rates.

The purpose of this case study is to evaluate how the implementation of Upstart's technology has influenced the lending performance of these partner banks. This analysis will be based on Upstart's annual reports, independent studies on its technology's performance, and a review of non-performing loan (NPL) rates before and after the technology was introduced. These results will offer clear insights into the effectiveness of fintech-based credit scoring models and thus aim to answer the thesis's research questions.

4.2 Data and Methodology

The data for this study is gathered from Upstart's annual reports from 2023 and 2024, independent performance studies conducted by NAFCU (2023) and CFPB (2019), and regulatory call reports for non-performing loan (NPL) data. These call reports are retrieved from the FFIEC website. The bank sample used is gathered from Upstarts website under partner banks. A comparative sample is also collected to assess whether these partner banks perform better than their peers. This sample consists of all US. banks that file FFIEC 041 and FFIEC 051 call reports. The sample is delimited to banks with sufficient loan-level data for NPL ratio calculation. A final sample size of 1650 banks is used.

Specifically, the NPL ratio is calculated by summing personal loans past due over 90 days (and in nonaccrual status) and dividing by total personal loans under code RCONK207, while non-performing loans use codes RCONK217 and RCONK218. Some partner banks are excluded due to insufficient data. Each remaining bank introduced Upstart's technology between 2018 and 2022, with four years of pre-implementation data

gathered (though only three years of data were used for all banks as some years lacked accurate data) and two post-implementation years. The actual adoption year is omitted, as precise implementation timing varies. Finally, average NPL ratios before and after adoption are compared, the percentage change is calculated, and standard deviations are determined to assess performance variability.

Reliability is supported by using standardized regulatory call reports, which follow uniform reporting guidelines. The accuracy of the information is improved by crosschecking it with Upstart's official filings to confirm important dates and the timeline of adoption. Excluding incomplete cases further increases data consistency. All data is gathered from publicly available sources. The sample size is limited to banks with adequate data, which may reduce generalizability. The sample also includes some banks with low personal lending volume, which may introduce greater variability in their NPL ratios. Other factors, such as broader economic conditions, could also influence NPL trends and are not fully isolated in this design. As such, the results should be only interpreted as indicative.

4.3 Review of Upstarts' Technology Performance

Upstart's technology performance is central to understanding its impact on lending outcomes. Internal studies from Upstart's annual reports show that the AI underwriting model increased approved borrowers by 44% with a 36% reduction in APR (annual percentage rate) in one study and by 101% with a 38% reduction in APR in a later study (Upstart, 2023; Upstart, 2024). These findings indicate that the model more accurately assesses borrower risk, allowing banks to extend credit more widely while maintaining controlled default levels. Independent analyses further support these results. For example, the National Association of Federally-Insured Credit Unions (NAFCU, 2023) found that Upstart's algorithm resulted in 53% fewer defaults at the same approval rate compared to traditional methods. Additionally, the Consumer Financial Protection Bureau (2019) noted that similar AI-based approaches can improve credit access without

increasing default rates. Collectively, these studies suggest that Upstart's technology offers a more precise risk assessment tool, contributing to better lending performance and improved asset quality.

4.4 Empirical Analysis

This empirical analysis evaluates the impact of Upstart's AI-driven credit technology on lending efficiency, specifically examining changes in non-performing loan (NPL) ratios among partner banks. The data utilized includes regulatory call reports, complemented by Upstart's annual reports and external research studies.

Overall, the mean NPL ratio across all partner banks decreased from approximately 1.76% before implementation to about 1.21% afterward, reflecting a roughly 31% reduction. This decline indicates that AI-driven underwriting models have the potential to mitigate default risks in specific segments of personal lending.

