Shadow Banks on the Rise: Evidence Across Market Segments*

Kim Fe Cramer† Pulak Ghosh‡ Nirupama Kulkarni§ Nishant Vats¶

Abstract

This paper uses credit bureau data on 648 million retail loans in India to examine the comparative advantages of shadow banks across market segments. Using weather shocks as a proxy for credit demand, we show that Fintechs respond more in uncollateralized markets. In contrast, non-Fintech shadow banks exhibit stronger responsiveness in collateralized markets. Exploiting geographic heterogeneity in the adoption of digital payments, we identify technology as the key advantage for Fintechs. Leveraging four natural experiments, we document the significance of lower regulation for non-Fintech shadow banks. Our results suggest that the comparative advantage of shadow banks differs across market segments.

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†London School of Economics, Email: k.f.cramer@lse.ac.uk

‡Indian Institute of Management Bangalore, Email: pulak.ghosh@iimb.ac.in

§CAFRAL, Reserve Bank of India, Email: nirupama.kulkarni@cafral.org.in

¶Olin Business School, Washington University at St Louis, Email: vats@wustl.edu

1 Introduction

A well-established hypothesis in financial economics posits that traditional banks have an informational monopoly over opaque borrowers. This information is borrower-specific, collected over repeated engagements, and difficult to transfer, making the borrower-lender relationship sticky. Despite the informational advantage that traditional banks hold, shadow banks – or non-deposit-taking financial institutions – that do not possess such soft information have experienced large growth over the past decade. This raises an important question: what comparative advantages enable shadow banks to capture market share?

Two theories have emerged regarding the rise of shadow banks. First, shadow banks might have a technological advantage, such as processing hard information to assess borrower credit risk and timely disbursal of credit (Fuster, Plosser, Schnabl, and Vickery, 2019). Second, shadow banks might have an advantage because they are less regulated than traditional banks (Irani, Iyer, Meisenzahl, and Peydro, 2021; Gopal and Schnabl, 2022). It is crucial to distinguish between these two explanations because they have different implications for consumer welfare and the long-term landscape of financial intermediation. If technology is the key factor, it could lead to an expansion of credit availability, greater consumer welfare, and a sustained growth of shadow banks. On the other hand, if lower regulation is the primary factor, consumer benefits may be limited, and shadow bank growth could decline as governments close regulatory gaps.

Since the seminal work of Buchak, Matvos, Piskorski, and Seru (2018), the comparative advantages of shadow banks have been primarily studied in the mortgage market after the financial crisis. This research emphasizes that the growth of shadow banks is driven largely by lower regulation, with technology playing a more modest role. While the mortgage market offers valuable insights, these may not be fully applicable to other market segments. Three characteristics of the mortgage market may lead to an overemphasis on regulatory advantages. First, the mortgage market is more heavily regulated than many other segments. Second, mortgages are collateralized loans, making technology to precisely assess risk less relevant. Third, mortgage loans involve long-term commitments, and the benefits of technology – such as convenience and speed – may even be more important in other market segments.

In this paper, we demonstrate that the comparative advantages of shadow banks differ across market segments. Specifically, we document that technology is the primary comparative advantage in uncollateralized markets, while lower regulation is the key comparative advantage in collateralized markets. This finding is important for two reasons. First, it suggests that the insights from mortgage markets are not directly applicable to other market segments. Second, it improves our understanding of the industrial organization of the credit market and its consequences for policy analysis and the real economy (Paravisini, Rappoport, and Schnabl, 2023; Buchak, Matvos, Piskorski, and Seru, 2024).

We utilize a novel and unique dataset on the universe of formal retail loans in India from TransUnion CIBIL, the country's largest credit bureau. This dataset is unique in its size, covering 648 million loans from 2016 to 2021. This is larger by a factor of eight compared to U.S. mortgage data and by a factor of more than a hundred compared to U.S. data on non-mortgage retail lending.

This data has three key advantages. First, we observe all lender types and can distinguish between Fintech shadow banks and non-Fintech shadow banks ("Nontechs"). Both lender types are subject to less stringent oversight, but Fintechs employ technology in their lending process.[1] Second, we observe all product types, ranging from secured or collateralized loans such as agricultural, gold, and vehicle loans to unsecured or uncollateralized loans such as business, consumption, and microfinance loans. This allows us to demonstrate that the primary factor driving shadow banks' comparative advantage varies by product type. In contrast, other studies often focus on a single product. Third, we observe a wide breadth of credit score types, which allows us to examine the borrower types that shadow banks cater to.

The ideal thought experiment to identify the comparative advantages of lenders involves examining their responses to demand shocks. Comparative advantage is a dynamic concept that assesses how different lenders can adapt their lending practices in response to changing market conditions. Simply comparing average differences in credit issuance among lender types is insufficient, as averages indicate lending patterns under existing conditions and may not reflect the challenges lenders face in reallocating resources. Therefore, a shift in lending in response to demand shocks is crucial to understanding their comparative advantages.

We identify credit demand shocks using weather shocks. Specifically, we utilize a geo-spatial measure of water balance, the Standardized Precipitation and Evapotranspiration Index (SPEI). We define a weather shock as a binary variable indicating a month in a ZIP code where the SPEI deviates from the historical distribution, following the approach outlined in Corno, Hildebrandt, and Voena (2020). We combine the weather shock observed at the year-month × ZIP level with the credit bureau data, which is at the level of year-month × ZIP × lender type × product type. A long-standing literature establishes the exogeneity of these weather shocks (Dell, Jones, and Olken, 2014) as well as the role of such events in increasing demand for credit (Cortés and Strahan, 2017).

We employ a differences-in-differences strategy. The coefficient of interest is the interaction term of the local weather shock with a lender-type indicator. Specifically, we capture the effect of the weather shock on the outcome variable for the Fintech and Nontech relative to traditional banks. The design allows us to incorporate three key sets of fixed effects. First, we include year-month × ZIP × product fixed effects, which control for local time-varying product-specific trends, local investment opportunity shocks, and local vulnerability and resilience to weather shocks. Second, we include ZIP

[1] Under Indian regulation, Fintechs and Nontechs are categorized as Non-Banking Financial Corporations (NBFCs).

$\times$ lender $\times$ product fixed effects, which control for all time-invariant characteristics that may cause a particular type of lender to offer a specific product in a given area. The two sets of fixed effects also control for non-random matching between lender types and ZIP codes by ensuring that the estimate of interest is identified using variation from within the same ZIP where Nontechs, Fintechs, and traditional banks operate. Third, we include year-month $\times$ lender $\times$ product fixed effects, which allows us to account for all time-varying shocks at the lender-product level. The key identifying assumption of the analysis is that the lending by shadow banks and traditional banks would have evolved similarly absent the demand shocks. We provide support for this assumption using a pre-trend analysis.

We begin by demonstrating that Fintechs show a substantially stronger response to demand shocks than other lender types. The response is economically meaningful and statistically significant. We document that Fintechs issue 1.55% more credit after weather shocks than traditional banks in the same year-month, the same ZIP code, and the same product category. This corresponds, in aggregate, to an effect of 3 million USD in a given month or 209 million USD during our study period. We benchmark these numbers against monthly household expenditures. For the median household, the relative increase in Fintech credit per borrower corresponds to 8% of monthly expenditure in urban areas and 12% of monthly expenditure in rural areas. The dynamic response indicates no pre-trends, suggesting that the assumption of parallel trends is likely to hold. We find that the relative increase in credit by Fintechs appears immediately after the shock and persists thereafter for at least the next five months.

We also observe an increase in credit issuance by Nontechs after weather shocks. Specifically, they extend 0.31% more credit compared to traditional lenders within the same year-month, ZIP code, and product category. Although Nontechs exceed traditional banks in credit disbursal, their response is less pronounced than that of Fintechs. This difference between Fintechs and Nontechs is both economically and statistically significant.

Next, we leverage the breadth of our data across product types to analyze how shadow banks' comparative advantage differs across collateralized and uncollateralized markets. This test is motivated by the observation that in collateralized markets, lower regulation may be the key factor driving the comparative advantage of shadow banks, as traditional banks face strong regulation. In contrast, technology might be the primary factor in uncollateralized markets, as without collateral, assessing borrowers' credit risk is more important. Our results suggest that Nontechs tend to respond more than traditional banks and Fintechs in collateralized markets (1.53%), while Fintechs respond stronger than traditional banks and Nontechs in uncollateralized markets (1.89%). This result suggests market segmentation in how shadow banks respond to demand shocks.

We document another dimension of the segmentation of shadow banks. We find that, following a demand shock, both Fintechs and Nontechs increase credit to borrowers with low credit scores and those new to credit. To highlight the importance of these borrower segments: 20% of the credit-eligible population in India is underserved due to low credit scores, and 50% is new-to-credit, accounting for a total of 572 million individuals (CIBIL Report, 2022). These borrowers are often subject to high levels of information asymmetry and excluded from traditional bank lending. This highlights the complementary role of shadow banks alongside traditional lenders. We document that this ex-ante risk does not translate into substantial ex-post risk, as measured by default rates.

Furthermore, we highlight additional ways in which shadow banks, particularly Fintechs, complement traditional banking. We document that Fintechs increase lending in regions with low presence of traditional banks and in regions where traditional banks experience lending constraints. Moreover, we show that Fintechs also complement informal risk-sharing. Utilizing Facebook data on social connections as a proxy for informal insurance, we find that Fintech lending is notably higher in areas with weak informal insurance. Finally, we document that Fintechs do not accumulate excess defaults due to their complementary role, suggesting they can effectively address gaps left by traditional banks and informal lending arrangements without increasing risk.

Next, we examine the reasons behind the comparative advantages of shadow banks in certain market segments. We begin by documenting that technology plays a key role in the comparative advantage of Fintechs. To this end, we exploit geographic variation in the adoption of India's zero-cost digital payment infrastructure, the Unified Payment Interface (UPI), which facilitates cashless transactions. Specifically, UPI allows customers applying for loans to share detailed and verifiable transaction data, which technologically proficient lenders can use to assess borrowers' risk.

However, directly using UPI transaction data may be prone to endogeneity concerns, as unobservable common factors may drive both cashless transactions and Fintech lending. To mitigate this, we construct a UPI index that captures quasi-random geographic variation in UPI-based digital transaction adoption based on insights presented in Dubey and Purnanandam (2023) and recently employed in Alok, Ghosh, Kulkarni, and Puri (2024). The key idea of the index is to leverage the fact that certain banks adopted UPI early, and these early adopters' geographic footprint leads to geographic variation in the adoption of UPI. While UPI adoption may be endogenous at the bank level, we document that the UPI index is uncorrelated with several ZIP characteristics conditional on district fixed effects. We also verify that the index predicts UPI transactions.

Sorting ZIP codes by the UPI index, we observe that the estimate of the interaction term of Fintech and weather shock monotonically increases as we move from the first (0.65%) to the fourth quartile (2.32%). Notably, this effect is primarily driven by the uncollateralized lending segment. This result suggests that the ability of Fintechs to respond to demand shocks increases with the adoption of cashless transactions, indicating that the technological advantage of Fintechs may be a key factor driving their comparative advantage. In contrast, we do not observe a similar trend for Nontechs.

To provide further evidence supporting the technological advantage of Fintechs, we analyze application-level data from a major Indian Fintech specializing in small business lending. This company assigns standardized scores to applicants based on their digital transactions. We find that these scores correlate positively with higher loan acceptance rates and quicker loan disbursements following weather shocks, especially for new-to-credit borrowers.

Next, we investigate whether shadow banks have an advantage relative to other lenders due to lower regulatory restrictions. To this end, we exploit two natural experiments that generate variation in regulation between shadow banks and traditional banks. First, we exploit a change in regulation issued by the Reserve Bank of India in November 2023, which raised the risk weight for MFI loans issued by traditional banks, while the MFI loans made by shadow banks were exempt from this change. If the regulatory advantage is key, we would expect an increase in MFI lending, especially for Fintechs, which are more responsive in MFI lending. However, we find that the response of Fintechs to the regulation is economically small and statistically insignificant. This suggests that Fintechs are not responding more strongly to demand shocks due to the less stringent regulatory environment.

Second, we exploit the August 2020 regulatory change by the Reserve Bank of India that increased the maximum permissible loan-to-value (LTV) ratio requirements for gold loans by traditional banks while leaving the LTV requirements for gold loans issued by shadow banks unchanged. If the regulatory advantage is critical, we would expect a decrease in gold lending by shadow banks, particularly for Nontechs, which are more responsive in this lending category. We find that Nontechs decrease their gold lending after the regulatory shock, suggesting that the regulatory environment is a key factor shaping Nontechs' response.

We further examine if the technological or regulatory advantage of shadow banks can increase their funding, allowing them to absorb credit demand shocks. In particular, shadow banks may have access to better investment opportunities due to the technological or regulatory advantage, attracting funding from traditional banks (Acharya, Khandwala, and Öncü, 2013; Jiang, Matvos, Piskorski, and Seru, 2020; Jiang, 2023; Acharya, Gopal, Jager, and Steffen, 2024; Acharya, Cetorelli, and Tuckman, 2024; Bhardwaj and Javadekar, 2024).

