The non-linear association between bank fintech and relationship lending: A panel threshold analysis of Indian banks

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ABSTRACT

This is the first study to examine the relationship between bank fintech and relationship lending. Using a panel threshold regression with data from Indian banks, we find evidence for a non-linear relationship between bank fintech and relationship banking. The empirical results indicate that higher levels of bank fintech is associated with an increase in relationship lending only after relationship lending crosses a threshold level, at which point banks are able to leverage fintech for strengthening relationships. Below the threshold level, more bank fintech is associated with a decline in relationship lending under certain specifications. We find similar results when we replace bank fintech with a specific type of fintech viz. artificial intelligence. These findings are robust under alternate measures and specifications and generate important insights about the use of fintech in the banking industry.

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1. Introduction

The advent of financial technology or 'fintech' promises a transformative shift for the banking sector. The use of mobile banking services, digital wallets, robot advisors and blockchain technology are some of the advancements that are reshaping the financial landscape. According to BCG (2024), the global fintech market is expected to reach $1.5 trillion in revenue by 2030 which is around five times of today's value. The possible benefits that fintech could bring for the banking sector along with the threat of being rendered obsolete has many banks 'jumping into the fray' to internalize these technological advancements. Banks are imbibing fintech either by developing inhouse products or by partnering with fintech companies. These developments underscore the need for research that examines the impact that banks' incorporation of fintech has on core banking strategies or functions.

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The literature on the impact of fintech on the banking sector is largely restricted to competition vs. complementarity between banks and fintech companies (Hodula, 2022; Kowalewski & Pisany, 2022; Sheng, 2021). These papers analyse how bank lending is affected when there is fintech development in a country. However, many banks themselves are internalizing advancements in financial technology either through developing their own applications or partnering with private players. The body of literature examining the impact of fintech adoption from a bank's perspective is still in its early stages but fast expanding. The focus has been mainly on the relationship between fintech adoption by banks and a bank's ability to create liquidity (Fang et al., 2023; Guo & Zhang, 2023), or reduce risk (Cheng & Qu, 2020; Fang et al., 2023) or increase performance (Bian et al., 2024; Zhao et al., 2022). Boot (2017) argues that information generated through big data and social media interactions which are core tenets of fintech would impact the value that relationship banking brings to a bank. However, the effect of bank fintech on relationship lending has not been empirically studied so far. Relationship lending is a strategy unique to banks that helps them to overcome information asymmetries associated with opaque borrowers (Berger & Udell, 1995; Boot & Thakor, 1994) There are only a couple of papers (Gangopadhyay et al., 2022; Sedunov, 2017) which study the impact of information technology on relationship banking, but they use indirect measures for relationship banking and narrow measures for a bank's technological prowess. Moreover, these two papers have found contrasting evidence for the relationship between information technology and relationship lending.

The objective of this paper is to compute a bank fintech score and use it to examine the association between bank fintech and relationship lending. We posit that the mixed results in the literature could be due to the non-linear relationship between bank fintech and relationship lending that the existing studies have ignored. It is possible that the relationship depends upon the stage of relationship lending which a bank is at. When a bank has crossed a certain threshold level of relationship lending, bank fintech can be leveraged to further strengthen relationship lending. But below the threshold level, bank fintech may not be of use for relationship lending and may in fact be deployed for diversifying the loan portfolio. The digital footprint that fintech captures along with existing level of soft/ hard information use at the bank decides whether fintech can be leveraged for strengthening relationship lending.

To examine this non-linear relationship, we use the panel threshold regression model proposed by Hansen (1999) which accounts for the heterogeneities of banks. We use data from Indian banks for a time period (post 2008) when fintech usage started picking up in the banking sector with the advent of digital technologies. Our empirical approach allows us to identify the threshold level of relationship banking beyond which its relationship with fintech changes. The use of artificial intelligence (AI), specifically generative AI which can be considered as a subset of fintech, is being touted as a transformative force in the banking sector. The Mckinsey Global Institute (2023) estimates that for banks across the globe, generative AI could create value of $200 billion annually. To understand the interplay of AI and relationship lending, we replace the bank fintech score with artificial intelligence score and find similar results.

This paper contributes to the literature in multiple ways. First, it contributes to an established literature on relationship lending. Within the plethora of existing studies (for instance, Boot & Thakor, 2000; Udell, 2008; Bonini et. al, 2016; Bhardwaj et al., 2022; Anderson et. al, 2023), we contribute to the understanding of the role played by technology in relationship lending. Second, while bank fintech has been studied before (Cheng & Qu, 2020; Fang et al., 2023; Bian et al., 2024), our study is the first to compute a bank fintech score (and a separate score for AI) to estimate the relationship between bank fintech and relationship lending. Third, this paper is a novel attempt to provide greater context for the relationship between technology and relationship lending by examining non-linearities i.e., by identifying a threshold which changes the nature of the relationship. Fourth, the study creates a bank level measure to capture relationship lending for Indian banks, whereas most studies have measured relationship lending at the firm level. Finally, the study is the first to develop a bank fintech score using advanced textual analysis for Indian banks where most existing studies have used measures such as IT spending which are indirect measures of bank fintech.

The results from our analysis show that, the relationship between bank fintech and relationship lending increases after relationship lending crosses a threshold level. Below the threshold, bank fintech leads to a decrease in relationship lending. The threshold effect continues to hold even when the bank fintech score is replaced by the AI score. The positive relationship between bank AI score and relationship lending becomes stronger after a threshold level of relationship lending. However, unlike bank fintech, the relationship does not become negative below the threshold. These results are robust for various specifications of relationship lending. The findings resolve the existing confusion in the empirical literature by showing that the

relationship is more nuanced than has been studied before. The study suggests that all types of banks may not utilize fintech in the same manner and there are different benefits to be enjoyed from bank fintech, depending on the level of relationship lending of the bank. The rest of the paper is organized as follows. The second section addresses the institutional context around fintech and relationship lending. The third section discusses the related literature and sets up the hypotheses. The fourth section details the data used as well as the calculation of both the bank fintech and relationship lending scores. The fifth section explains the empirical methodology used for analysis. The sixth section presents the results of the study highlighting the key findings and interpretations. The final section discusses the main findings of the paper, its implications, limitations, and future research directions.

2. Institutional Context

2.1 History of fintech

The buzz around "fintech" would have us believe that this is an entirely new phenomenon. However, technology has always been part of the banking sector. Bian et al., (2024) outlines three waves of technological advancements in finance. The first wave from 1866 to 1967 saw the introduction of wire transfers and credit cards. The second wave from 1967 to 2008 brought about SWIFT technology and saw the emergence of online banking. The third wave triggered by the 2008 financial crisis, saw the erosion of trust in traditional financial institutions and brought about the current wave of financial technology or fintech. There are two major factors which differentiate the third wave of fintech from the previous waves. One, this wave of innovations seems to be spearheaded by companies outside of the traditional financial sector such as large technology firms and startups. Second, synchronous advancement of non-financial technology such as the proliferation of mobile internet and availability of low-cost smart phones have significantly widened the reach of these financial innovations.

2.2 Defining fintech

Defining fintech is a challenge. A commonly quoted definition of fintech is the Financial Stability Board's definition: "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."

Schueffel (2016) examined over 200 articles mentioning fintech over a period of 40 years across academia and practise and arrived at "Fintech is a new financial industry that applies technology to improve financial activities". While we broadly adhere to these definitions, our focus is on capturing fintech developments incorporated by banks. To this purpose, in the absence of bank-level data on fintech use, we use textual analysis to capture what constitutes 'bank fintech' similar to other papers in this area (Bian et al., 2024; Cheng & Qu, 2020; Fang et al., 2023).