Table 1. Changes in Average NPL Ratios for Partner Banks Before and After Upstart Integration (Own Analysis)

Bank Name	Avg. NPL Ratio PreImpl.	Avg. NPL Ratio PostImpl.	% Change
Customers Bank	0.0623	0.0044	-92.95%
Colony Bank	0.0084	0.0012	-85.92%
Carver Federal Savings Bank	0.0132	0.0046	-65.22%
Associated Bank	0.0518	0.0572	10.48%
WSFS Bank	0.0268	0.0304	13.36%
Apple Bank	0.0020	0.0050	151.45%
First National Bank of Omaha	0.0037	0.0041	10.91%
Mascoma Bank	0.0004	0.0003	-31.79%
First Financial Bank	0.0034	0.0041	20.44%
NBKC Bank	0.0034	0.0098	186.68%
All Banks	0.0176	0.0121	-30.98%

	Pre-Implementation	Post-Implementation

Std. Dev. (All Partner Banks)	0.0223	0.0180

However, the impact of the technology varied substantially across individual banks. Customers Bank had the most substantial improvement, with its NPL ratio dropping by about 93%, from an average of 6.23% to 0.44%. Similarly, Colony Bank and Carver Federal Savings Bank saw considerable reductions of approximately 86% and 65%, respectively. Conversely, Apple Bank and NBKC Bank observed considerable increases in their NPL ratios, approximately 151% and 187%, respectively. This shows how bankspecific strategies, local economic conditions, or implementation differences may influence the outcomes.

Table 2. Comparative NPL Ratio Statistics: Partner vs. Non-Partner Banks (Own Analysis)

Bank Sample	Average NPL ratio	Median NPL Ratio	Standard deviation
Partner Banks	0.0121	0.0045	0.0180
Non-Partner Banks	0.0157	0.0043	0.0789

The standard deviation among partner banks also dropped from 2.23% prior to adoption to 1.80% following adoption, indicating improved consistency in lending performance, in addition to improvements in average NPL ratios. Compared to non-partner banks, partner banks had a lower average NPL ratio (1.21%) and a much smaller variability of performance (standard deviation of 1.80%). Non-partner banks had an average NPL ratio of 1.57% and a standard deviation of 7.89%. However, median NPL ratios were similar between partner (0.45%) and non-partner banks (0.43%), indicating that benefits from AI-driven models might be most pronounced among banks initially facing higher default risks.

These results show that Upstart's AI-driven underwriting generally helps with lending efficiency and asset quality, but the results are greatly affected by bank-specific factors and the state of the economy as a whole. Thus, observed improvements should be seen

as indications rather than proof of causation, since lending performance outcomes are complex.

4.5 Summary of Findings

The empirical analysis of regulatory call report data reveals that banks partnering with Upstart's AI-driven credit underwriting platform achieved significant improvements in loan performance. On average, the non-performing loan (NPL) ratio among Upstart partner banks declined from approximately 1.76% before adoption to 1.21% after adoption (roughly a 31% reduction in NPLs). This indicates a notable increase in lending efficiency for those banks. The extent of improvement, however, varied by institution: some banks saw especially dramatic declines in NPLs (for example, one partner bank's NPL ratio fell by 93%), while a few others experienced a post-adoption increase in NPLs. Although a handful of banks were exceptions, the partner banks overall showed more stable loan outcomes. Put differently, most of them not only cut their share of bad loans but also achieved similar results across the group.

When compared to a broad sample of 1,650 similar banks that did not use Upstart's platform, the partner banks stood out with a lower average NPL ratio and far less variability in NPL outcomes (even though the median NPL levels were roughly comparable between the two groups). This contrast with non-partner banks reinforces the link between Upstart's AI model and better-managed credit risk. These findings provide clear evidence in support of the thesis's main hypothesis. The observed efficiency gains correspond to Hypothesis H1, which proposed that FinTech lenders (or FinTech lending models) are more efficient in lending. The significant reduction in NPLs among Upstart-enabled banks, alongside more stable loan performance, suggests that the FinTech approach can indeed improve operational efficiency in lending.