To investigate this, we leverage two natural experiments. First, we employ the regulatory change in November 2023 that raised the risk weight for bank loans to shadow banks, except for loans designated for lending to special sectors, known as priority sector lending. This change led to an increase in bank lending to shadow banks focused on priority sectors, particularly benefiting Nontechs that are more responsive in agricultural lending. We find that Nontechs increased their agricultural lending in response to weather shocks following this regulatory change.

Second, we exploit a non-regulatory shock impacting bank lending to shadow banks – the unexpected collapse of the Infrastructure Leasing & Financial Services (IL&FS) group, a major shadow bank in India. This incident sent shock waves through the market regarding the safety of shadow banks, and banks reduced their lending to shadow banks substantially (Bhardwaj and Javadekar, 2024). We exploit this non-regulatory funding shock and document that the response of Nontechs to demand shocks decreases following the IL&FS crisis. In contrast, we find no significant impact on Fintechs' responses to these demand shocks due to the IL&FS crisis.

Our results indicate that bank funding plays an important role in Nontechs' ability to respond to demand shocks. However, these shocks do not appear to affect the response of Fintechs. Therefore, these results suggest that one reason banks may extend credit to shadow banks is the relatively lenient regulatory environment that Nontechs operate under.

Concluding our analysis on comparative advantages, we explore why Fintechs seem to underutilize their comparative advantages in collateralized markets, despite operating under less stringent regulation. We posit that in collateralized markets, the presence of a local office is crucial, as it facilitates effective inspection and seizure of collateral. A key distinguishing feature of Fintechs is that they primarily function through online platforms, which inhibit their ability to inspect and seize collateral, thereby creating a significant operational constraint. Consistent with this argument, we find that the increase in Nontech lending after demand shocks is concentrated in areas where they have a local presence.

Lastly, we document that the increase in shadow bank credit in response to demand shocks correlates with the muted impact of these weather shocks on local economic activity. This result suggests that shadow banks can smooth fluctuations in economic activity.

We present a battery of robustness tests. A potential threat to our analysis is that weather shocks could adversely impact bank capital, resulting in a decrease in lending by traditional banks. This decline could, in turn, cause the positive relative coefficients observed for shadow banks. We confirm that a decline in lending from traditional banks does not drive our results. Additionally, we find that our weather shocks do not exhibit temporal persistence or spatial correlation, indicating that they act as idiosyncratic shocks. Our findings remain consistent across various regression specifications and definitions of weather shocks. Finally, we conduct a placebo test to demonstrate that our results are unlikely to be spurious.

The key contribution of this paper is documenting that comparative advantages driving shadow bank growth differ across market segments. We present two new findings: First, the rise of Nontech shadow banks in the collateralized market may be driven by lower regulation. Second, the growth of Fintech shadow banks in the uncollateralized market may be attributed to their technological expertise. Prior literature that examines the reasons behind the rise of shadow banks has almost exclusively focused on mortgage markets and collateralized business lending.[2] This focus of the literature on

[2]See Berger (2003), Buchak, Matvos, Piskorski, and Seru (2018), Fuster, Plosser, Schnabl, and Vickery (2019), Irani, Iyer, Meisenzahl, and Peydro (2021), Gopal and Schnabl (2022), Chernenko, Erel, and Prilmeier (2022), Lee, Lee, and Paluszynski (2024), and Erel and Inozemtsev (2024), among others. We direct readers to Philippon (2016), Adrian, Ashcraft, Breuer, and Cetorelli (2018), Vives (2019),

specific products has primarily been driven by data availability. In contrast, our data uniquely equips us to distinguish between technology and regulation for the first time across different dimensions, including product types, credit scores, and geography. Therefore, to the best of our knowledge, we are the first to examine the role of regulation and technology across products and document the differences in their relative importance across these market segments. Examining the effect across market segments is crucial, as noted by Paravisini, Rappoport, and Schnabl (2023) and Buchak, Matvos, Piskorski, and Seru (2024), who argue that a complete policy analysis must incorporate the industrial organization of the credit markets. Our findings on funding are important for understanding the boundaries between shadow banks and traditional banks as well as the way regulatory differences create closer ties between them (Acharya, Schnabl, and Suarez, 2013; Acharya, Cetorelli, and Tuckman, 2024). Lastly, our finding that shadow banks can fill the gaps left by traditional banks and informal lending arrangements contributes to a literature that discusses the complementary role of shadow banks in the context of borrower types (Tang, 2019; De Roure, Pelizzon, and Thakor, 2022; Gopal and Schnabl, 2022).

This paper also speaks to the literature on financial intermediation and climate. Prior work has focused on the mortgage market, generally finding an increase in credit following natural disasters.[3] Other studies have focused on agricultural credit by traditional banks or microfinance institutions (Albert, Bustos, and Ponticelli, 2021; Rajan and Ramcharan, 2023; Lane, 2024). We add to this literature by documenting the role of shadow banks in mitigating the effects of weather shocks, in a highly relevant context of emerging economies, which are more vulnerable to climate change and are adopting technology at a fast pace.

Lastly, we contribute to the emerging literature on cashless transaction technology, which has examined the determinants of technology adoption and the subsequent effect on income, consumption, and production.[4] More recently, this literature has examined the effect of different digital transaction technologies on deposits, bank lending, and banking competition (Jiang, Yu, and Zhang, 2022; Whited, Wu, and Xiao, 2022; Dubey and Purnanandam, 2023; Koont, 2023; Sarkisyan, 2023; Babina, Bahaj, Buchak, De Marco, Foulis, Gornall, Mazzola, and Yu, 2024; Koont, Santos, and Zingales, 2024). We contribute to the literature by providing micro-evidence on how cashless payments affect credit market outcomes. Our analysis is based on credit bureau data, unlike previous studies focused on a single Fintech (Ouyang, 2021; Ghosh, Vallee, and Zeng, 2022). An exception is Alok, Ghosh, Kulkarni, and Puri (2024), who link UPI adoption to consumption loans. While this work focuses on one of the

Thakor (2020), Allen, Gu, and Jagtiani (2021), and Berg, Fuster, and Puri (2022) for a detailed review. Other studies have looked at a single lender, such as the P2P lending platform (Tang, 2019; Chava, Ganduri, Paradkar, and Zhang, 2021). Alternatively, studies rely on a random subset of credit bureau data but do not distinguish between types of shadow banks, as in Di Maggio and Yao (2021).

[3] See Morse (2011), Cortés (2014), Cortés and Strahan (2017), Kundu, Park, and Vats (2021), Allen, Shan, and Shen (2023), Collier, Hartley, Keys, and Ng (2024), and Collier, Howell, and Rendell (2024) among others. Qi, Li, and Sun (2021) use data from one P2P lender in the United States to show an increase in credit after earthquakes.

[4] See Jack and Suri (2014), Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020), Higgins (2022), Crouzet, Gupta, and Mezzanotti (2023), Dubey and Purnanandam (2023) and Agarwal, Ghosh, Li, and Ruan (2024) among others.

uncollateralized product categories in our sample, we take a comprehensive view to examine how the comparative advantage of shadow banks differs across market segments. Moreover, we trace the response of shadow banks to weather shocks, which allows us to examine the real effects and inform the theoretical literature on the welfare implications of cashless payments (Brunnermeier and Payne, 2022; Parlour, Rajan, and Zhu, 2022; Goldstein, Huang, and Yang, 2022; He, Huang, and Zhou, 2023).

This paper proceeds as follows. Section 2 describes the data. Section 3 provides background information on the credit markets in India and the summary statistics of the data. Section 4 discusses the relationship between weather shocks and credit demand. Section 5 delineates the empirical strategy. Sections 6 and 7 present the results. Section 8 concludes.

2 Data

2.1 Lender Types

The Indian lending landscape is divided into two broad types: traditional banks (including state-owned, private, and foreign banks) and shadow banks. Shadow banks are financial institutions that issue loans but do not provide demand deposits (RBI, 2021).[5] Furthermore, shadow banks are split into Fintechs and Nontechs. Fintechs are shadow banks that utilize technological innovations and have a digital-first approach to their lending business (RBI, 2017). In contrast, Nontechs are non-Fintech shadow banks that do not have a digital-first approach to their financial services.

2.2 Credit Bureau Data

We utilize a novel and unique dataset of 648 million loans, the universe of formal retail loans in India from 2016 to 2021. We obtain data from India's oldest credit bureau - TransUnion CIBIL.[6] The 2005 Credit Information Companies Regulation Act (CICRA) mandates all financial institutions to submit lending and repayment data to bureaus. Financial institutions submit monthly data on all new loans granted to credit bureaus. Almost all financial institutions report their data to CIBIL, and the bureau extensively cross-checks submissions for integrity (Mishra, Prabhala, and Rajan, 2022).

The data is recorded at a granular level of year-month $\times$ ZIP $\times$ lender type $\times$ product type. At this level, the data is further divided into credit score categories. We obtain this data from January 2016 until December 2021 for all ZIP codes, approximately 19 thousand. We observe three outcomes: the number of loans issued, the total loan amount issued, and the number of defaulted loans that were issued in this year-month $\times$ ZIP $\times$ lender $\times$ product. A loan is classified as defaulted once it reaches 90

[5] A very small fraction of shadow banks (49 compared to 9,467 in 2022) take non-demand deposits, such as term deposits that are locked in for a specific period.

[6] CIBIL or Credit Information Bureau (India) Limited is one of the four credit information companies in India and has partnered with American multinational firm TransUnion.

days past due (DPD) within one year of being issued. We define the default rate as the fraction of loans issued each month that have surpassed the 90 DPD mark within one year of issuance.

This data has three key advantages. First, we observe all lender types in the data. This allows us to distinguish between Fintech shadow banks ("Fintechs"), non-Fintech shadow banks ("Nontechs"), and traditional banks (state-owned, private, foreign, and other). We utilize the classification by the Credit Bureau, in contrast to other studies that rely on a manual lender classification.[7] The reader should note that while lender-type information is available, CIBIL does not provide individual lender identifiers in the data for data protection reasons.

Second, we observe all product types, ranging from collateralized loans such as loans for agriculture, loans backed by gold as collateral, and loans for vehicles, to unsecured loans such as loans to businesses, loans for consumption, and microfinance loans (MFI).[8] This allows us to investigate how the comparative advantage of shadow banks varies by product type. Prior work has focused on one specific product type, such as mortgages or collateralized business loans. Note that we observe mortgage loans in the data but do not include them in our sample because regulatory mandates governing shadow banks in housing markets (Housing Finance Companies) are very different from those of other shadow banks. Instead, to understand the secured loan market, we focus on agricultural, gold, and vehicle loans.

Third, we observe a wide range of credit score types. Our credit score categories encompass super-prime, prime-plus, prime, near-prime, sub-prime, and new-to-credit borrowers.[9] New-to-credit borrowers do not yet have a credit score; thus, lenders experience the highest information asymmetry for these borrowers. Our breadth of borrowers is wider than what researchers observe in the mortgage market, which often excludes individuals who have a very low or no credit score.

Finally, we complement our main dataset with the inquiry dataset from CIBIL to get a proxy of credit applications, following Jiménez, Ongena, Peydró, and Saurina (2014). In contrast to the loan issuance and default data, this information is available on the annual level - year $\times$ ZIP $\times$ lender $\times$ product. It is worth highlighting that not all loans are inquired. For instance, Mishra, Prabhala, and Rajan (2022) document that state-owned banks typically conduct fewer inquiries compared to private banks for loan applications from customers with an existing relationship. This characteristic is not exclusive to our study and is also observed in Jiménez, Ongena, Peydró, and Saurina (2014). Thus, inquiries are a proxy of credit applications but not a perfect measure.

[7] CIBIL classifies Fintechs based on their market expertise and whether lenders are members of industry bodies like the Fintech Association for Consumer Empowerment (FACE), Digital Lenders Association of India (DLAI), or Internet and Mobile Association of India (IAMAI).

[8] Loans to businesses in retail credit bureau data differ from those given to corporates. These loans are primarily unsecured and are typically extended to small businesses, such as small shops, hawkers, and street vendors. Microfinance loans are loans of a comparatively smaller amount, often with a shorter duration, higher repayment frequency, and higher interest rates. They are particularly targeted at low-income individuals (especially women) in rural areas. Borrowers typically have an annual household income of less than 300,000 rupees or 4,380 USD.

[9] Credit scores range from 300 to 900. The definitions for the different score buckets are — sub-prime (300 to 680), near-prime (681 to 730), prime (731 to 770), prime-plus (771 to 790), super-prime (791 and above), and new-to-credit (no credit score).