2.3 Fintech development in India

India and China tie for the highest fintech adoption rate of 87% according to the 2019 EY Global Fintech Adoption report (E&Y, 2019). The fintech market in India has emerged as a force to reckon with, with a highly efficient payment system in bot and value. India's digital infrastructure also called 'India Stack' is supported by digital biometric identification (known as Aadhar), zero-balance accounts (called Jan Dhan accounts) and mobile for cashless transactions. India Stack's unique infrastructure enables both banks and private players to deploy fintech applications.

The payments ecosystem in India is a road map for emerging as well as certain developed nations (RBI, 2022). The Unified Payment Interface (UPI) developed by the National Payments Corporation of India (NPCI) has been a game changer in this field. The system which facilitates instant inter-bank transactions initially onboarded 21 banks as part of its pilot program in 2016 and is now ubiquitous with 602 banks using the system. In 2022, the RBI mandated card-less cash withdrawals with UPI acting as the authorization gateway. As a testimony to the success of the payment system, the RBI's digital payment index has seen a steady increase since 2018, with a 10% growth year over year in 2023 compared to 2022. There have been other developments in the payment infrastructure such as the introduction of interoperable bill payments with a push towards making it friendly for remittances and the tokenization of credit card data with regulations in place for safe handling and data privacy.

The introduction of Application Program Interfaces (APIs) and data sharing norms have aided banks in partnering with fintech companies to reap the gains that fintech provides. The State Bank of India (SBI) created the Fintech Incubation Program in 2018 to aid young startups in developing innovative technology solutions for the financial sector. Programs such as these

provide young fintechs with an opportunity to scale up while giving banks access to cutting-edge ideas.

2.4 Relationship Banking

India's banking sector being relationship oriented (Bhue et al., 2015) offers a suitable setting to study the association of bank fintech and relationship banking. Banks can glean soft information about borrowers through greater interaction with them over multiple interactions, exclusive relationships, and over diverse products (Boot & Thakor, 2000). Soft information can include a bank's assessment of a firm's future performance through interacting with its suppliers, customers, or other business associations (Udell, 2008). By collecting soft information over the course of the relationship, banks can provide credit at lower interest rates (Berger & Udell, 1995; Peltoniemi, 2007; Bonini et. al, 2016), while demanding less collateral (Ono & Uesugi, 2009; Anderson et. al, 2023). Relationship banking has been widely considered beneficial for small firms for whom the relationship capital acts as a substitute for the hard information that large firms generate to obtain credit. Identifying relationship lending is a challenging task. However, literature has commonly captured relationship lending in the following three ways. First, the length of relationship has been captured by number of years of association between bank and borrower where longer association shows greater strength (Petersen & Rajan, 1994). Second, the breadth of relationship or scope has been measured by the number of products which bank and borrower interact over as more products signify deeper relationship (Degryse & Van Cayseele, 2000). Third, the number of banks a borrower banks with has been considered as a measure, where fewer number of banks or a single bank signify greater relationship lending (Bhardwaj et al., 2022).

3. Related Literature and Hypotheses

The early literature on relationship banking finds that banks who only engage in relationship lending are likely to reduce it in response to inter-bank competition (Petersen & Rajan, 1994) but those banks who also do transaction lending would increase their relationship lending in order to insulate themselves from price competition (Boot & Thakor, 2000). Thakor (2020) examines the tension between peer-to-peer lending (P2P), which represents fintech, and bank lending to posit that banks would continue to sustain an advantage in relationship lending compared to P2P businesses. However, this does not specifically address the scenario when

banks themselves incorporate fintech into their business models. While literature on the subject acknowledges an impact of fintech on relationship lending (Flögel & Beckamp, 2020; Jakšič & Marinč, 2019) there are no existing studies which empirically examine the relationship between bank fintech adoption and relationship banking.

3.1 The role of bank fintech in generating new information

As financial institutions imbibe fintech innovations, it is expected to activate economies of scale by using large data sets, aid in cheaper and efficient transmission of information while reducing verification costs (Thakor, 2020). The use of policies such as open banking and increasing integration across various banking applications through Application Program Interfaces (APIs) have helped in aggregating large amounts of data. Berg et al. (2020) shows that digital footprints which users leave such as while registering on a website, can be as effective as credit bureau scores in predicting consumer default. Advancements in fintech also help in strengthening the transmission and collection of already existing data mechanisms. He et al. (2022) finds that when banks invest in communication information technology (IT), it aids them in transmitting and producing soft information while the investment in software IT helps facilitates the transmission of hard information. Hard information in comparison to soft information is easier to transmit across various levels of the bank (Udell, 2008).

3.2 Use of technology and relationship lending

Though there are no papers which explicitly examine the relationship of bank fintech and relationship lending, Gangopadhyay et al., (2022) and Sedunov (2017) address the relationship between information technology usage by banks and relationship lending. Gangopadhyay et al. (2022) finds that use of information technology leads to an increase in relationship lending owing to IT's ability to enhance the soft information collection mechanism. They attribute a concomitant rise in profit frontiers and cost frontiers to an increase in relationship banking, but do not explicitly measure the extent of relationship banking. Their study measures bank technology as a ratio of IT expenses to non-interest expenses. Conversely, Sedunov (2017) finds that the use of IT leads to a reduction in relationship lending. The paper argues that as the technological prowess of a bank increases, it may prioritise lending based on hard information at the expense of soft-information lending. The study captures relationship lending as an increase in small business loans and assumes that an increase in small business loans is akin to

an increase in relationship lending. Sedunov (2017) captures back-office technology as total number of employees to total bank assets and front office technology based on having an interactive website or not. Along with a lack of consensus on the results of the two papers, their measures for relationship lending do not explicitly capture any characteristics about the nature of relationship between bank and firm. Additionally, the technology measures are narrow in scope and may be unable to capture the recent advances in fintech. We propose to address these limitations in the extant literature by employing a comprehensive bank fintech measure using textual analysis which has recently gained prominence as it is considered an improvement in capturing bank technological capabilities in a holistic manner (Fang et al., 2023; Bian et al., 2024).

Some other papers touch upon the relationship between technology and relationship banking in a more indirect manner. Kowalewski and Pisany (2022) finds that fintech credit grows complementarily with bank lending whereas big tech credit grows at the expense of bank lending. They find that domestic and private banks face greater competition from big tech companies and interpret it to be a threat to traditional relationship banking. The paper measures fintech development at a regional level without capturing bank level differences in technology and does not explicitly measure relationship lending. Sutherland (2018) finds that lenders who join credit reporting bureaus reduce their lending to deliquenent borrowers compared to before joining the bureau. The joining of the bureau brings with it greater transperancy and access to hard information about firms. The deliquent borrowers, many of whom may ultimately recover, are denied a chance of obtaining credit due to the prioritisation of hard information over soft information. DeYoung et al. (2007) suggests that as technology advances, large banks will prefer to disburse loans based on hard information.

The contrasting results we see in literature might be due to the complexity of the relationship, and we propose that it depends on the level of relationship lending of the bank. Berger & Udell (2006) argue that various lending technologies of banks such as transactional lending based on "hard information" and relationship lending based on "soft information" can be used simultaneously and are not mutually exclusive. Information is pivotal to lending (Berger & Udell, 1995). As fintech usage helps banks codify information about customers that earlier could not be captured, it generates new information or a "digital footprint" (Berg et al., 2020) while strengthening existing data collection mechanisms. Moreover, specialisation may depend upon what kind of information is being used in the production process (Liberti & Petersen,

2019). A bank which is a "relationship lender", may use fintech to strengthen the existing soft information mechanism by using the new information in tandem with the soft information to do more relationship lending. On the other hand, "transactional lenders" may use the "digital footprint" which fintech generates to reinforce hard information lending which leads to a reduction in relationship lending. Therefore, we hypothesize that the relationship between bank fintech and relationship lending depends on the threshold level of relationship lending of the bank. If a bank is above a threshold level of relationship banking, bank fintech is associated with greater relationship lending. However, if a bank is below the threshold level, increase in bank fintech is associated with lower relationship lending. In what follows, we empirically test the following two hypotheses.