This outcome directly contradicts the null hypothesis (H0) that there would be no difference in efficiency between FinTech lenders and traditional banks. Instead, the data indicate that banks leveraging a FinTech credit model outperformed their peers on key risk metrics. It is important to note that H1 in this context does not imply that traditional banks' performance must deteriorate; rather, it implies that FinTech-powered institutions achieve superior results. In fact, the partner banks in this study benefited from FinTech integration, improving their own performance (e.g., lower default rates) rather than suffering losses. The variation between banks also shows that even though the overall trend favors H1, the outcomes for each bank depend on factors like underwriting practices and borrower segments. Overall, the evidence supports the idea that FinTech innovations, like Upstart's AI-driven lending model, have made lending more efficient compared to traditional methods. This validates the thesis's hypothesis that FinTechs can compete with, and even augment, banks in the modern lending market.

5 CONCLUSION

This thesis looked at how efficient FinTech lending models are compared to traditional banks by combining information from other studies with a real-world case study of Upstart Inc. The findings indicate that technology-driven lending practices can significantly improve loan outcomes. On average, banks partnering with Upstart saw the share of non-performing loans reduce by roughly 31%. In comparison, a broad sample of over 1,650 non-partner banks displayed higher average NPL ratios and far more variability in results. These results are consistent with research demonstrating that FinTechs can more successfully identify creditworthy borrowers and lower default rates by utilizing sophisticated algorithms and alternative data.

However, the benefits weren't the same for all banks, reflecting that outcomes depend on context. Some partner banks saw huge improvements, for example, one bank's NPL ratio dropped from about 6.2% to 0.44% (a 93% decrease), while a few others saw their default rates rise. This difference suggests that factors like underwriting practices, customer segments, or the state of the local economy can have an effect on the results. Even so, most partner banks not only lowered their share of bad loans but also achieved more consistent performance relative to peers. These findings are in line with theories of disruptive innovation, which suggest that firms adopting breakthrough technologies can gain competitive advantages when implementation matches their circumstances.

These findings provide clear support for Hypothesis H1: FinTech lenders are more efficient in lending. The significant drop in NPLs among Upstart-enabled banks, along with their steadier loan performance, directly contradicts the null hypothesis of no efficiency difference. Importantly, the data show that banks integrating FinTech solutions improved their own loan portfolios rather than suffering losses. This indicates that FinTech innovations augment, rather than undermine, traditional banking performance. This kind of cooperation effect matches industry observations that many banks now work with FinTech firms to enhance their services instead of ceding market share to them.

The results have practical implications for policymakers, banks, and FinTech firms. Regulators should make it easier for responsible innovation to happen by updating frameworks for lending. For instance, authorities could give advice on data-driven credit models to make sure they are fair and transparent, and they could set up controlled testing environments (also known as regulatory sandboxes) for new lending approaches. These steps would balance consumer protection with efficiency gains. Traditional banks, in turn, are advised to embrace technology proactively. By partnering with FinTech platforms or building in-house analytics teams, banks can modernize credit scoring and risk management, which should lower default losses and operating costs over time. FinTech companies themselves should continue refining their models and expanding collaborations. They can increase their beneficial effects by strengthening data inputs, guaranteeing algorithmic fairness, and focusing on underserved borrower segments. Trust in technology-enhanced lending will also grow by having open and transparent conversations with regulators about these models.

This study has several limitations. The sample of Upstart-partner banks is small and self-selected, so the results might not apply to all banks or regions. The analysis is based on average NPL ratios over a short time period, which may not show long-term trends (like during recessions) or other measures of efficiency (like cost per loan or borrower satisfaction). Also, banks had the choice to use the Upstart platform, so improvements could be partly due to factors that weren't observed, like innovative methods of managing. Future research could address these issues by examining larger or different samples of FinTech partnerships, using longer time spans, and employing more rigorous techniques (such as matched comparisons) to isolate the technology’s effect. Also, comparisons between different regions and sectors would help to generalize these findings. More research could also look at related outcomes, including interest rates, loan approval rates, or borrower welfare, to provide a more comprehensive view of efficiency.

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