2.3 Local Weather Shocks

To obtain credit demand shocks, we rely on local weather shocks. These are based on the Standardized Precipitation and Evapotranspiration Index (SPEI) (Beguería, Serrano, Reig-Gracia, and Garcés, 2023). The construction of the SPEI is outlined in detail in Vicente-Serrano, Beguería, and López-Moreno (2010). Here, we provide a brief description of the index. The foundation of the SPEI is a measure of monthly water balance for a 0.5×0.5-degree area, with approximately four thousand squares in India. This water balance is calculated as the difference between precipitation and potential evapotranspiration. The latter describes the loss of water from the soil both by evaporation from the soil surface and by transpiration from the leaves of the plants growing on it. Potential evapotranspiration is also a function of temperature.

This monthly water balance measure closely follows a log-logistic distribution. An individual distribution is fitted for each month and geographic area. The parameters of these distributions are estimated using historical data for that specific month in a specific area, starting in 1901.[10] The next step is to make the measure comparable across months and geographical areas. For this purpose, the water balance measures are standardized, utilizing characteristics of their individual distributions. This results in the SPEI, which has an average value of zero and a standard deviation of one. A SPEI value of zero indicates no change in water balance relative to observed historical values for that month in that given area. An SPEI value greater than zero indicates a water surplus and, in extreme cases, a flood. An SPEI lower than zero indicates a water deficit and, in extreme cases, a drought.

To integrate the SPEI with the credit bureau data, we need to translate the 0.5×0.5-degree rectangles from the SPEI data to Indian ZIP codes. We calculate a weighted average of SPEI for each ZIP code, where the weights are the proportion of the area covered by each 0.5×0.5-degree rectangle within the ZIP code. Figure 1 presents the geographic distribution of the continuous SPEI measure across ZIP codes in December 2020 to provide an example. We use the ZIP code-level SPEI to construct our local weather shock variable. Our local weather shock is a binary variable that takes a value of one if the SPEI observation (at the year-month-ZIP level) is below the 20th or above the 80th percentile of its historical distribution in that ZIP code from January 2001 to December 2021.[11] This is motivated by the observation that extreme weather shocks can increase credit demand among businesses and households, see Section 4 for details. Our approach – including the choice of percentiles – follows a long-standing literature that investigates the impact of weather shocks in similar contexts (Jayachandran, 2006; Shah and Steinberg, 2017; Corno, Hildebrandt, and Voena, 2020). In contrast to

[10] For instance, to fit the distribution of March in a 0.5 x 0.5-degree area in Delhi, the historical water balance measures starting March 1901 from that location are utilized.

[11] We discuss the properties of these weather shocks in Section 5 and show that our results are robust to alternative shock definitions, such as employing a continuous water balance measure, in Section 6.8.

these papers, we utilize a water balance measure observed at a more granular level – monthly instead of annual, and ZIP code instead of district.

2.4 UPI Index

In addition to the credit bureau and local weather shocks datasets, we employ several other data sources to assess the role of technology in the comparative advantage of shadow banks. Specifically, we utilize the data on the Unified Payment Interface (UPI). Launched in 2016 and funded by the National Payments Corporation of India (NPCI), UPI is a no-cost, instant payment system that facilitates transactions between bank accounts. In 2022, India led the world in instant payments, accounting for 46% of global transactions (Business Wire, 2023).

Crucially, UPI enables customers applying for loans to share detailed transaction data with lenders, generating accessible and verifiable information that technologically proficient lenders can use. This data can inform various borrower metrics, including income, income volatility, and spending habits, offering insights beyond traditional lending relationships (Parlour, Rajan, and Zhu, 2022; Goldstein, Huang, and Yang, 2022; He, Huang, and Zhou, 2023).

We obtain monthly ZIP code-level data on UPI transaction volume and value from India's largest state-owned bank State Bank of India (SBI) from January 2017 to December 2019. However, using these transactions directly raises endogeneity concerns, as common factors may influence both the increase in cashless transactions and lending. To address this, we utilize a UPI Index, designed to predict UPI adoption while mitigating these identification concerns. This index is based on the approach initially proposed in Dubey and Purnanandam (2023) for creating a district-level index and later applied in Alok, Ghosh, Kulkarni, and Puri (2024) to develop a similar index at the ZIP code level.

The index exploits two key sources of variation: the timing of banks' participation in the UPI platform and its heterogeneous impact on consumer adoption of digital payments across different ZIP codes based on the geographic footprints of adopting banks. First, to fully utilize the UPI system, customers must link their bank accounts to a UPI application, making their bank's participation crucial for enabling digital transactions. Different banks joined the UPI platform at varying times, leading to disparities in customer access. Second, banks cater to distinct geographic areas, meaning that the timing of a dominant bank's UPI adoption can create regional differences in usage among its customers. Specifically, when a leading bank adopts UPI early, it increases the likelihood of widespread and persistent adoption in that area, both directly through early engagement of their depositors (Dubey and Purnanandam, 2023) and indirectly through network effects (Higgins, 2022; Crouzet, Gupta, and Mezzanotti, 2023).

The UPI index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. By construction, it thus ranges from zero to one and is a cross-sectional measure. Following Dubey and Purnanandam (2023), we define early adopters as banks that were providing UPI services as of November 2016.[12] Data on deposits is from the Basic Statistical Returns (BSR) database maintained by the RBI. The BSR is a comprehensive statistical database of branch-level data on deposits recorded at the end of every fiscal year. The UPI index is defined for ZIP codes with at least one bank branch. We use deposits measured as of March 2016 and create a deposit-weighted index of early adopter banks. Appendix Figure A.3a presents the spatial distribution of the UPI index.

$$\text{UPI Index}_z = \frac{\text{Total Deposits of Early Adopter Banks}_z}{\text{Total Deposit of all Banks}_z} \tag{1}$$

One might be concerned that the ZIP codes that have a high fraction of deposits of early adopter banks are special in two ways. First, specific ZIP code characteristics might drive the early adoption of banks. The decision to provide UPI services was made at the bank level – not the bank-ZIP level – and was driven by aggregate factors and adaptation by large peer banks rather than characteristics of individual ZIP codes. Second, early adapter banks might select into certain ZIP codes. We address this concern in our empirical strategy by including ZIP code × year-month fixed effects, which controls for potential endogeneity arising from the presence of early adopters in specific ZIP codes. Lastly, Section 7.1 documents that the UPI index generates quasi-random variation in the adoption of UPI-based digital transactions.

2.5 Fintech Micro Data

We collect detailed data from one of the largest Fintechs in India. The provider focuses on lending to small businesses. It is a financial technology company with a primary focus on streamlining digital payments and delivering financial services to merchants. Their business model is built on simplifying payment processes for small and medium-sized businesses (SMBs) by offering a comprehensive suite of services through their mobile app and QR code-based payment system. Through this system, merchants receive QR code stickers that customers can easily scan to complete transactions using a variety of digital payment methods, such as credit/debit cards, digital wallets, and other UPI powered applications. This approach eliminates the necessity for physical point-of-sale (POS) terminals, paving the way for seamless cashless transactions.

Moreover, the company extends merchant cash advance (MCA) loans to its partner merchants, leveraging their transaction history as a basis for offering quick funding without the need for collateral. This service aids merchants in managing their working capital requirements more effectively. We observe application-level information, including the date of application, the ZIP code of the applicant, the credit score (if available), and a proprietary score created by the Fintech based on digital transactions

[12] November 2016 is an important date in the history of digital transaction adoption in India due to the demonetization of outstanding paper currency. The adoption dates of UPI by banks are public information and can be accessed here.

done by the merchant. Additionally, we observe if the application was accepted, and conditional on acceptance, we observe days to disbursal of loan, interest rate, default rate, and loan amount issued.

2.6 Other Datasets

We employ multiple other datasets for supplementary analysis. We collect data on ZIP-level digital transactions conducted through YONO (You Only Need One), a State Bank of India payment service that does not allow data sharing among lenders, to conduct a falsification test for the UPI analysis. To evaluate whether shadow banks are complementing traditional banks, we examine detailed ZIP-level bank credit and deposit data and obtain measures of local bank presence and constraints. To assess whether shadow banks are complementing informal lending, we utilize Facebook data that proxies for social connections across areas. Finally, we employ ZIP-level nightlight luminosity to explore the impact of weather shocks on local economic activity and examine real effects. Appendix A.1 describes the details of these measures and respective datasets.

3 Summary Statistics

Table A.1 provides an overview of the Indian lending landscape. Nontechs were already established at the start of our sample. In 2016, they issued 25 million loans, amounting to 2.59 trillion rupees (38 billion USD), representing 33% of the market by loan count and 23% by loan amount. Over the sample period, Nontechs exhibited moderate growth; by 2021, they issued 44 million loans worth 3.14 trillion rupees (46 billion USD), capturing 41% of the market by loan count and 24% by loan amount.

In comparison, Fintech lenders were nascent in 2016 but experienced significant growth during the period. In 2016, Fintechs issued 76k loans totaling 22 billion rupees (316 million USD). By 2021, these figures had grown to 8.81 million loans, amounting to 228 billion rupees (3.32 billion USD). This corresponds to 8% of the market by loan count and 2% by loan amount. Over the sample period, traditional banks lost 16% of market share by loan count and 3% by loan amount.

Nontechs maintain a diverse portfolio spanning both collateralized and uncollateralized loans. In 2021, 58% of their loan amount was in collateralized products—agriculture (5%), gold (21%), and vehicles (32%)—with 33% in uncollateralized loans, including business (7%), consumption (25%), and microfinance (0.11%) loans. By contrast, Fintechs are concentrated in uncollateralized markets, with 86% of their loan portfolio in products such as business (19%) and consumption (67%) loans.

Both Nontechs and Fintechs primarily lend to prime and near-prime borrowers, accounting for 55% and 65% of their loan amounts, respectively. However, they also service sub-prime borrowers (12% for Nontechs; 7% for Fintechs) and new-to-credit borrowers (13% for Nontechs; 8% for Fintechs). Default rates for Nontechs and Fintechs are 5% and 8%, as opposed to 3% to 6% observed for traditional banks. The median loan sizes of Nontechs and Fintechs are 106k rupees (1,550 USD) and 21k rupees

(304 USD), respectively. Both are lower than the median loan size of traditional lenders, with 187k rupees (2,731 USD).

Appendix Tables A.2-A.5 highlight the granular structure of the data, which is recorded at the year-month × ZIP × lender × product level. The median number of loans in a given cell is six, corresponding to a median loan amount of 938k rupees (14k USD). On average, each cell contains 32 loans with a total loan amount of 4 million rupees (63k USD).

Appendix Table A.2 summarizes statistics by lender type. Appendix Table A.3 presents data by product type. Appendix Table A.4 categorizes statistics by lender type and credit score type, while Appendix Table A.5 organizes them by lender type and product type. Lastly, Appendix Figure A.2 presents the geographic distribution of lending by different lender types.

4 Weather Shocks and Credit Demand

This paper examines the comparative advantages of lender types across market segments. Simply comparing average differences among lender types is insufficient, as averages indicate static efficiency. Such a comparison represents lending patterns under existing conditions and not necessarily the challenges lenders face in reallocating resources. In contrast, comparative advantage is a dynamic concept that assesses how different lenders can adapt their lending practices in response to changing market conditions. At its essence, comparative advantage is tied to opportunity cost, which refers to the value of what is forgone when reallocating resources from producing one good to another. Specifically, lenders with the lowest opportunity cost for adjustments are better positioned to increase lending in response to demand shocks. Therefore, comparative advantage is revealed only when there is a shock, and a shift in lending in response to these shocks becomes a sufficient statistic to understand lenders' marginal opportunity costs and, consequently, their comparative advantages.

To identify credit demand shocks, we rely on local weather shocks. Using a Jordà (2005) projection that traces the effect of weather shocks on average nightlight luminosity over time, we document that weather shocks negatively affect local economic activity (see Appendix Figure B.1). Following Cortés and Strahan (2017), we argue that the negative effect of these shocks on local economic activity can increase credit demand. Specifically, we discuss the literature that establishes the relationship between weather shocks, local economic activity, and credit demand.

First, weather disturbances can disrupt the day-to-day operations of firms. These disruptions can increase their credit demand to meet working capital needs, via the effect on the labor force or consumer demand. Extreme rainfall and temperatures can increase absenteeism among workers and a heightened incidence of work-related injuries, leading to a decline in labor productivity (Graff Zivin and Neidell, 2014; Somanathan, Somanathan, Sudarshan, and Tewari, 2021; Filomena and Picchio, 2024). Similarly, extreme weather events can also deter consumers from engaging in outdoor activities, reducing consumer demand (Bas and Paunov, 2025). Therefore, firms' credit demand to meet working capital needs is likely to rise following these shocks, especially for product types such as agricultural, business, and microfinance loans.

Second, weather disturbances can result in a loss of income or and increase in expenditure of households, thereby increasing their credit demand to meet immediate liquidity needs. The reduction in income may occur due to a decline in labor supply or labor demand (Dell, Jones, and Olken, 2009). As noted earlier, extreme weather events can considerably make it difficult for workers to go to work an increase the incidence of work-related injuries. As a result, workers, especially those earning daily wages and those working non-contractual labor, may suffer a loss of income. Additionally, the negative effects of weather shocks on firms can reduce their labor demand. For instance, Acharya, Bhardwaj, and Tomunen (2023) document that firms respond to local weather shocks by reducing employment in the affected locations. Lastly, extreme weather conditions can increase household expenditure as food prices, rental prices, and healthcare costs increase under extreme weather conditions (BBC, 2020, 2022; Indian Express, 2023; Economic Times, 2023). This likely translates into an increase in credit demand for consumption loans, loans backed by gold as collateral, and microfinance loans.