H1: There is a positive association between bank fintech and relationship lending

H2: The positive association between bank fintech and relationship lending is stronger after bank relationship lending crosses a threshold level

4. Data and Variables

Our study uses a balanced panel of 21 Indian banks from 2009-2022. We calculate the bank fintech score using textual analysis of the annual reports of banks. The reports are collected manually from either the bank websites or the Prowess database (provided by the Centre for Monitoring Indian Economy) which maintains a repository of bank annual reports. The relationship lending variables are also calculated based on data from Prowess. Many papers (Bhardwaj et al., 2022; Vig, 2013) use this database for analyzing Indian firms and banks. The bank control variables are from the Reserve Bank of India (RBI)'s Statistical Tables on Banks in India. The firm control variables are calculated using data from Prowess. The macroeconomic controls are obtained from the RBI website.

4.1 Calculating the bank fintech score

We begin by creating a data dictionary for fintech adoption by banks, following the machine learning approach adopted by Bian et al., (2024). We create the fintech data dictionary using term frequency-inverse document frequency(Christian et al., 2016). The below mentioned techniques are implemented using the python software and it's various machine learning packages. We train two libraries one which is fintech related and one which is not related to

fintech. Bian et al. (2024) uses the technology section of the Chinese central bank's reports whereas we use fintech related documents from the RBI as well as reports from top accounting and consulting companies[3]. While Bian et al. (2024) use the commercial banking law of China as the library for documents not related to fintech, we use the Banking Regulation Act of 1949 that provides banking rules in India. Using term frequency-inverse document frequency which identifies the importance of words which appear within a document as well as across a set of connected documents (fintech-related/fintech non-related), we arrive at a list of 2000 words. We then manually cross check whether these words are fintech related or not and narrow down the list to 73 keywords[4] which represent fintech developments. Next, for calculating the score, we count the mentions of these fintech keywords in the annual reports of all the banks in the sample for each year. Then the score is scaled to fintech words per 10000 words of the annual report.

4.2 Calculating the bank relationship lending measures

We follow a similar approach to Bhardwaj et al., (2022) who define relationship lending in terms of exclusive relationship between bank and firm as well as the duration of these exclusive relationships as a secondary measure. However, their aim is to perform a firm level analysis and hence they capture these measures at the firm-level. However, since our objective is to study relationship lending at the bank-level, we convert the firm level data to bank level and arrive at bank level measures. We capture relationship lending using two specifications. The first is the number of exclusive relationships for a bank across all its clients for a particular year. Second, as a secondary measure of relationship lending, we calculate the duration of these exclusive relationships.

We collect data from Prowess to identify bankers for each firm. When a firm lists only one banker for a specific year, we count this as one exclusive relationship for the bank (definition 1). This check is done across all the firms within the database for a specific year. Each bank in our sample gets a total of the number of exclusive relationships for a year based on the number of firms that list the bank as their sole banker. As a secondary measure, we capture the duration of all exclusive relationships of a bank for every year by calculating how long these

[3] A detailed list of the fintech related documents is provided in the appendix
[4] The entire list of fintech keywords is provided in the appendix

exclusive relationships last. For robustness we calculate an alternate measure of total exclusive relationships, where we only count a relationship as exclusive when it has lasted at least a year i.e., if the bank has been listed as the sole banker at least for two consecutive years (definition 2). Additionally, we calculate total exclusive relationship to total bank relationships in a year using definition 1 and 2 of exclusive relationships.

4.3 Control Variables

Following the literature on the relationship between technological development and relationship lending (Gangopadhyay et al., 2022; Sedunov, 2017), we choose bank controls such as total asset size, total capital, return on assets of the bank and total number of bank branches. Bank size is documented to have a significant effect on whether banks employ relationship lending as a strategy (Berger et al., 2005). Smaller banks do more of relationship lending whereas larger banks do more of transactional lending. The number of bank branches may contribute to how well banks can nurture relationships. Total capital and return on assets indicate the overall health and profitability of the bank. Additionally, we include certain median firm level controls such as median firm size and median firm profitability which represent the exclusive clients of a bank for a year. We include these to control any firm specific factors which may affect the strength of the relationship. We also incorporate macroeconomic controls such as Gross Domestic Product (GDP) and Inflation. The variable definitions are provided in Table 1.

Table 1
Definition of the variables

Variable	Definitions
Dependant Variables	
Total Exclusive Relationships	Log of the total number of exclusive relationships of a bank for all its clients
Duration of Exclusive Relationships	Log of the duration(years) of all exclusive relationships of a bank in a year
Exclusive to Total	is Total exclusive relationships/Total relationships of the bank
Independent Variables	
Bank Fintech	Count of fintech keywords per 10,000 words of the annual report
Bank AI	Count of AI keywords per 10,000 words of the annual report
Bank Size	Log of the total assets of the bank
Bank Capital	Log of the total capital of the bank
Return on Assets (ROA)	Ratio of bank net income to total assets

Bank Branches	Total number of bank branches
Median Firm Size	Log of the Median firm assets of the exclusive clients of a bank
Median Firm Profitability	Median firm profitability of the exclusive clients of a bank
Macroeconomic variables	
GDP	Growth of Real GDP (%)
Inflation	Inflation rate based on consumer price index (%)

5. Econometric Methodology

First, we study the relationship between bank fintech and relationship lending without a threshold which has the following specification:

$$Relationship\ Lending_{it} = \alpha_0 + \alpha_1 Bank\ Fintech_{it} + \alpha_2 Bank\ Controls + \alpha_4 Median\ Firm\ Controls + Macroeconomic\ Controls_t + Bank_i + Year_t + \varepsilon_{it}$$

Subscript i and t stand for bank and time. The relationship lending indicator is captured using total exclusive relationship and duration of exclusive relationships respectively. The bank fintech score is captured using textual analysis sourced from the annual reports of each bank. We have a vector of bank controls such as bank asset size, bank capital, number of bank branches and bank return on assets. The median firm controls are median firm asset size and median firm profitability. The macroeconomic controls are GDP (growth) and inflation (rate). We have both time and bank dummies to control for time effects as well as bank-specific effects.

We examine the non-linear association between bank fintech and relationship lending using the following specification:

$$Relationship\ Lending_{it} = \alpha_0 + \alpha_1 Bank\ Fintech_{it}(Relationship\ Lending_{it} \leq \gamma) + \alpha_2 Bank\ Fintech_{it}(Relationship\ Lending_{it} > \gamma) + \alpha_3 Bank\ Controls_{it} + \alpha_4 Median\ Firm\ Controls + Macroeconomic\ Controls_t + Bank_i + \varepsilon_{it}$$

The relationship lending variable splits the sample into two thresholds — one where the relationship lending variable is below the threshold ($Relationship\ Lending_{it} \leq \gamma$) and the other where the relationship lending variable is above the threshold ($Relationship\ Lending_{it} > \gamma$). γ is the threshold parameter. We use (Hansen, 1999)'s

threshold regression model with individual (bank) specific fixed effects to determine the existence of a threshold as well as the value of γ. The model endogenously determines the threshold by using the data provided.

In an alternate specification to control for potential endogeneity we use lagged values of the bank explanatory variables.

$$\begin{aligned} Relationship\ Lending_{it} \\ = \alpha_0 + \alpha_1 Bank\ Fintech_{it-1}(Relationship\ Lending_{it} \leq \gamma) \\ + \alpha_2 Bank\ Fintech_{it-1}(Relationship\ Lending_{it} \\ > \gamma) + \alpha_3 Bank\ Controls_{it-1} + \alpha_4 Median\ Firm\ Controls \\ + Macroeconomic\ Controls_t + Bank_i + \varepsilon_{it} \end{aligned}$$

6. Results

First, we discuss the results for the model without a threshold. Next, we introduce the results of the threshold regression model. Finally, to account for potential endogeneity, we present the results of the model with lagged explanatory variables.

Table 2 indicates the descriptive statistics of the variables in our model. An average Indian bank has a score of 62 exclusive relationships on average (definition 1) or 35 exclusive relationships (definition 2). The average return on assets is 0.7%. Table 3 indicates the year wise average fintech score for Indian banks. We can observe a steady increase in the fintech score through the years.

Table 2
Descriptive Statistics

Variable	Observations	Mean	Std. dev	Min	Max
Log of total exclusive relationships (definition 1)	294	3.46	1.151	0.693	6.263
Log of total exclusive relationships (definition 2)	294	2.911	1.163	0	5.565
Log of duration of exclusive relationships	294	4.720	1.21	1.386	7.494
Exclusive to total (definition 1)	294	0.115	0.075	0.024	0.529
Exclusive to total (definition 2)	294	0.07	0.053	0.009	0.438
Bank Fintech	294	1.609	0.703	0.389	4.711
Bank Size	294	14.55	1.187	11.435	17.727
Bank Capital	294	8.741	1.203	5.768	12.15

Bank Number of Branches	294	3149.918	3854.635	117	22620
Bank ROA	294	0.725	1.049	-5.39	2.92
Median Firm Assets	294	5.519	0.662	2.901	7.55
Median Firm Profitability	294	0.049	0.02	-0.004	0.112
GDP (growth)	294	6.049	3.571	-5.831	9.05
Inflation (rate)	294	6.947	2.741	3.328	11.989

Table 3
Average Fintech Score

Year	Average Fintech Score
2009	1.12
2010	1.021
2011	1.226
2012	1.144
2013	1.143
2014	1.259
2015	1.37
2016	1.684
2017	1.877
2018	1.96
2019	2.129
2020	2.033
2021	2.106
2022	2.454

6.1 Model without threshold

Table 3 indicates the results of non-threshold model. The coefficient of Bank Fintech score is statistically insignificant for both specifications of relationship lending. We can conclude that bank fintech is not significantly related to relationship lending when only a single regime is considered.

Table 4
Non-threshold regression

	Model 1	Model 2
	Exclusive Relationships	Duration of Relationships
Bank Fintech	-0.025	0.089

	(0.061)	(0.063)
Bank Size	1.038***	0.876***
	(0.164)	(0.297)
Bank Capital	-0.039	0.094
	(0.078)	(0.078)
Number of Bank Branches	-0.0001***	-0.0001***
	(0.00002)	(0.00002)
Bank ROA	-0.023	-0.047
	(0.025)	(0.041)
Median Firm Size	-0.205	-0.026
	(0.165)	(0.046)
Median Firm Profitability	4.133	2.361**
	(1.86)	(0.975)
GDP	-0.013	0.219**
	(0.114)	(0.103)
Inflation	0.137	0.175
	(0.098)	(0.102)
Constant	-10.863**	-11.767*
	(4.244)	(6.244)
FEs	Yes	Yes
R squared	0.754	0.628

*Notes: We have two measures of relationship lending: log of total exclusive bank relationships (Model 1) and duration of exclusive relationships (Model 2). Here the total exclusive relationships are calculated as per definition 1 of total exclusive relationships. We also add bank fixed effects and year fixed effects. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

6.2 Model with a single threshold and two regimes

Now we examine the model with a single threshold where the threshold is the log of the total exclusive relationships in Model 1 and 2 and the log of the duration of the relationship in model 3 and 4. For Model 1 and Model 2, the null hypothesis of no threshold is rejected at the 1% level. We see that when the threshold value of the total exclusive relationships is greater than 3.663, Bank Fintech score is positively and significantly associated with relationship lending. However, for models 1 and 2 we see a negative but insignificant relationship when the threshold of exclusive relationships is below 3.663. When the dependent variable is duration of the exclusive relationship (Model 3 and Model 4), the null hypothesis of no threshold is rejected

at the 1% level. Here along with a positive and significant effect of bank fintech on relationship lending when the duration indicator crosses the threshold, we also observe a negative and significant effect below the threshold. This implies that an increase in bank fintech is positively related to an increase in relationship lending after relationship lending has crossed a threshold and below the threshold, we see a decline in relationship lending

Interestingly, we see that bank size has a significant and positive association with both specifications of relationship lending which contrasts with the idea that small banks tend to favor relationship lending (Berger et al., 2005; Berger & Udell, 2002). Median firm assets of a bank's client show a negative and significant relationship with relationship lending which is in line with the conventional idea that smaller and more opaque firms engage in greater relationship lending. The median profitability of a bank's clients is positively associated with relationship lending indicating that profitable firms continue to engage in relationship banking. The number of bank branches is seen to have a negative relationship with relationship banking indicating than increasing the number of bank branches does not necessarily foster relationship lending.

Table 5
Panel threshold regression with total exclusive relationships and duration of exclusive relationships

		Model 1	Model 2	Model 3	Model 4
		Exclusive Relationships	Exclusive Relationships	Duration of Relationships	Duration of Relationships
Threshold		**3.663**	**3.663**	**3.044**	**3.044**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
Bank Fintech		-0.069	-0.069	-0.361***	-0.352***
		(0.079)	(0.081)	(0.098)	(0.096)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
Bank Fintech		0.241***	0.239***	0.08*	0.086**
		(0.065)	(0.065)	(0.041)	(0.039)
Bank Size		0.674***	0.663***	0.445***	0.494***
		(0.086)	(0.084)	(0.123)	(.146)
Bank Capital		-0.043	-0.036	-0.017	-0.22
		(0.055)	(0.057)	(0.036)	(0.036)

Number of Bank Branches	-0.0001***	-0.0001***	-0.00008***	-0.00008
	(0.00002)	(0.00002)	(0.000002)	(0.00002)
Bank ROA	-0.078***	-0.082***	-0.024	-0.035
	(0.036)	(0.031)	(0.032)	(0.031)
Median Firm Size	-0.182***	-0.18***	-0.032	-0.036
	(0.158)	(0.155)	(0.051)	(0.053)
Median Firm Profitability	3.015**	2.996**	2.308	2.32*
	(1.311)	(1.306)	(1.169)	(1.174)
GDP		0.007		0.0006
		(0.004)		(0.004)
Inflation		-0.005		0.144
		(0.016)		(0.012)
Constant	-4.786***	-4.691***	-1.342	-2.092
	(0.759)	(0.891)	(1.751)	(2.091)
R squared	0.584	0.586	0.649	0.653

*Notes: We have two measures of relationship lending: log of total exclusive bank relationships (Model 1 and 2) and log of duration of exclusive relationships (Model 2 and 3). Here the total exclusive relationships score is calculated as per definition 1. The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. Model 2 and Model 4 do not include the macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table 5 shows the results for the regression which incorporates lagged values of the bank explanatory values to account for possible endogeneity. Here we see similar results to Table 4, with the coefficients of Regime 2 in Table 5, higher in magnitude when compared to the coefficients of Regime 2 in Table 4. Bank size, number of bank branches and median firm profitability continue to have a significant relationship with measures of relationship lending.