5 Empirical Strategy

We employ a differences-in-differences (DID) estimation strategy to examine the lending response of Fintechs and Nontechs relative to traditional lenders following a weather shock using the specification outlined in Equation 2:

$$\begin{aligned} y_{ym,z,l,p} = {} & \beta \cdot \text{Shock}_{ym,z} \times \text{Fintech}_l + \gamma \cdot \text{Shock}_{ym,z} \times \text{Nontech}_l \\ & + \text{FE}_{ym,z,p} + \text{FE}_{z,l,p} + \text{FE}_{ym,l,p} + \epsilon_{ym,z,l,p} \end{aligned} \tag{2}$$

$y_{ym,z,l,p}$ refers to the outcome of interest, the natural logarithm of the loan amount, measured for the year-month (ym), ZIP code (z), lender-type (l), and product-type (p). $\text{Shock}_{ym,z}$ is an indicator variable that is one if the ZIP code experienced a weather shock in the given year-month and zero otherwise. Fintech_l is an indicator variable that is one if the lender is classified as Fintech and zero otherwise. Nontech_l is an indicator equal to one if the lender is a non-Fintech shadow bank and zero otherwise.

The coefficients of interest are β and γ, which capture the effect of weather shocks on the outcome variable for Fintechs and Nontechs relative to traditional lenders. We include granular fixed effects: year-month × ZIP × product fixed effects ($\text{FE}_{ym,z,p}$), ZIP × lender × product fixed effects ($\text{FE}_{z,l,p}$), and year-month × lender × product fixed effects ($\text{FE}_{ym,l,p}$). The standard errors are estimated by clustering at the ZIP level, as our shock variable exhibits heterogeneity at the ZIP level.

A key assumption of our analysis is that the credit demand shocks – proxied using weather events – are plausibly exogenous. A long literature establishes the exogeneity of shocks as constructed in this paper. Dell, Jones, and Olken (2014) conclude that by *"exploiting exogenous variation in weather outcomes over time within a given spatial area, these methods can causatively identify effects of temperature, precipitation, and windstorm variation"* (p. 741). We verify that these weather shocks exhibit a lack of temporal dynamics – with no clear trend – and a low spatial correlation, aligning with the characteristics of an idiosyncratic shock (see Appendix Figure A.1). Moreover, the year-month × ZIP × product fixed effect ($FE_{ym,z,p}$) incorporates the year-month × ZIP fixed effect, which controls for geographic clustering, local vulnerability, and resilience developed over time to weather shocks.

Equipped with the exogeneity of the shock, we need to address two potential threats to the identification of β and γ. First, Fintechs and Nontechs might react more strongly than traditional lenders because they specialize in products that experience a large increase in credit demand after weather shocks. For instance, a weather shock might induce extra demand for consumption loans, an important product category for Fintechs and Nontechs. We include year-month × ZIP × product fixed effect ($FE_{ym,z,p}$) to address this concern. This ensures that we are comparing the response of Fintechs or Nontechs to weather events with the response of traditional providers at the same time, within the same ZIP, and for the same product. Thus, we control for product-specific demand shocks that may be collinear with weather shocks. One can interpret this fixed effect ($FE_{ym,z,p}$) as directly controlling for time-varying local economic conditions and the aggregate investment opportunity set available to lenders in an area à la Drechsler, Savov, and Schnabl (2017).[13]

A second potential concern is the non-random matching between lender types and ZIP codes. In the presence of such non-random matching, the estimated average difference in the lending of shadow banks and traditional banks may not reflect their comparative advantages but rather differences in the geographic focus of these lender types. We address this issue in two ways. First, we include the ZIP × lender × product fixed effect ($FE_{z,l,p}$). This accounts for all geographic and other time-invariant characteristics that might cause a particular type of lender to offer a specific product in a given area. Additionally, the year-month × ZIP × product fixed effect ($FE_{ym,z,p}$) ensures that we are identifying the estimate using variation from an area where Fintechs, Nontechs, and traditional lenders operate, thereby abstracting away from the confounding factor of non-random matching of lender types to locations.[14]

Finally, the inclusion of the year-month × lender × product fixed effect ($FE_{ym,l,p}$) accounts for all time-varying shocks at the lender-product level. Thus, our fixed effects control for a wide set of confounding variables. Ultimately, we require the parallel trends assumption to hold. This ensures that the estimate is not influenced by pre-existing trends between Fintechs or Nontechs and traditional

[13] Vats (2020) and Kundu, Park, and Vats (2021), among others, also rely on a similar identification assumption.

[14] Such an identification strategy has been employed previously in Fracassi, Petry, and Tate (2016) and Kempf and Tsoutsoura (2021) to address the non-random matching between credit rating analysts and the firms they cover.

lenders. While this assumption is untestable, we will document parallel pre-trends in an event study analysis.[15]

6 Baseline Results

We begin our analysis by investigating the response of shadow banks to weather shocks, relative to traditional banks. Table 1 presents the results. Column 1 presents the results using the simplest specification examining the interaction term of shadow banks and shock. A takeaway from the results reported in Column 1 is that the variation in loan amounts can be partly attributed to the type of lender, the shock, and the interaction between the two. Specifically, these elements collectively account for 14% of the observed variation in loan amounts.

We sequentially add fixed effects from Columns 1 to 3, estimating our strictest specification in Column 3, which includes year-month × ZIP × product fixed effects, year-month × lender × product fixed effects, and ZIP × lender × product fixed effects. Our estimate of interest, the interaction term of shadow banks and shock, is consistently positive and statistically significant across all columns. This indicates that shadow banks increase credit relative to traditional banks following weather shocks. Our estimate based on the strictest specification indicates that shadow banks increase credit by 0.55% relative to traditional banks following weather shocks.

Furthermore, the magnitude of our key estimate remains relatively stable, even though the model R^2 increases significantly by 70 percentage points from Columns 1 to 3. Under the Oster (2019) framework, the stability of the magnitude of our estimate, despite a significant increase in the model's explanatory power, suggests that omitted variables are unlikely to account for our key findings. In fact, the increase in the magnitude of the estimate indicates that these omitted variables likely bias the estimate downwards.

Column 4 splits shadow banks into its two components – Fintech shadow banks and Nontech shadow banks – to estimate our baseline specification, presented in Equation 2. The coefficient of interest associated with the interaction terms of Fintech and Nontechs with Shock are both positive and statistically significant. Specifically, we find that Fintechs issue 1.55% more credit after weather shocks than traditional lenders in the same year-month, the same ZIP code, and the same product category. While Nontechs also exhibit an increase in credit after weather shocks, their response is muted relative to that of Fintechs. Specifically, they increase credit by 0.31%, and this effect is statistically different from the response of Fintechs.

[15] Baker, Larcker, and Wang (2022) offers a detailed overview of the challenges associated with the standard Difference-in-Differences (DID) estimator, discusses potential solutions, and provides practical guidance. However, applying the alternative estimators suggested in Baker, Larcker, and Wang (2022) poses two key challenges in our context. First, most of these new estimators assume the shock is permanent and one off, but our setting involves a unit experiencing multiple shocks over time. Second, our primary interest lies in the interaction term between the shock and lender type rather than the shock coefficient itself. The extension of these estimators to include the interaction term in a setting where the same unit experiences multiple shocks is non-trivial and beyond the scope of this paper.

6.1 Magnitude of the Effect

This section discusses the economic significance of the magnitude of the baseline effect. The point estimate in Table 1 indicates a 1.55% increase in Fintech credit following a weather shock at the unit of observation, year-month × ZIP × product. We investigate how this relates to an increase in credit per borrower. The average monthly Fintech loan amount within a year-month-ZIP-product cell is 705k rupees (≈10k USD). This corresponds to an average of 28.56 loans per cell, and an average loan size of 24,694 rupees (≈361 USD). Thus, an effect size of 1.55% translates to an increase of 383 rupees (≈6 USD) in credit per borrower.

This effect is economically meaningful for the Indian population. To contextualize these numbers, we compare them with average monthly expenditures based on the Household Consumption Expenditure Survey Data (see Appendix Table A.6). For households in the bottom 5$^{\text{th}}$ percentile of monthly expenditure, the increase in Fintech credit per borrower represents approximately 19% of the average monthly expenditure for urban households and 28% for rural households. For those in the 40$^{\text{th}}$ to 50$^{\text{th}}$ percentiles, the increase corresponds to about 8% of the average monthly expenditure for urban households and 12% for rural households. In the top 5$^{\text{th}}$ percentile, this effect constitutes 2% for urban households and 4% for rural households. In Section 6.5, we document that marginal and new-to-credit borrowers benefit the most from the increase in Fintech credit. Hence, it may be more appropriate to benchmark our estimates against households closer to the lower percentiles of monthly expenditure in this context.

Given the cyclical nature of income, we prefer using average monthly expenditures to benchmark our estimates. However, for completeness, we also compare our estimates against average income and average savings. Assuming an average annual income of 234,551 rupees (Bharti, Chancel, Piketty, and Somanchi, 2024), the increase in Fintech credit translates to 2% [=383/(234,551/12)] of monthly income. For the bottom 50% of earners, whose average annual income is 71,163 rupees, the increase corresponds to 6% of their average monthly income. Similar estimates are drawn from the Periodic Labour Force Surveys (PLFS), which show that using the 2019 average salary of 19,568 rupees, the Fintech credit increase represents 2% of monthly income. However, given the more pronounced impact on marginal borrowers, a more relevant benchmark may be the average monthly salary of 7,591 rupees for casual workers. In this case, the increase in Fintech credit constitutes 5% of their average monthly salary. Furthermore, this effect is economically meaningful when compared to the average monthly savings of 15,625 rupees, representing 2%.

We also provide back-of-the-envelope calculations to give a brief overview of the overall impact. Specifically, we estimate that the average Fintech loan amount across various products and ZIP codes in a given year-month is 190 million USD, and 13 billion USD over the entire sample period. Multiplying with the effect size of 1.55% translates into an aggregate increase of 3 million USD in Fintech credit in any given month, totaling 209 million USD over the course of our study period.

6.2 Dynamic Response

Next, we investigate the dynamic response of credit issuance over time. This corresponds to Equation 2 but additionally includes specific dummies for pre- and post-periods. Figure 2 presents the results. There are two key takeaways from this analysis. First, the results indicate that the pre-trends are unlikely to drive our results and the parallel trends assumption is likely to hold. Second, we find that the relative increase in credit by Fintechs appears immediately after the shock and persists thereafter for at least the next four months. Overall, the results indicate that the response of Fintech is both immediate and persistent. In contrast, we document a substantially smaller response for Nontechs, relative to Fintechs.

6.3 Heterogeneity by Collateralization

This section examines the differences in the baseline effects of shadow banks across collateralized and uncollateralized market segments. In particular, which comparative advantage dominates likely depends on the market segment. For instance, lower regulation may be a key comparative advantage in collateralized markets, which are more heavily regulated. In contrast, technology may play a more crucial role in uncollateralized markets, where evaluating borrowers' credit risk is particularly important. Moreover, studying the heterogeneous effect also informs our understanding of the industrial organization of credit markets.

Table 2 presents the results. Column 2 focuses on collateralized loans – specifically, agriculture, gold, and vehicle loans – while Column 3 examines uncollateralized loans, which include business, consumption, and MFI loans. Our results show that in the collateralized loan segment, Nontechs exhibit a stronger response (1.53%) compared to Fintechs and traditional banks. Conversely, in the uncollateralized loan segment, Fintechs demonstrate a stronger response (1.89%) relative to Nontechs and traditional banks.

Next, we present a dynamic assessment of the effect of Fintechs in uncollateralized markets (Figure 3a) and Nontechs in collateralized markets (Figure 3b). The results from this assessment resonate with our baseline dynamic assessment, shown in Figure 2. They indicate that the pre-trends are unlikely to drive our results and the parallel trends assumption is likely to hold. Additionally, we find that the relative increase in credit by Fintechs in uncollateralized appears immediately after the shock and persists thereafter for at least the next four months. We find similar results for Nontechs in collateralized markets, but the effect disappears three months after the shock.

We further validate our findings by estimating the baseline specification for each product type separately. Appendix Table B.1 presents the results. They consistently show that Nontechs exhibit a stronger response than both Fintechs and traditional banks for collateralized loan products, including agriculture loans (1.42%), gold loans (3.24%), and vehicle loans (0.32%). The Nontech coefficients are statistically significantly different from those of traditional banks in all cases, and they differ from Fintechs in the cases of gold and vehicle loans. In contrast, in the uncollateralized loan segment, Fintechs display a stronger response across all product types: business loans (4.41%), consumption loans (1.06%), and MFI loans (8.33%). The differences between Fintechs and both traditional banks and Nontechs are statistically significant at the one percent level.