Table 6
Panel threshold regression with lagged values of dependent variables

		Model 1	Model 2	Model 3	Model 4
		Exclusive Relationships	Exclusive Relationships	Duration of Relationships	Duration of Relationships
Threshold		**4.318**	**4.318**	**3.61**	**3.61**
	Regime 1 $(\boldsymbol{RL \leq \gamma})$				

Bank Fintech (t-1)		-0.063	-0.056	-0.139*	-0.143**
		(0.071)	(0.073)	(0.07)	(0.062)
	Regime 2 ($RL > \gamma$)				
Bank Fintech (t-1)		0.261***	0.27***	0.141**	0.145***
		(0.085)	(0.086)	(0.049)	(0.048)
Bank Size (t-1)		0.882***	0.823***	0.5***	0.583***
		(0.124)	(0.099)	(0.111)	(0.126)
Bank Capital (t-1)		-0.107**	-0.097*	-0.055	-0.072
		(0.042)	(0.049)	(0.048)	(0.045)
Number of Bank Branches (t-1)		-0.0001***	-0.0001***	-0.00009***	-0.00009***
		(0.00003)	(0.00003)	(0.00002)	(0.00002)
Bank ROA (t-1)		0.002	0.01	-0.005	-0.02
		(0.023)	(0.019)	(0.029)	(0.024)
Median Firm Size		-0.195	-0.189	-0.03	-0.039
		(0.164)	(0.16)	(0.04)	(0.041)
Median Firm Profitability		2.664*	2.719*	3.36***	3.245***
		(1.351)	(1.369)	(0.777)	(0.755)
GDP			0.001		0.005
			(0.005)		(0.003)
Inflation			-0.015		0.022**
			(0.016)		(0.009)
Constant		-7.015***	-6.203***	-1.875	-3.046
		(1.187)	(0.91)	(1.613)	(1.802)
R squared		0.60	0.604	0.652	0.664

*Notes: Here we use lagged values of all bank variables to control for potential endogeneity. Here the total exclusive relationships score is calculated as per definition 1 of total exclusive relationships. The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. Model 1 and Model 3 do not include macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

6.3 Robustness Tests

As a robustness measure, we modify the definition of what constitutes as an exclusive relationship, and we classify a relationship as exclusive only if a bank is listed as the sole banker for a firm for two consecutive years. In Table 6 we see that the threshold results in terms of significance and direction hold when compared to the earlier specifications. When the lagged explanatory variables are used (see Table 7) along with definition 2 of exclusive relationships, the coefficients of regime 2 though positive cease to be significant. As an additional robustness test, we use a different measure of relationship lending which is total exclusive relationships to total relationships of a bank which is calculated using both definitions of exclusive relationships. The results shown in Table 8 provide further support for our initial hypotheses. Bank fintech is positively associated with relationship lending after relationship lending crosses a threshold level.

Bank size continues to be positively related (Model 2) to relationship lending even after a number of exclusive relationships are scaled using total bank relationships (see Table 9). This indicates that larger Indian banks continue to employ relationship lending as a strategy.

Table 7
Panel threshold regression with an alternate definition of exclusive relationship

	Model 1 Exclusive Relationships	Model 2 Exclusive Relationships
Threshold	**1.09**	**1.09**
Regime 1 $(\boldsymbol{RL} \leq \boldsymbol{\gamma})$		
Bank Fintech	-0.577**	-0.579**
	(0.218)	(0.216)
Regime 2 $(\boldsymbol{RL} > \boldsymbol{\gamma})$		
Bank Fintech	0.129***	0.1333***
	(0.044)	(0.041)
Bank Size	0.612***	0.648***
	(0.112)	(.115)
Bank Capital	-0.149**	-0.155**
	(0.056)	(.057)
Number of Bank Branches	-0.0000919***	-0.00009***
	(0.000279)	(0.00003)
Bank ROA	-0.073	-0.079
	(0.04)	(0.038)

Median Firm Size	-0.207	-0.211
	(0.131)	-0.131
Median Firm Profitability	3.240	3.251
	(2.055)	(2.079)
GDP		-0.002
		(0.004)
Inflation		0.012
		(0.019)
Constant	-3.53**	-4.061***
	(1.282)	(1.374)
R squared	0.498	0.499

*Notes: Here a relationship is considered exclusive only if a firm reports a bank as its sole lender for two consecutive years (definition 2). The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table 8

Panel threshold regression with lagged values of bank explanatory variables

	Model 1 Exclusive Relationships	Model 2 Exclusive Relationships
Threshold	**1.09**	**1.09**
Regime 1 $(\boldsymbol{RL} \leq \boldsymbol{\gamma})$		
Bank Fintech (t-1)	-0.485***	-0.495***
	(0.143)	(0.151)
Regime 2 $(\boldsymbol{RL} > \boldsymbol{\gamma})$		
Bank Fintech (t-1)	0.085	0.079
	(0.162)	-0.056
Bank Size (t-1)	0.691***	0.713***
	(0.143)	(0.123)
Bank Capital (t-1)	-0.193***	-0.197***
	(0.043)	(0.046)
Number of Bank Branches (t-1)	-0.00008**	-0.00007**
	(0.00003)	(0.00003)
Bank ROA (t-1)	-0.141	-0.016
	(0.033)	(0.03)
Median Firm Size	-0.164	-0.167
	(0.146)	(0.145)
Median Firm Profitability	3.244	3.218
	(2.204)	(2.228)
GDP		-0.002
		(0.004)

Inflation		0.006
		(0.019)
Constant	-4.518***	-4.811***
	(1.554)	(1.30)
R squared	0.503	0.504

*Notes: Here we use lagged values of all bank variables to control for potential endogeneity. Here the total exclusive relationships are calculated as per definition 2 of total exclusive relationships. The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. Model 1 does not include macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table 9

Panel threshold with exclusive relationship to total relationships

		Model 1 Exclusive to Total	Model 2 Exclusive to Total	Model 3 Exclusive to Total	Model 4 Exclusive to Total
Threshold		**0.368**	**0.368**	**0.21**	**0.21**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
Bank Fintech		0.007	0.008*	0.006	0.007
		(0.004)	(0.087)	(0.004)	(0.004)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
Bank Fintech		0.135***	0.138***	0.099***	0.099***
		(0.007)	(0.006)	(0.005)	(0.005)
Bank Size		0.015	0.022**	-0.003	0.002
		(0.009)	(0.008)	(0.008)	(0.008)
Bank Capital		0.006	0.006	-0.002	-0.002
		(0.007)	(0.007)	(0.002)	(0.002)
Number of Bank Branches		-0.000004*	-0.000004*	-0.000002	-0.000002
			(0.000002)	(0.000002)	(0.000001)
Bank ROA		0.001	-0.001	-0.002	-0.003
		(0.001)	(0.002)	(0.001)	(0.002)
Median Firm Size		-0.015	-0.015	-0.008	-0.001
		0.011	(0.011)	(0.004)	(0.004)
Median Firm Profitability		0.294**	0.291**	0.196*	0.198**
		(0.134)	(0.134)	(0.096)	(0.094)
GDP			0.001**		-0.00001
			(0.0005)		(0.0003)
Inflation			0.002		0.002**
			(0.001)		(0.0007)

Constant	-0.086	-0.209*	0.125	0.047
	(0.120)	(0.102)	(0.094)	(0.094)
R squared	0.402	0.42	0.411	0.422

*Notes: Model 1 and Model 2 use definition 1 of exclusive relationship to calculate total exclusive relationships to total relationships whereas Model 3 and Model 4 use definition 2 of exclusive relationship to calculate total exclusive relationships to total relationships. RL stands for the respective relationship lending variable. Model 1 and Model 3 do not include macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

6.4 Artificial Intelligence and Relationship Lending

To understand the relationship between a specific kind of financial technology i.e., artificial intelligence, we replace the bank fintech score in our regression with the AI score. We calculate the score using the count of the word 'artificial intelligence' or 'AI' per 10000 words of the annual report. As an alternate measure, we expand the AI score using certain other keywords from our bank fintech keywords which captures artificial intelligence similar to Bian et al., (2024)[5]. For the non-threshold regression (see Table 10), we see that there is a positive and significant relationship between the AI score and relationship lending when relationship lending is captured by the total duration of exclusive relationships.

Table 10
Non-threshold regression

	Model 1	Model 2
	Exclusive Relationships	Duration of Relationships
AI Score	0.381	0.562**
	(0.305)	(0.221)
Bank Size	0.992***	0.843**
	(0.172)	(0.302)
Bank Capital	-0.038	0.085
	(0.073)	(0.072)
Bank Number of Branches	-0.00009***	-0.00009***
	(0.00003)	(0.00002)
Bank ROA	-0.025	-0.047
	(0.023)	(0.037)
Median Firm Size	-0.208	-0.023
	(0.169)	(0.045)

[5] The expanded AI Score keywords are provided in the Appendix within Exhibit A

Median Firm Profitability	4.217**	2.289**
	(1.958)	(0.979)
GDP	-0.016	0.175*
	(0.101)	(0.101)
Inflation	0.125	0.138
	(0.918)	(0.102)
Constant	-10.561**	-11.058*
	(4.108)	(6.270)
FEs	Yes	Yes
R squared	0.75	0.66

*Notes: We have two measures of relationship lending: log of total exclusive bank relationships (Model 1) and duration of exclusive relationships (Model 2). Here the total exclusive relationships are calculated as per definition 1 of total exclusive relationships. We add both bank fixed effects and year fixed effects. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table 11
Non-threshold regression

	Model 1	Model 2
	Exclusive Relationships	Duration of Relationships
AI Score Expanded	0.393	0.669**
	(0.347)	(0.256)
Bank Size	0.972***	0.80**
	(0.179)	(0.296)
Bank Capital	-0.038	.084
	(0.072)	(0.068)
Number of Bank Branches	-0.00009***	-0.00009***
	(0.00003)	(0.00003)
Bank ROA	-0.023	-0.044
	(0.023)	(0.034)
Median Firm Size	-0.209	-0.024
	(0.169)	(0.044)
Median Firm Profitability	4.209**	2.285**
	(1.951)	(0.949)
GDP	-0.02	0.166
	(0.1)	(0.098)
Inflation	0.121	0.127

	(0.091)	(0.099)
Constant	-10.221**	-10.397
	(4.125)	(6.108)
FEs	Yes	Yes
R squared	0.75	0.65

*Notes: We have two measures of relationship lending: log of total exclusive bank relationships (Model 1) and duration of exclusive relationships (Model 2). Here the total exclusive relationships are calculated as per definition 1 of total exclusive relationships. We use the expanded version of the AI Score in this specification. We add both bank fixed effects and year fixed effects. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

The non-threshold regression shows a significant and positive relationship between the AI score and relationship lending when relationship lending is captured by the total age of the exclusive relationships. Table 12 shows the results for AI Score using a panel threshold regression. Similar to the relationship between bank fintech and relationship lending, the association between the AI Score and relationship lending becomes stronger after a threshold. An interesting point of difference is that under the threshold, bank fintech and relationship lending exhibit a negative relationship under certain specifications, whereas AI technology and relationship lending does not seem to exhibit this. We can infer that the use of AI can be complementary to relationship lending even for banks at lower levels of relationship lending. This relationship holds when we expand the AI score to include other words which are representative of AI technology (see Table 13). Tables 14 and 15 repeat the exercises with lagged independent variables. The tables in the Appendix report additional specifications for the relationship between AI score and relationship lending based on definition 2 of exclusive relationships, it's lags as well exclusive to total relationships.

Table 12
Panel threshold regression with non-expanded AI score

		Model 1	Model 2
		Exclusive Relationships	Duration of Relationships
Threshold		**3.663**	3.044
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)		
AI Score		0.338	-0.142
		(0.286)	(0.215)
	Regime 2 ($\boldsymbol{RL > \gamma}$)		

AI Score	1.016***	0.542***
	(0.219)	0.156
Bank Size	0.595***	0.511***
	(0.087)	(0.135)
Bank Capital	-0.039	-0.015
	(0.061)	(0.035)
Number of Bank Branches	-0.00007***	-0.00007**
	(0.00002)	(0.00002)
Bank ROA	-0.089**	-0.044
	(0.034)	(0.029)
Median Firm Size	-0.127	-0.034
	(0.133)	(0.042)
Median Firm Profitability	2.691**	2.317*
	(1.25)	(1.176)
GDP	0.007*	0.0008
	(0.003)	(0.003)
Inflation	-0.01	0.013
	(0.013)	(0.012)
Constant	-4.626***	-2.873
	(0.98)	(1.955)
R squared	0.64	0.66

*Notes: We have two measures of relationship lending: log of total exclusive bank relationships and log of duration of exclusive relationships (Model 1 and 2). Here the total exclusive relationships score is calculated as per definition 1. The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. We use the non-expanded AI score as the independent variable. Model 2 and Model 4 do not include the macroeconomic controls. We report robust standard error. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table 13
Panel threshold regression with expanded AI score

	Model 1	Model 2
	Exclusive Relationships	Duration of Relationships
Threshold	**3.663**	**3.045**

	Regime 1 $(\boldsymbol{RL} \leq \boldsymbol{\gamma})$		
AI Score		0.301	-0.035
		(0.328)	(0.218)
	Regime 2 $(\boldsymbol{RL} > \boldsymbol{\gamma})$		
AI Score 1		0.948***	0.623***
		(0.247)	(0.182)
Bank Size		0.582***	0.491***
		(0.085)	(0.132)
Bank Capital		-0.034	-0.011
		(0.061)	(0.132)
Number of Bank Branches		-0.00007***	-0.00006**
		(0.00002)	(0.00002)
Bank ROA		-0.088**	-0.042
		(0.034)	(0.027)
Median Firm Size		-0.131	-0.035
		(0.135)	(0.041)
Median Firm Profitability		2.643**	2.305
		(1.224)	(1.147)
GDP		0.007**	0.0009
		(0.004)	(0.003)
Inflation		-0.009	0.012
		(0.013)	(0.011)
Constant		-4.445	-2.719
		(0.95)	1.908
R squared		0.64	0.67

*Notes: We have two measures of relationship lending: log of total exclusive bank relationships and log of duration of exclusive relationships (Model 1 and 2). Here the total exclusive relationships score is calculated as per definition 1. The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. We use the expanded AI score as the independent variable. Model 2 and Model 4 do not include the macroeconomic controls. We report robust standard error. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table 14
Panel threshold regression with lagged dependent variables – using non-expanded AI score

		Model 1 Exclusive Relationships	Model 2 Exclusive Relationships	Model 3 Duration of Relationships	Model 4 Duration of Relationships
Threshold		**4.22**	**4.22**	**3.61**	**3.61**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
AI Score (t-1)		0.241	0.296	0.094	0.014
		(0.348)	(0.338)	(0.159)	(0.185)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
AI Score (t-1)		0.945***	0.99***	0.584***	0.513***
		(0.293)	(0.287)	(0.128)	(0.152)
Bank Size (t-1)		0.838***	0.807***	0.502***	0.558***
		(0.092)	(0.087)	(0.105)	(0.127)
Bank Capital (t-1)		-0.134***	-0.128***	-0.056	-0.066
		(0.036)	(0.039)	(0.047)	(0.048)
Number of Bank Branches (t-1)		-0.00009***	-0.00009***	-0.00006**	-0.00006**
		(0.00002)	(0.00002)	(0.00002)	(0.00003)
Bank ROA (t-1)		0.014	0.0169	-0.02	-0.029
		(0.019)	(0.018)	(0.026)	(0.023)
Median Firm Size		-0.165	-0.161	-0.027	-0.032
		(0.145)	(0.144)	(0.03)	(0.031)
Median Firm Profitability		3.029**	3.027**	3.296***	3.252***
		(1.34)	(1.368)	(0.765)	(0.759)
GDP			0.003		0.003
			(0.004)		(0.003)
Inflation			-0.009		0.014
			(0.011)		(0.011)
Constant		-6.911***	-6.545***	-2.376	-3.083*
		(0.879)	(0.868)	(1.512)	(1.741)
R squared		0.65	0.65	0.66	0.66