Overall, these findings suggest that Nontechs have a comparative advantage in collateralized markets for absorbing demand shocks, while Fintechs hold a comparative advantage in uncollateralized markets. This indicates a clear market segmentation in how shadow banks respond to demand shocks.

6.4 Effect on Credit Inquiries

Next, we complement our baseline results on credit issuance and heterogeneity across collateralized and uncollateralized markets, by examining the effect on credit inquiries. We conduct this analysis at ZIP $\times$ product $\times$ lender $\times$ year level since the inquiry data is available at annual frequency. Appendix Table B.2 presents the results. We find that Fintechs conduct more inquiries after the shock relative to traditional providers. Moreover, we note that the increased number of inquiries by Fintech is primarily driven by uncollateralized markets. In contrast, we find that Nontechs increase inquiries in collateralized markets following weather shocks. This result resonates with our baseline findings on credit issuance and heterogeneity across collateralized and uncollateralized market segments. However, the readers should note that this measure may not perfectly proxy loan applications or acceptance rate for two reasons. First, lenders may not necessarily conduct an inquiry at the credit bureau (Mishra, Prabhala, and Rajan, 2022). Second, borrowers may apply for loans with multiple lenders.

6.5 Heterogeneity by Credit Score Type

Next, we examine the heterogeneity in the effect by credit score categories to understand the borrower segments that shadow banks serve. This analysis seeks to clarify whether shadow banks compete with or complement traditional banks. This distinction is important because if shadow banks complement traditional banks, they could enhance financial inclusion by providing credit to underserved borrowers. Conversely, if they compete directly with banks, the credit expansion may primarily benefit borrowers who are already eligible for traditional loans. Thus, understanding the borrower segments served by shadow banks is essential for assessing the broader welfare implications of the rise of shadow banks (Tang, 2019; De Roure, Pelizzon, and Thakor, 2022; Gopal and Schnabl, 2022).

To this end, we estimate our baseline Equation 2 for each credit score category separately. Panel A of Table 3 presents the results. We find that Fintechs react stronger than Nontechs and traditional banks for prime borrowers (0.73%), near-prime borrowers (1.10%), and sub-prime borrowers (1.74%). This effect is monotonically increasing. The most significant response occurs among new-to-credit borrowers, at 2.66%, who face the highest information asymmetry. Notably, Nontechs display a positive effect for new-to-credit borrowers as well, although this effect is much smaller at 1.15%. In contrast, we observe no increase for higher credit score categories, such as super-prime and prime-plus borrowers, for either Fintechs or Nontechs.

Panel B and C of Table 3 show the effects categorized by credit score types for collateralized and uncollateralized products, respectively. In collateralized markets, the overall effect for Nontechs is 1.53%, primarily driven by credit issuance to prime, near-prime, sub-prime, and new-to-credit borrowers. The most significant response occurs among new-to-credit borrowers. In contrast, Fintechs do not show a response for these credit score categories in the collateralized market. Conversely, in the uncollateralized market, Fintechs demonstrate an overall effect of 1.89%, attributed to prime, near-prime, sub-prime, and new-to-credit borrowers. As before, the most significant response occurs among new-to-credit borrowers. Nontechs, however, show minimal impact in the uncollateralized segment, with only a minor effect observed among new-to-credit borrowers.

One possible explanation for the increasing pattern observed for Fintechs across the credit score distribution is that lower credit score borrowers are more affected by these shocks and exhibit higher credit demand, which is targeted at shadow banks. We investigate this hypothesis by examining the relationship between credit inquiries and local weather shocks by credit score type. Appendix Table B.3 presents the results for all loans (Panel A), collateralized loans (Panel B), and uncollateralized loans (Panel C). While new-to-credit borrowers display the strongest inquiry effects, the trend across credit scores does not support the demand-side hypothesis. Specifically, as we move from prime to sub-prime borrowers, we see a decreasing effect while there is an increasing trend in credit issuance. Thus, the inquiry effects among scored borrowers are unlikely to explain the heterogeneity in loan issuance documented in Table 3.

These results suggest that both Nontechs and Fintechs have a comparative advantage in lending to borrowers with low credit scores and those who are new to credit. Alongside the findings in Section 6.2, this highlights a clear market segmentation in how shadow banks respond to demand shocks. Specifically, while shadow banks differentiate across product types, they often target similarly risky borrower populations within these segments. Furthermore, these findings indicate that shadow banks may complement traditional banks in both collateralized and uncollateralized markets by increasing lending to borrower segments that traditional banks are unable to serve.

6.6 Default Rates

Next, we analyze default rates on new loans issued by shadow banks following weather shocks. Section 6.5 documents that shadow banks cater primarily to borrower segments with high information asymmetry and low credit scores. Therefore, the objective of this section is to examine if this ex-ante exposure to risky borrowers results in a substantial ex-post risk for shadow banks.

Table 4 presents the results. The main outcome variable is the default rate measured as the fraction of loans that default within one year of disbursal. We do not observe a substantial increase in default rates of Fintechs or Nontechs relative to traditional lender types. Specifically, the results in Column 1 suggest that the default rate for these shadow banks is neither economically nor statistically significantly different from traditional banks. For collateralized loans, Nontechs experience a decrease in default rates, while Fintechs show some increase in default rates for uncollateralized loans. These results suggest that although Fintechs and Nontechs appear to take on higher risk ex-ante, as indicated by credit scores, the ex-post differences in the riskiness of their portfolio, as indicated by default rates, are not substantial.

6.7 Complementary Role of Shadow Banks

So far, we have shown that both Fintechs and Nontechs extend more credit to new-to-credit customers, borrowers who experience high information asymmetry and are often underserved by traditional banks. This finding indicates that shadow banks serve as complements to traditional banking across borrower segments, supporting the conclusions of Tang (2019), De Roure, Pelizzon, and Thakor (2022), and Gopal and Schnabl (2022). In this section, we extend this literature by documenting additional ways in which shadow banks can complement traditional banking and informal risk-sharing arrangements. The results of this section highlight the important role of shadow banking in filling the gap in regions where other forms of lending may be limited, enhancing access to credit in underserved markets.

6.7.1 Heterogeneity by Presence of Traditional Banks

First, we examine the heterogeneity of the impact across regions with low and high levels of access to traditional banking services. Understanding this heterogeneity is important to assess whether shadow banks can effectively address regional disparities in financial access. To this end, we examine the differences in impact between rural and urban areas. Rural regions often encounter significant barriers to financial access, while urban areas benefit from a more developed banking infrastructure. We classify all ZIP codes into four categories: metro, urban, semi-urban, and rural, and estimate our baseline specification for each category. Results in Panel A of Table 5 indicate that Fintechs lend more in rural areas compared to metro areas after a demand shock. As before, we do not observe Fintechs having greater defaults in rural areas (see Panel A of Appendix Table B.4). This suggests that Fintechs are instrumental in addressing credit gaps, especially in less-served regions. This heterogeneity is also significant from a welfare standpoint, as prior research has shown that improved financial intermediation in rural areas can reduce poverty (Burgess and Pande, 2005; Cramer, 2021; Barboni, Field, and Pande, 2024).

We further support this claim by examining the heterogeneity of the impact across regions with low and high levels of banking concentration. We categorize ZIP codes into two groups based on the Herfindahl-Hirschman Index (HHI) – a measure of banking competitiveness – using three criteria: the number of banks, total credit, and deposit amounts as of 2015, one year before the beginning of our data sample. Appendix A.1 describes the construction of HHI. Results in Panel A of Appendix Table B.5 indicate that Fintechs lend more in low-competition (high HHI) areas following a demand shock, suggesting they play a vital role in mitigating demand fluctuations, particularly where traditional banks may have a monopoly. Moreover, we note that this does not result in a greater ex-post risk for shadow banks as measured by default (see Panel B of Appendix Table B.5). This suggests Fintechs' potential to alleviate regional disparities in financial services without building up risk.

6.7.2 Heterogeneity by Bank Lending Constraints

Next, we investigate whether shadow banks can effectively fill lending gaps that emerge when traditional banks encounter lending constraints. To analyze this, we develop a measure of geographic variation in credit gaps linked to bank constraints. Specifically, we calculate a weighted average of lending shares of each traditional bank at the ZIP code level, weighted by each bank's total non-performing assets (NPA) ratio. This measure captures the extent to which the key lenders in a given ZIP code may face significant balance sheet constraints, thereby limiting their ability to provide credit during periods of increased demand. Appendix A.1 provides details of the measure.

We split all ZIP codes into four groups based on the quartile values of the ZIP-year level NPA ratio and estimate our baseline specification for each group. Quartile one corresponds to the lowest bank constraints, while quartile four corresponds to the highest level of bank constraint. Panel B of Table 5 presents the results. We document that Fintechs lend more in regions where key traditional lenders face high balance sheet constraints. This result suggests that shadow banks act as complements to traditional banks, addressing credit gaps in regions that are generated due to bank balance sheet constraints. Furthermore, we document that increased Fintech lending in areas where banks face lending constraints does not lead to higher risk, as indicated by default rates for Fintechs (see Panel B of Appendix Table B.4).

6.7.3 Heterogeneity by Informal Insurance

This section investigates the heterogeneity in the baseline response by informal insurance – risk-sharing arrangements within social networks. We posit that shadow banks can provide insurance against weather shocks via credit in regions with a lower degree of informal insurance, as affected individuals are unable to meet their liquidity needs through social connections. Prior research supports the notion of a negative correlation between formal and informal insurance in India (Mobarak and Rosenzweig, 2013; Ghosh and Vats, 2022).

To test this hypothesis, we use Facebook data on social connections as a proxy for informal insurance. We measure these connections using the social connectedness index (SCI), described in Appendix A.1. Based on the SCI, we categorize ZIP codes into four quartiles, with quartile one representing the lowest social connectedness and quartile four the highest.

Results in Panel C of Table 5 show that the impact of Fintechs is significantly greater in low social connectedness areas (2.26%) compared to high social connectedness areas (0.87%). This indicates that Fintechs complement informal insurance, providing necessary credit when such support is limited, without affecting default rates (see Panel C of Appendix Table B.4). Conversely, we find no similar pattern for Nontechs. The lack of association between social networks and Nontech responses may be due to the limited role of informal networks in collateralized lending, where loan amounts are typically larger than those exchanged among family and friends (Karaivanov and Kessler, 2018).

6.8 Robustness and Placebo

This section presents a series of robustness tests to validate our baseline findings. First, our specification in Equation 2 examines the effect of Fintechs and Nontechs compared to traditional banks. A potential concern is that both shadow banks and traditional banks may reduce lending after weather shocks, with traditional banks potentially cutting back more due to deposit withdrawals or negative capital shocks (Bergman, Iyer, and Thakor, 2020; Kundu, Park, and Vats, 2021). To address this, we separately regress the loan amounts for Fintechs, Nontechs, and traditional banks on the weather shock variable. The results, shown in Appendix Table C.1, indicate that both Fintechs and Nontechs increase lending following weather shocks, while the impact on most traditional banks is minimal, although state-owned banks show a positive response. This suggests that our findings are unlikely to be driven by weather shocks negatively affecting credit supply by traditional banks.

Second, Appendix Table C.2 verifies that our results hold at the extensive margin. Moreover, consistent with our baseline results, we show that the number of loans increases for Nontechs in the collateralized market, whereas it increases for Fintech in uncollateralized markets.

Third, our main specification analyzes year-month $\times$ ZIP $\times$ lender $\times$ product categories with any credit issuance. As an alternative, we include categories that transition from zero to positive credit and vice versa and estimate a Poisson regression following the suggestion in Cohn, Liu, and Wardlaw (2022). The results, shown in Appendix Table C.3, remain robust under this specification. Fourth,

Appendix Table C.4 demonstrates that our results remain robust when excluding observations from the peak of the COVID-19 period in 2020 and 2021.

Fourth, we discuss a set of robustness tests related to the construction of weather shocks. We find that our results are robust to using the continuous measure of the weather shock – the standardized water balance measure (Appendix Table C.5); re-defining the shock variable based on whether the continuous measure is below the 10th percentile or above the 90th percentile of a ZIP's historical distribution (Appendix Table C.6); and analyzing responses to droughts and floods (Appendix Table C.7).

Finally, we run a placebo test. We replace our weather shock dummy with a placebo shock variable that is randomly set to one for 40% of the year-month observations in a ZIP code to mirror the distribution of the weather shock in our baseline analysis. We repeat this exercise 1,000 times. Figure C.1 plots the kernel density of the resulting coefficients associated with the interaction terms of Fintech and placebo shocks in Panel A and Nontech and placebo shocks in Panel B. The distributions of both coefficients are centered around zero, and less than 1% of the estimated placebo coefficients have a magnitude greater than those reported in Table 1. This suggests that our results are unlikely to be spurious.