*Notes: We have two measures of relationship lending: log of total exclusive bank relationships (Model 1 and 2) and log of duration of exclusive relationships (Model 3 and 4). Here the total exclusive relationships score is calculated as per definition 1. The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. We use the non-expanded AI score as the independent variable. Model 2 and Model 4 do not include the macroeconomic controls. The bank variables are in their lagged form. We report robust standard error. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table 15
Panel threshold regression with lagged dependent variables – using expanded AI score

		Model 1 Exclusive Relationships	Model 2 Exclusive Relationships	Model 3 Duration of Relationships	Model 4 Duration of Relationships
Threshold		**4.22**	**4.22**	**3.61**	**3.61**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
AI Score Expanded (t-1)		0.2562755	0.315	0.139	0.071
		(0.359)	(0.359)	(0.172)	(0.199)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
AI Score Expanded (t-1)		0.921***	0.968***	0.614***	0.555***
		(0.304)	(0.305)	(0.15)	(0.175)
Bank Size (t-1)		0.826***	0.793***	0.488***	0.541***
		(0.098)	(0.092)	(0.102)	(0.125)
Bank Capital (t-1)		-0.128***	-0.122***	-0.053	-0.062
		0.036	(0.039)	(0.046)	(0.047)
Number of Bank Branches (t-1)		-0.00009***	-0.00009***	-0.00006**	-0.00006**
		(0.00003)	(0.00002)	(0.00002)	(0.00003)
Bank ROA (t-1)		0.016	0.018	-0.017	-0.027
		(0.02)	(0.018)	(0.025)	(0.022)
Median Firm Size		-0.169	-0.166	-0.029	-0.034
		(0.146)	(0.146)	(0.03)	(0.031)
Median Firm Profitability		2.989**	2.98**	3.218***	3.172***
		(1.335)	(1.357)	(0.747)	(0.742)
GDP			0.003		0.003
			(0.004)		(0.003)
Inflation			-0.01		0.013
			(0.011)		(0.011)
Constant		-6.785***	-6.404***	-2.242	-2.919
		(0.912)	(0.868)	(1.469)	(1.713)
R squared		0.64	0.64	0.67	0.67

Notes: We have two measures of relationship lending: log of total exclusive bank relationships (Model 1 and 2) and log of duration of exclusive relationships (Model 3 and 4). Here the total exclusive relationships score is calculated as per definition 1. The threshold variables are the respective relationship lending measures. RL stands for the respective relationship lending variable. We use the expanded AI score as the independent variable. Model 2 and Model 4 do not include the macroeconomic controls. The bank variables are in

*their lagged form. We report robust standard error. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

7. Conclusion and Discussion

The empirical results in this paper indicate that when banks are at higher level of relationship lending, bank fintech development further strengthens relationship lending which is robust to various specifications of relationship lending. However, when banks are at a lower level of relationship lending or for those banks who might be transaction oriented, bank fintech may promote transactional lending at the expense of relationship lending. We see similar results when we test the association between AI and relationship banking. An additional insight is that the relationship between AI and relationship lending continues to be positive below the threshold. These results provide a contrasting view to the idea that growth in fintech happens at the expense of relationship lending. The findings of this paper indicate that bank fintech can help in strengthening relationship lending depending upon the threshold level of relationship lending at the bank. Banks can reap the benefits that fintech offers without losing what makes them unique. The notion that when banks face competition from external parties such as fintech companies, they respond by intensifying relationship lending can be extended. When banks themselves imbibe fintech, they can use the advances that fintech provides to intensify relationship lending.

These findings have significant implications for various stakeholders. Banks can employ fintech to gain deeper insights about their customers which helps create more personalized products with a goal of enhancing relationship lending. Also, if a bank identifies its own relationship orientation, it will help in fine-tuning the effect bank fintech has. For regulators, there is a need to support fintech growth within a strong regulatory framework. They need to ensure that the integration of fintech into a bank's ecosystem enhances transparency while ensuring security and compliance. Policymakers need to foster an ecosystem which is both collaborative and competitive for banks and fintech companies. Creating a level playing field for innovation will go a long way in promoting greater relationship lending, which would be beneficial for small and medium firms, that form the backbones of economies like India.

While the bank fintech score is important for indicating a bank's technological prowess especially in newer technologies, it may not be able to exactly capture adoption. Data on actual fintech investment at a bank level would highly enhance studies in this area.

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Appendix

Table A.1
Panel threshold regression with alternate definition of exclusive relationships

		Model 1 Exclusive Relationships	Model 2 Exclusive Relationships	Model 3 Exclusive Relationships	Model 4 Exclusive Relationships
Threshold		**2.64**	**2.64**	**2.64**	**2.64**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
AI Score /AI Score Expanded		0.429*	0.43*	0.444*	0.446*
		(0.207)	(0.211)	(0.256)	(0.258)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
AI Score/AI Score Expanded		1.096***	1.098***	1.072***	1.075***
		(0.171)	(0.178)	(0.211)	(0.215)
Bank Size		0.523***	0.515***	0.504***	-0.094***
		(0.089)	(0.079)	(0.09)	(0.045)
Bank Capital		-0.098***	-0.099**	-0.093**	-0.094**
		(0.043)	(0.045)	(0.043)	(0.045)
Number of Bank Branches		-0.00007***	-0.00007***	-0.00007***	-0.00007***
		(0.00002)	(0.00002)	(0.00002)	(0.00002)
Bank ROA		-0.079**	-0.075**	-0.074**	-0.071**
		(0.033)	(0.031)	(0.033)	(0.031)
Median Firm Size		-0.023	-0.023	-0.028	-0.028
		(0.152)	(0.152)	(0.152)	(0.152)
Median Firm Profitability		3.209**	3.216**	3.168*	3.175*
		(1.526)	(1.523)	(1.526)	(1.524)
GDP			-0.002		-0.002
			(0.004)		(0.004)
Inflation			-0.002		-0.002
			(0.017)		(0.017)
Constant		-4.442***	-4.309***	-4.217***	-4.083***
		(0.74)	(0.662)	(0.709)	(0.654)
R squared		0.53	0.53	0.53	0.53

*Notes: Models 1 and 2 use the non-expanded AI Score as the independent variable. Model 3 and 4 use the expanded AI score as the independent variable. All four specifications use Definition 2 of exclusive relationships as the dependent variable. Model 1 and Model 3 do not include macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table A.2
Panel threshold regression with alternate definition of exclusive relationships – with lagged bank variables