7 What Explains the Comparative Advantage of Shadow Banks?

This section examines the comparative advantages of shadow banks, focusing on why Fintechs respond more strongly in uncollateralized markets, while Nontechs react more in collateralized markets. We first highlight two key pieces of evidence showing that technology is an important driver of responses of Fintech, whereas it has less impact on Nontechs. Next, we leverage four natural experiments demonstrating that lower regulation benefits Nontechs by creating regulatory arbitrage opportunities and easing funding from banks. In contrast, regulation has minimal effects on Fintech responses.

7.1 Role of Technology: UPI Index

We evaluate whether Fintechs' technological advantage facilitates credit expansion after a shock by examining variation in the baseline effect based on differences in UPI adoption. We measure UPI adoption using the UPI index discussed in Section 2.4. The intuition of this test is that UPI allows users to create a digital transaction history that is readily shareable across financial intermediaries. Therefore, in ZIP codes with a higher UPI index – indicating greater UPI activity – we expect to observe stronger credit responses if technology is the key comparative advantage.

We provide two pieces of evidence that support the notion that the UPI index generates quasi-random variation in the adoption of UPI based digital transactions. First, we examine if the differences across ZIP codes can explain the variation in our UPI index. While this assertion is inherently not testable, Table 6 provides suggestive evidence using observable characteristics at the ZIP code level.

Within a district, we find no statistically significant or economically meaningful correlations between our UPI index and various observable factors, such as (1) geographic and demographic characteristics – geographic area, population size, lower social class share, (2) educational – literacy rate, number of schools and colleges, and (3) economic characteristics – nightlight intensity, the number of firms, employment levels, and sectoral employment share in manufacturing and services.

Second, we examine if our UPI index can explain variation in the adoption of digital transactions via UPI. Figures 4a and 4b present binscatter plots of the unconditional relationship between the UPI index and UPI transaction volume and value, respectively. We find that the relationship is positive, and UPI transaction volume and value are monotonically increasing in the UPI exposure index. To further analyze this, we use a regression framework, with results presented in Table 7. We sequentially add fixed effects across columns to estimate our preferred specification in Column 6. We find that the UPI exposure index is positively correlated with UPI transaction volume and value. Specifically, a 1 pp increase in the UPI index is associated with a 1.5% increase in UPI transaction volume and a 1.6% increase in UPI transaction value.

Panel A of Table 8 presents the heterogeneity in the baseline effect by the UPI exposure index. We document that the interaction between Fintech and Shock increases in magnitude as we move from the first quartile (lowest UPI exposure) to the fourth quartile (highest UPI exposure) of the UPI index distribution. In terms of the magnitude of the effect for Fintechs, in the first quartile, the effect is 0.65% and statistically insignificant. In the fourth quartile, the coefficient is 2.32% and statistically significant at the 1% level. A Wald test confirms that the coefficients in the first and fourth quartiles are significantly different from each other. Additionally, Panels B and C of Table 8 show that the increasing trend in the interaction term of Fintech and Shock is driven by uncollateralized lending. Meanwhile, we do not observe a consistent pattern for Nontechs in either collateralized or uncollateralized lending. Lastly, Appendix Table C.8 documents that this additional lending does not translate into an increase in default rate.

While Table 6 provides suggestive evidence that the UPI index is unlikely to be correlated with several observables, it cannot rule out the potential effect of all unobservables. We address this concern by conducting a falsification test using data from YONO (You Only Need One), the digital banking platform of the State Bank of India (SBI), the largest state-owned bank in India. We analyze total monthly YONO transactions at the ZIP-code level, scaled by population. Since YONO is also a digital transaction platform, it could correlate with similar unobservables as the UPI index. However, YONO transaction data is private to SBI and it cannot be readily shared with other lenders. If the observed pattern were driven by unobservables linked to both digital transactions and Fintech lending, we would expect a similar pattern for YONO transactions. Appendix Table C.9 presents the results. The estimate of interest is similar in magnitude across the distribution of YONO transactions. This result suggests that the increasing coefficients across UPI exposure quartiles are more likely due to Fintechs' ability to access data rather than unobservables.

Overall, these results suggest that Fintechs' technological advantage is a key driver of their comparative advantage in uncollateralized markets. Specifically, our findings indicate that Fintechs respond more to weather shocks when they can effectively evaluate the risk of potential borrowers by analyzing their digital transactions. In contrast, we do not find that technology—especially as measured by data provision—is a crucial determinant of the comparative advantage for Nontechs. Thus, the ability to harness technology effectively distinguishes Fintechs in credit markets, especially in the uncollateralized segment.

7.2 Role of Technology: Application-Level Fintech Data

This section provides application-level evidence consistent with the technological advantage of Fintechs. Specifically, we show that the technology-based lending model for Fintechs can alleviate frictions in credit markets, such as removing information asymmetry and lengthy credit disbursal processes, especially in times of need.

We exploit data from one of the largest Fintechs in India that specializes in uncollateralized small business lending. This company generates a standardized score for each applicant based on their digital transactions (see Section 2.5 for more details). Our objective is to examine the role of the availability of this alternative data on digital transactions in affecting loan acceptance decisions and other outcomes, such as speed of disbursal, default, and interest rate at the application level.

Panel A of Table 9 present the results on acceptance decisions for the entire sample of applicants as well as the split by new-to-credit and not new-to-credit applicants. We leverage the standardized score assigned by the lender to the applicant, based on digital transactions conducted by the merchant. We find that a rise in this score by one standard deviation increases the likelihood of acceptance after a shock by 0.80 percentage points (1.57% at a mean acceptance rate of 50.90%). Moreover, we find that the effect is primarily driven by new-to-credit borrowers, who experience an increase in approval by 2.37 percentage points (6.21% at a mean acceptance rate of 38.14%). In contrast, those not new-to-credit see only an increase of 0.41 percentage points (0.75% at a mean acceptance rate of 54.39%). These findings suggest that technology – in particular alternative data generated through digital transactions – plays a key role in allowing Fintechs to serve credit after shocks, especially to new-to-credit borrowers.

Additionally, we examine the effect of the score on other dimensions of borrowing. We begin by examining the effect on days to disbursal (Panel B of Table 9). This is an important metric, especially in our setting, as timely provision of liquidity for small businesses navigating extreme weather shocks can be critical. Moreover, an analysis of this variable can indicate whether Fintechs can reduce frictions in credit markets, such as lengthy loan processing. We document that a higher digital transaction-based score is associated with a more speedy disbursal following weather shocks. Specifically, a one standard deviation increase in the score reduces the days to disbursal for new-to-credit borrowers by half a day (-5.25% at a mean of 10.52 days). In contrast, those not new-to-credit experience a somewhat smaller reduction of 0.14 days (-1.60% at a mean of 8.69 days). This result of a faster speed of disbursal is consistent with the findings of Fuster, Plosser, Schnabl, and Vickery (2019). Lastly, we examine the relationship of the score with the default on loans (Panel C of Table 9) and interest rate (Panel D of Table 9) after weather shocks. We do not observe a significant change in default and interest rates with the score for new-to-credit borrowers.

7.3 Role of Regulation

Next, we investigate whether shadow banks have an advantage relative to other lenders due to fewer regulatory restrictions. To this end, we exploit two natural experiments that generate variation in regulation between shadow banks and traditional banks. We find that while regulation plays little role in explaining the response for Fintechs, it plays an important role in explaining Nontech's response to demand shocks.

7.3.1 Fintech & Regulation

First, we exploit a regulatory change issued by the Reserve Bank of India in November 2023.[16] Specifically, the regulatory change raised the risk weight for retail loans issued by banks and shadow banks from 100% to 125%. A feature of this measure was that MFI loans made by shadow banks were exempt from this regulatory change, while MFI loans from banks faced an increase in risk weight of 25 percentage points. We leverage this regulatory disparity between shadow banks and banks regarding MFI loans to analyze the importance of this channel in creating a comparative advantage for shadow banks. We primarily focus on Fintechs for this analysis as the results in Appendix Table B.1 suggest that they tend to lend more in this sector following the increase in demand. We want the readers to note that November 2023 is outside the range of our baseline sample. Therefore, we collect a more recent wave of data from the credit bureau spanning from July 2021 until June 2024.

We hypothesize that if the less stringent regulatory environment for Fintechs is a key factor explaining their higher lending to MFI following demand shocks, we would expect to see a rise in Fintech lending to this sector after the regulatory change in November 2023. Column 1 of Table 10 presents the results. Consistent with our baseline findings, the interaction term between Fintech and the demand shock is positive and statistically significant, indicating that our baseline results remain valid for the sample period from July 2021 to June 2024.

The key coefficient of interest is associated with the interaction term of Fintech, the demand shock, and the post-regulatory change indicator, where the post variable equals one for periods after

[16]We refer to the November 16, 2023 Reserve Bank of India circular that can be accessed here.

November 2023 and zero otherwise. This term assesses the response of Fintechs to demand shocks before and after the regulatory change. The estimate for this interaction term is both economically small and statistically insignificant. This result suggests that Fintechs are not responding more strongly to demand shocks due to a less stringent regulatory environment.

7.3.2 Nontech & Regulation

Second, we exploit the August 2020 regulatory change by the Reserve Bank of India that increased the maximum permissible loan-to-value (LTV) ratio requirements for gold loans by traditional banks from 75% to 90%.[17] At the same time, there was no change in the LTV requirements for gold loans disbursed by shadow banks, which stayed at 75%. As a result, the regulatory requirements for traditional banks for gold loans were relaxed, whereas those for shadow banks, specifically Nontechs, were unchanged. We focus on Nontechs for this analysis as the results in Appendix Table B.1 suggest that they tend to lend more in the gold loan segment following the increase in demand.

We hypothesize that if the regulatory advantage of shadow banks is a key determinant of their response to demand shocks, we would expect to see a decline in Nontech lending backed by gold after the regulatory change in August 2020. Column 2 of Table 10 presents the results. The key coefficient of interest is associated with the interaction term of Nontech, the demand shock, and the post-regulatory change indicator, where the post variable equals one for periods after August 2020 and zero otherwise. This term assesses the response of Nontechs to demand shocks before and after the regulatory change, which made regulatory requirements for traditional banks less stringent. The estimate for this interaction term is negative, statistically significant and economically meaningful, suggesting that Nontechs are responding more strongly to demand shocks due to their regulatory advantage.

7.4 Role of Funding

A significant source of funding for shadow banks is bank lending, which accounted for 22% of their liabilities in 2011 (Acharya, Khandwala, and Öncü, 2013) and remains an important funding source for shadow banks (Bhardwaj and Javadekar, 2024).[18] Bank credit to shadow banks is not an isolated feature of Indian markets but is also prominent in the U.S. (Jiang, Matvos, Piskorski, and Seru, 2020; Jiang, 2023; Acharya, Gopal, Jager, and Steffen, 2024; Acharya, Cetorelli, and Tuckman, 2024).

We conjecture that a primary reason traditional banks lend to shadow banks is that these entities operate under lower regulation and possess superior technology to identify lending opportunities. As a result, traditional banks lend to shadow banks to take advantage of higher return opportunities that

[17] We refer to the August 6, 2020 circular that can be accessed here. Furthermore, because this change was in effect until March 31, 2021, we limit our sample to conclude in March 2021 for the purposes of this analysis.

[18] While some shadow banks, in principle, can take some types of deposits, such as term deposits, the number of institutions that have such deposits is small, 49 compared to 9,467 in 2022. Public deposits make up only two percent of the total liabilities of the shadow bank sector (CAFRAL, 2023) and represented a mere 0.22% of total public deposits in 2011 (Acharya, Khandwala, and Öncü, 2013).

would otherwise be unavailable. Thus, we hypothesize that if superior technology (less regulation) is the main motivator for bank lending to Fintech (Nontech), then shocks to bank lending to shadow banks are likely to be passed on to Fintechs (Nontechs). This section exploits a regulatory shock and a non-regulatory shock to examine this hypothesis.

7.4.1 Regulatory Shock to Funding

We begin with a regulatory shock. In November 2023, regulators implemented a significant policy change targeting one of the primary funding sources for shadow banks: bank credit. The regulation raised the risk weights on bank loans to shadow banks by 25 percentage points unless these loans were meant to be used for priority sector lending by shadow banks.

We posit that this regulatory change increased the bank lending to shadow banks meant for priority sector lending, such as lending to agriculture. Therefore, we focus on Nontechs for this analysis as the results in Appendix Table B.1 suggest that they tend to lend more in the agricultural sector following the increase in demand.

We hypothesize that if the increased funding for Nontechs due to their comparative regulatory advantage is a key factor explaining their higher lending, we would expect to see a rise in Nontech lending to the agricultural sector after the regulatory change in November 2023. Column 3 of Table 10 presents the results. The key coefficient of interest is associated with the interaction term of Nontech, the demand shock, and the post-regulatory change indicator, where the post variable equals one for periods after November 2023 and zero otherwise. This term assesses the response of Nontechs to demand shocks before and after the regulatory change, which made funding easier for Nontechs in the agricultural sector. The estimate for this interaction term is positive, statistically significant, and economically meaningful. This result suggests that Nontechs are responding more strongly to demand shocks due to their regulatory advantage, which can increase bank funding to them.

7.4.2 Non-Regulatory Shock to Funding

Next, we examine a non-regulatory shock. We exploit the unexpected downfall of the Infrastructure Leasing & Financial Services (IL&FS) group, a major shadow bank in India, which created a significant funding shock for the industry. IL&FS was a large conglomerate that was involved in financing and implementing infrastructure projects across the country. However, it faced challenges such as construction delays, cost overruns, and governance issues, leading to defaults on its loan and commercial paper obligations in late 2018.

The difficulties began when IL&FS's transport subsidiary failed to repay 4.5 billion rupees (65.7 million USD) in inter-corporate deposits owed to the Small Industries Development Bank of India (SIDBI). This was soon followed by the group's financial arm defaulting on repayments to its commercial paper investors in August 2018. Key rating agencies subsequently downgraded the conglomerate's long- and short-term debt ratings to junk status. In September 2018, the Reserve Bank of India launched a special audit of IL&FS to assess the situation.

The default was unexpected, as IL&FS held the highest credit rating of AAA just before it failed. This incident sent shockwaves through the market regarding the safety of shadow banks. For example, Bajaj Finserv, India's largest retail shadow bank, had minimal direct exposure to sectors impacted by IL&FS (such as energy and infrastructure) but still experienced a sharp decline in its equity price by approximately 25% between September and October 2018. Consequently, banks began to tighten lending to shadow banks. Bhardwaj and Javadekar (2024) document that banks substantially reduced lending to shadow banks after the IL&FS crisis.

We exploit the funding shock resulting from the IL&FS crisis to examine the role of funding in the response of shadow banks to demand shocks. Specifically, we investigate how shadow banks' response to demand shocks changed after the IL&FS default in August 2018. Table 11 presents the findings for total lending as well as lending in collateralized and uncollateralized markets. We find that the response of Nontechs to demand shocks decreases following the IL&FS crisis. In contrast, we find no significant impact on Fintechs' responses to these demand shocks due to the IL&FS crisis. Additionally, the reduction in lending by Nontechs after the IL&FS crisis is primarily driven by collateralized lending.

Our results indicate that bank funding plays an important role in Nontechs' ability to respond to demand shocks. However, these shocks do not appear to affect the response of Fintechs. Therefore, these results suggest that a reason behind bank lending to shadow banks may be the less stringent regulation faced by these entities. This result is important for understanding the boundaries between shadow banks and traditional banks as well as the way regulatory differences create closer ties between them, with consequences for aggregate risk in the economy (Acharya, Schnabl, and Suarez, 2013; Acharya, Cetorelli, and Tuckman, 2024).

7.5 Role of Local Presence in Collateralized Markets

Compared to Nontechs, Fintechs appear to under-utilize their comparative advantages in collateralized markets, even though they also operate under less stringent regulation. This section emphasizes the critical role of a local presence in collateralized markets. We argue that having a local office where loans are issued is important for efficiently inspecting and seizing collateral in the event of default, especially when dealing with politically sensitive assets like agricultural land or smaller items such as vehicles. A key distinguishing feature of Fintechs is that they primarily function through online platforms, which inhibit their ability to inspect and seize collateral, thereby creating a significant operational constraint.

We categorize ZIP codes into two groups based on the median per-capita number of shadow bank loans at the beginning of 2016. Below-median ZIP codes represent areas with low shadow bank presence, while above-median ZIP codes indicate areas with high shadow bank presence. The rationale behind this classification is that regions with higher per-capita shadow bank loans are more likely to have a branch nearby, given that online lending was minimal at that time, and most shadow bank lending was conducted through physical branches.

Table 12 presents the results. We find that the increase in Nontech lending following demand shocks is primarily concentrated in above median ZIP codes. Moreover, this effect is entirely driven by Nontech lending in collateralized markets. Meanwhile, we do not find such an effect for Fintechs. These results suggest that local presence is likely a key factor contributing to comparative advantage in collateralized lending, as such proximity increases the lender's ability to inspect collateral while approving the loan and seize collateral in the event of default.

7.6 Real Effects of the Comparative Advantage of Shadow Banks

Lastly, we document the real economic effects of the comparative advantages of shadow banks. Specifically, we focus on Fintechs and their comparative advantage due to technology as a case study to highlight their role in smoothing demand fluctuations. To this end, we estimate a two-stage least squares (2SLS) specification and report the results in Appendix Table C.10. In the first stage, we generate exogenous variation in Fintech credit in response to weather shocks by leveraging geographic disparities in the adoption of digital transaction technology, as indicated by the UPI index. The second stage utilizes this exogenous variation to assess how Fintech credit mitigates fluctuations in economic activity due to weather shocks. Our results suggest that increased Fintech credit in response to demand shocks correlates with a muted impact of weather shock on local economic activity.

8 Conclusion

In conclusion, our study leverages novel and comprehensive credit bureau data on formal retail loans to examine the comparative advantages of shadow banks across market segments. Our findings indicate that the comparative advantages of shadow banks vary significantly across market segments.

The first part of the paper demonstrates that shadow banks have a comparative advantage in smoothing fluctuations in credit demand. Specifically, we show that shadow banks increase credit more than traditional banks following weather shocks. We then document that Nontechs exhibit a stronger response in collateralized markets, whereas Fintechs exhibit a stronger response in uncollateralized markets. This result indicates a market segmentation by loan types in response to demand shocks. Next, we find that these shadow banks increase credit to borrowers with lower credit scores and those new to credit, typically subject to the highest levels of information asymmetry. Indicating another dimension of complementarity, we show that Fintechs increase lending in regions with low presence of traditional banks, in regions where traditional banks experience lending constraints, and in regions with weaker informal insurance. These results suggest that shadow banks act as complements, addressing the gaps left by traditional banks and informal lending arrangements.

The second part of the paper investigates the reasons underlying the comparative advantage of shadow banks. Exploiting geographic heterogeneity in the adoption of a digital payment technology, UPI, we document that the technological advantage of Fintechs may be a key driver of their comparative advantage in uncollateralized markets. We further supplement this result using detailed application-level data from one of India's largest Fintech lenders.

Next, we exploit four natural experiments across time, products, and lender types to establish the importance of less stringent regulation in explaining the comparative advantage of Nontechs. We show that this regulatory advantage for Nontechs may increase their funding, by incentivizing traditional banks to lend to Nontechs and, therefore, take advantage of opportunities that are unavailable to traditional banks. Lastly, we highlight the importance of the local presence of Nontechs in explaining their dominance in collateralized markets relative to Fintechs. Local presence is important for effectively inspecting collateral during the loan process and for seizing it in the event of default.

Overall, our research expands our understanding of shadow banking beyond the mortgage market, providing new evidence on how technology and regulation may shape the growth of these institutions across different segments of the credit market. Specifically, our results provide insight into the industrial organization of the credit market and its consequences for policy analysis and the real economy.

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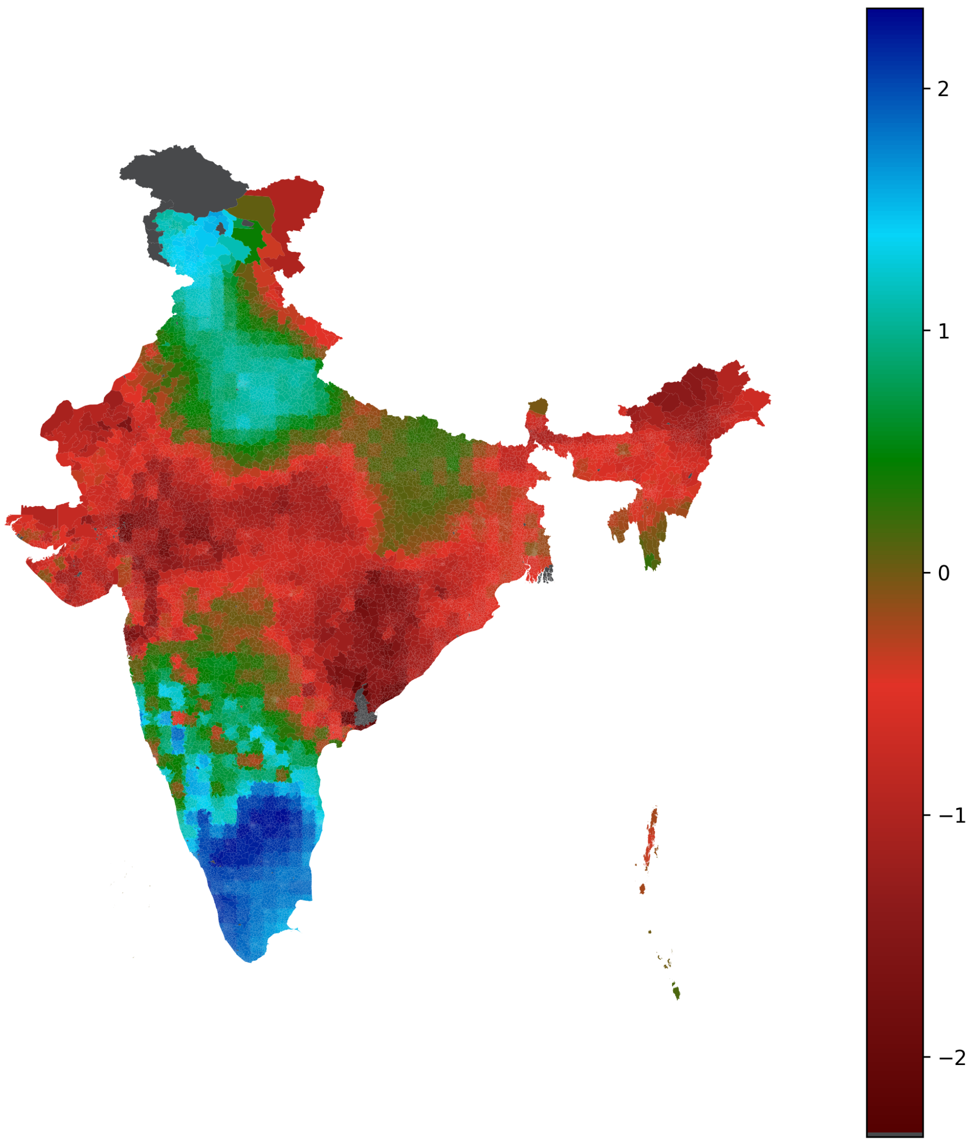
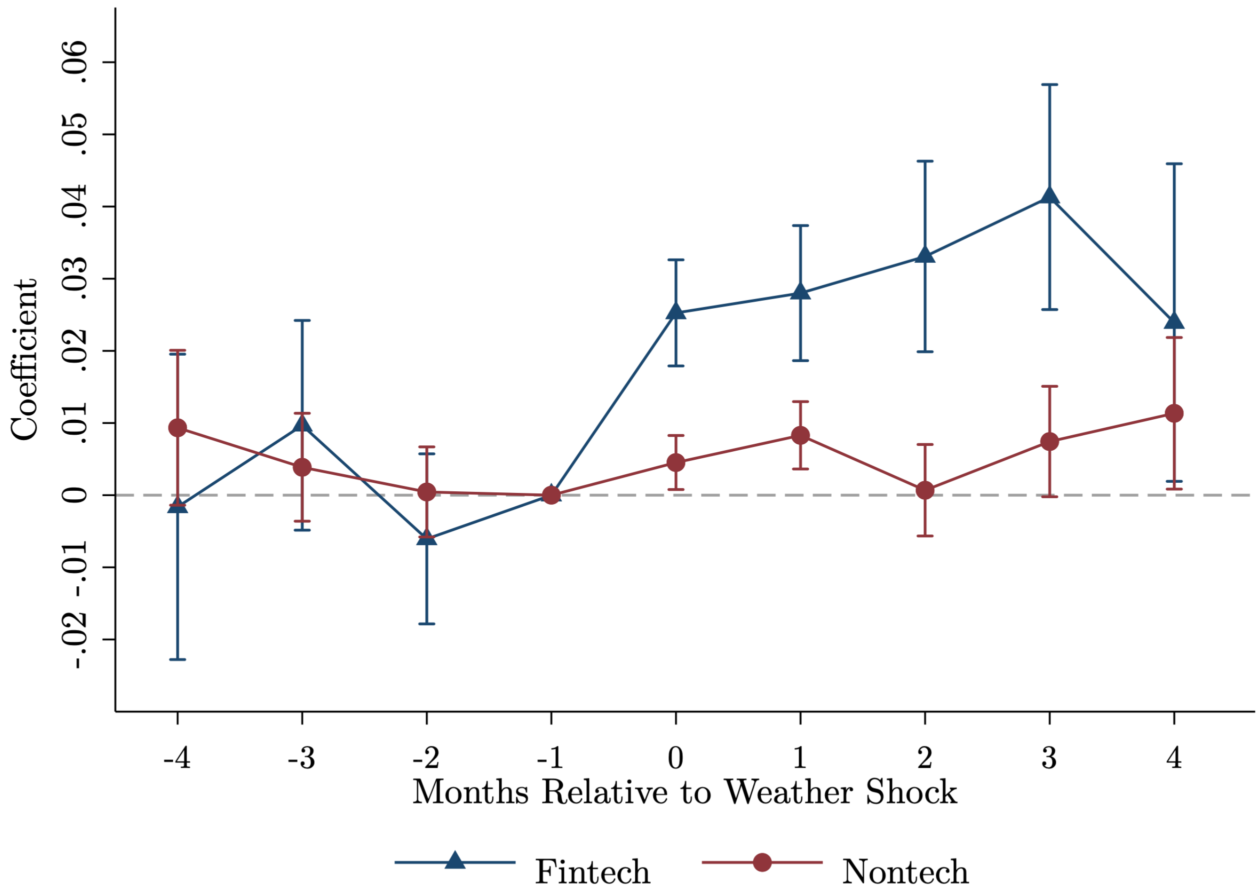
Figure 1: Continuous Water Balance Variable (SPEI)



This figure presents the geographic ZIP-level distribution of the continuous water balance variable SPEI, for December 2020 as an example. The definition of the SPEI is outlined in Section 2. It has a mean of zero and a standard deviation of one. A higher continuous SPEI indicates a higher water balance, in extreme cases a flood. A lower continuous SPEI indicates a lower water balance, in extreme cases a drought. The continuous SPEI forms the basis for our weather shock indicator.