		Model 1	Model 2	Model 3	Model 4
		Exclusive Relationships	Exclusive Relationships	Exclusive Relationships	Exclusive Relationships
Threshold		**2.89**	**2.89**	**1.09**	**1.09**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
AI Score /AI Score Expanded (t-1)		0.149	0.155	-0.315	-0.352
		(0.274)	(0.263)	(0.564)	(0.57)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
AI Score/AI Score Expanded (t-1)		0.856***	0.862***	0.585	0.557
		(0.206)	(0.195)	(0.492)	(0.483)
Bank Size (t-1)		0.589***	0.583***	0.715***	0.735***
		(0.087)	(0.081)	(0.137)	(0.118)
Bank Capital (t-1)		-0.123**	-0.122**	-0.189***	-0.193
		(0.048)	(0.051)	(0.04)	(0.043)
Number of Bank Branches (t-1)		-0.00009***	-0.00009***	-0.00007**	-0.00007**
		(0.00002)	(0.00002)	(0.00003)	(0.00003)
Bank ROA (t-1)		-0.052	-0.051	-0.017	-0.018
		(0.039)	(0.04)	(0.03)	(0.027)
Median Firm Size		-0.017	-0.016	-0.183	-0.186
		(0.140)	(0.14)	(0.141)	(0.14)
Median Firm Profitability		2.912*	2.919*	3.219	3.227
		(1.429)	(1.445)	(2.134)	(2.159)
GDP			-0.0001		-0.003
			(0.005)		(0.004)
Inflation			-0.002		0.006
			(0.016)		(0.018)
Constant		-4.817***	-4.729***	-5.301***	-5.535***
		0.893	(0.896)	(1.329)	1.118
R squared		0.56	0.56	0.53	0.53

Notes: Models 1 and 2 use the non-expanded AI Score as the independent variable. Model 3 and 4 use the expanded AI score as the independent variable. All four specifications use

*Definition 2 of exclusive relationships as the dependent variable. The bank independent variables are in their lagged form. Model 1 and Model 3 do not include macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table A.3
Panel threshold regression with non-expanded AI score and exclusive relationships to total

		Model 1	Model 2	Model 3	Model 4
		Exclusive to Total	Exclusive to Total	Exclusive to Total	Exclusive to Total
Threshold		**0.28**	**0.28**	**0.21**	**0.21**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
AI Score		0.043*	0.04*	0.029**	0.026*
		(0.021)	(0.02)	(0.012)	(0.013)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
AI Score		0.195***	0.192***	0.163***	0.159***
		(0.027)	(0.024)	(0.015)	(0.015)
Bank Size		0.011	0.015*	0.002	0.006
		(0.01)	(0.008)	(0.005)	(0.005)
Bank Capital		0.001	0.0008	-0.001	-0.002
		(0.003)	(0.003)	(0.002)	(0.002)
Number of Bank Branches		-0.000002	-0.000002	-0.000002*	-0.000002*
		(0.000003)	(0.000003)	(0.000001)	(0.000001)
Bank ROA		-0.001	-0.002	-0.002	-0.003*
		(0.002)	(0.002)	(0.001)	(0.001)
Median Firm Size		-0.008	-0.009	-0.00003	-0.0003
		(0.009)	(0.009)	(0.004)	(0.004)
Median Firm Profitability		0.373**	0.372**	0.185*	0.185*
		(0.147)	(0.148)	(0.105)	(0.104)
GDP			0.0001		-0.00007
			(0.0005)		(0.0003)
Inflation			0.001		0.001
			(0.001)		(0.0008)
Constant		-0.072	-0.136	0.021	-0.033
		(0.095)	(0.097)	(0.052)	0.055
R squared		0.52	0.52	0.45	0.45

Notes: Model 1 and Model 2 use definition 1 of exclusive relationship to calculate total exclusive relationships to total relationships whereas Model 3 and Model 4 use definition 2 of exclusive relationship to calculate total exclusive relationships to total relationships. We use

*the non-expanded AI Score as the independent variable. Model 1 and Model 3 do not include macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table A.4
Panel Threshold Regression with expanded AI score and exclusive relationships to total

		Model 1	Model 2	Model 3	Model 4
		Exclusive to Total	Exclusive to Total	Exclusive to Total	Exclusive to Total
Threshold		**0.28**	**0.28**	**0.21**	**0.21**
	Regime 1 ($\boldsymbol{RL \leq \gamma}$)				
AI Score Expanded		0.035	0.032	0.027**	0.024*
		(0.023)	(0.022)	(0.012)	(0.013)
	Regime 2 ($\boldsymbol{RL > \gamma}$)				
AI Score Expanded		0.183***	0.179***	0.156***	0.152***
		(0.027)	(0.024)	(0.014)	(0.014)
Bank Size		0.01	0.015	0.001	0.005
		(0.01)	(0.009)	(0.005)	(0.005)
Bank Capital		0.001	0.001	-0.001	-0.002
		(0.003)	(0.003)	(0.002)	(0.002)
Number of Bank Branches		-0.000001	-0.000002	-0.000002	-0.000002
		(0.000002)	(0.000003)	(0.000001)	(0.000001)
Bank ROA		-0.001	-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.001)	(0.001)
Median Firm Size		-0.009	-0.009	-0.0001	-0.0004
		(0.009)	(0.009)	(0.004)	(0.004)
Median Firm Profitability		0.373**	0.372**	0.184*	0.185*
		(0.147)	(0.149)	(0.104)	(0.103)
GDP			0.0001		-0.00008
			(0.0005)		(0.0003)
Inflation			0.001		0.001
			(0.001)		(0.0008)
Constant		-0.054	-0.121	0.032	-0.023
		(0.096)	(0.097)	(0.052)	0.056
R squared		0.51	0.51	0.44	0.45

Notes: Model 1 and Model 2 use definition 1 of exclusive relationship to calculate total exclusive relationships to total relationships whereas Model 3 and Model 4 use definition 2 of exclusive relationship to calculate total exclusive relationships to total relationships. We use

*the expanded AI Score as the independent variable. Model 1 and Model 3 do not include macroeconomic controls. We report robust standard errors. *** p value < 0.01, ** p value <0.05, * p value < 0.1*

Table A.5
Documents which make up the fintech related repository

Name of Document	Year	Source
Report on the working group of fintech and digital lending	2017	RBI
Report on the working group of digital lending including online platforms and mobile apps	2021	RBI
India Fintech Report, the winds of change	2022	Ernst & Young
Unleashing the potential of fintech in banking	2017	Ernst & Young
The Indian Payments Handbook	2023	PricewaterhouseCoopers
India Fintech Report	2022	Bain & Company

Exhibit A

Fintech Keywords:
'AI', 'Algorithm', 'Analytics', 'API', 'Automation', 'Bigtech', 'Biometric', 'Bitcoin', 'Blockchain', 'CBDC', 'Chatbots', 'Computing', 'Cryptocurrencies', 'Digitalisation', 'Digitisation','Digital', 'Fintech', 'Hackathons', 'Innovation', 'Insurtech', 'Interfaces', 'Internet', 'IOT', 'Ledger', 'Metaverse', 'Mobile', 'Neobank', 'Network', 'OTP', 'Paytech', 'RegTech', 'Cloud', 'Robotics', 'Robot', 'Sandboxes', 'Stack', 'Online', 'Technology', 'Tokenisation', 'UPI', 'Wealthtech', 'Wallet', 'Account Aggregator', 'Artificial Intelligence', 'Big Data', 'Blockchain Technology', 'Cards Upi', 'Data Analytics', 'Digital Adoption', 'Digital Banking', 'Digital Lending', 'Digital Payment', 'Digital Transactions', 'Distributed Ledger', 'Emerging Technologies', 'Growth Digital Payments', 'Information Technology', 'Innovation Hub', 'Interface Upi', 'Ledger Technology', 'Machine Learning', 'Mobile Banking', 'Online Payments', 'Open Banking', 'Payment Infrastructure', 'Regulatory Sandbox', 'Technological Innovation', 'Upi Payments', 'Cloud Computing', 'Data Mining', 'Cloud Technology', 'Data Layer'

AI Keywords:
AI', 'Artificial Intelligence', 'Biometric',' Chatbots', 'Robotics', 'Robot', 'Machine Learning'