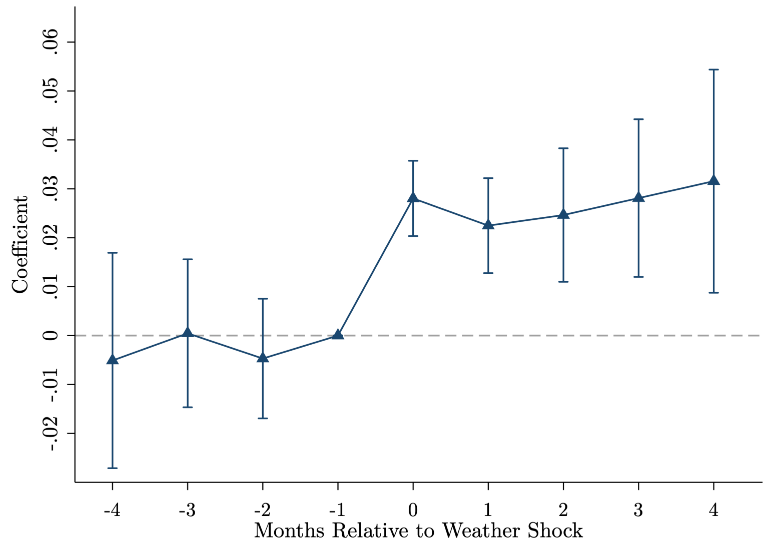
Figure 2: Dynamics of Fintech and Nontech Credit Issuance



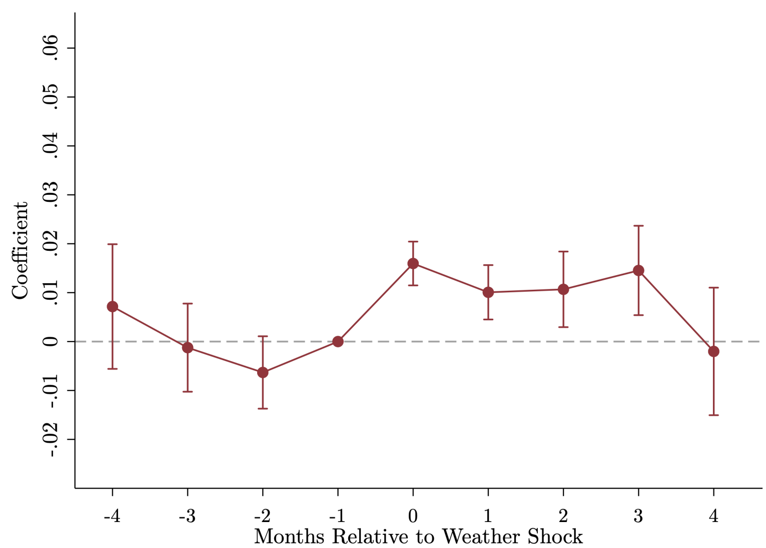
This figure presents the dynamic relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 3. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. The outcome variable is winsorised at 1% on both ends. The figure shows the point estimates and the associated 95% confidence intervals estimated by clustering of the standard errors at the ZIP code level. Navy blue triangles represent the estimates associated with Fintech and red circles represent the estimates associated with Nontechs.

$$y_{z,ym,l,p} = \sum_{t=-K}^{T} \beta_t \text{Shock}_{z,ym} \times \text{Fintech}_l + \sum_{t=-K}^{T} \gamma_t \text{Shock}_{z,ym} \times \text{Nontech}_l + \text{FE}_{ym,z,p} + \text{FE}_{ym,l,p} + \text{FE}_{z,l,p} + \epsilon_{z,ym,l,p} \tag{3}$$

Figure 3: Dynamics of Fintech and Nontech Credit Issuance, by Collateralization



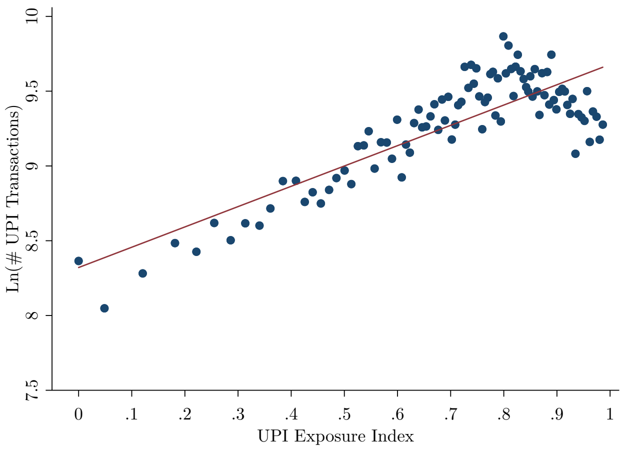
(a) Fintech (Uncollateralized)



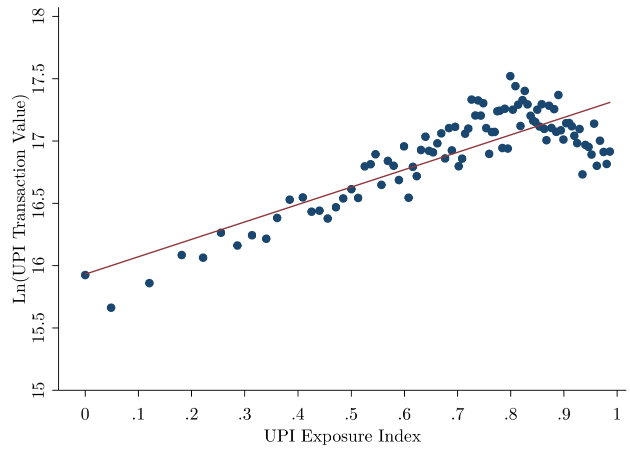
(b) Nontech (Collateralized)

This figure presents the dynamic relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 3. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). Figure 3a presents results for Fintechs and uncollateralized loans. Figure 3b presents results for Nontechs and collateralized loans. The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. The outcome variable is winsorised at 1% on both ends. The figure shows the point estimates and the associated 95% confidence intervals estimated by clustering of the standard errors at the ZIP code level.

Figure 4: UPI Transactions & UPI Exposure Index



(a) UPI Transaction Volume



(b) UPI Transaction Value

The figure presents the binscatter plots of UPI transactions and the UPI exposure index. The Y-axis of Figure 4a plots the natural logarithm of UPI transaction volume or the number of UPI transactions. The Y-axis of Figure 4b plots the natural logarithm of UPI transaction value. The X-axis plots the UPI exposure index. The UPI index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. Early adopter banks are banks that were providing UPI services as of November 2016. The unit of observation is at the ZIP code - month-year level from January 2017 until December 2022. All variables are winsorized at 1% on both ends.

Table 1: Baseline Results: Effect on Credit Issuance

	ln(Amount)			
	(1)	(2)	(3)	(4)
Shadow × Shock	0.0025*	0.0029**	0.0055***	
	(0.0014)	(0.0014)	(0.0010)	
Shock	0.0215***			
	(0.0017)			
Fintech × Shock				0.0155***
				(0.0022)
Nontech × Shock				0.0031***
				(0.0011)
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	.	.	.	0.00
Lender FE	✓	✓		
Month-year × ZIP FE		✓		
Year-month × ZIP × Product FE			✓	✓
Year-month × Lender × Product FE			✓	✓
ZIP × Lender × Product FE			✓	✓
ZIPs	19,060	19,060	19,060	19,060
Years	6	6	6	6
R-squared	0.14	0.39	0.84	0.84
Observations	20,459,958	20,459,958	20,459,958	20,459,958

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Shadow Banks, split by Fintechs and Nontechs in Column 4, as well as traditional banks. The primary independent variables are interactions of Shadow Banks, Fintechs, and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 3 describe results with different sets of fixed effects. Column 4 splits shadow banks by Fintech and Nontech. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table 2: Effect on Credit Issuance: Heterogeneity by Collateralization

	ln(Amount)		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0155***	-0.0231**	0.0189***
	(0.0022)	(0.0099)	(0.0023)
Nontech × Shock	0.0031***	0.0153***	-0.0031*
	(0.0011)	(0.0013)	(0.0018)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00
Month-year × ZIP × Product FE	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,006	19,052
Years	6	6	6
R-squared	0.84	0.85	0.84
Observations	20,459,958	9,262,879	8,045,001

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table 3: Effect on Credit Issuance: Heterogeneity by Credit Score Type

	ln(Amount)						
	Total (1)	Super-Prime (2)	Prime-Plus (3)	Prime (4)	Near-Prime (5)	Sub-Prime (6)	New-to-Credit (7)
	Panel A: All Loans						
Fintech × Shock	0.0155***	-0.0051	-0.0017	0.0073***	0.0110***	0.0174***	0.0266***
	(0.0022)	(0.0074)	(0.0043)	(0.0028)	(0.0030)	(0.0042)	(0.0034)
Nontech × Shock	0.0031***	0.0017	-0.0034	-0.0042***	0.0021	-0.0014	0.0115***
	(0.0011)	(0.0036)	(0.0021)	(0.0015)	(0.0017)	(0.0022)	(0.0016)
Fintech × Shock = Nontech × Shock	0.00	0.38	0.71	0.00	0.00	0.00	0.00
R-squared	0.84	0.78	0.79	0.80	0.79	0.78	0.78
Observations	20,459,958	3,161,724	7,524,047	13,167,634	11,077,601	7,214,411	12,308,208
	Panel B: Collateralized Loans						
Fintech × Shock	-0.0231**	0.1532*	-0.0178	-0.0112	-0.0119	0.0000	-0.0228
	(0.0099)	(0.0873)	(0.0291)	(0.0158)	(0.0200)	(0.0265)	(0.0142)
Nontech × Shock	0.0153***	0.0040	-0.0001	0.0082***	0.0108***	0.0059**	0.0161***
	(0.0013)	(0.0054)	(0.0031)	(0.0021)	(0.0022)	(0.0026)	(0.0018)
Fintech × Shock = Nontech × Shock	0.00	0.09	0.54	0.22	0.26	0.82	0.01
R-squared	0.85	0.78	0.79	0.80	0.78	0.76	0.78
Observations	9,262,879	1,366,665	3,033,653	5,755,172	5,238,180	3,702,319	5,893,921
	Panel C: Uncollateralized Loans						
Fintech × Shock	0.0189***	-0.0053	0.0012	0.0060**	0.0102***	0.0104**	0.0249***
	(0.0023)	(0.0075)	(0.0044)	(0.0029)	(0.0031)	(0.0045)	(0.0036)
Nontech × Shock	-0.0031*	0.0069	-0.0029	-0.0083***	-0.0018	-0.0046	0.0049*
	(0.0018)	(0.0046)	(0.0027)	(0.0022)	(0.0027)	(0.0038)	(0.0026)
Fintech × Shock = Nontech × Shock	0.00	0.12	0.38	0.00	0.00	0.00	0.00
R-squared	0.84	0.79	0.80	0.81	0.79	0.77	0.77
Observations	8,045,001	1,443,266	3,684,609	5,654,787	4,409,128	2,623,645	4,796,111

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by credit score type. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 to 7 focus on different credit score types. Panel A displays results for all loans, while Panel B and C display results for collateralized loans (agricultural, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 4: Effect on Default Rate of Loans Issued Following Weather Shocks

	Default Rate		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0003	0.0018	0.0007*
	(0.0003)	(0.0019)	(0.0003)
Nontech × Shock	0.0001	-0.0004**	0.0009***
	(0.0001)	(0.0002)	(0.0002)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.54	0.24	0.60
Month-year × ZIP × Product FE	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,006	19,052
Years	6	6	6
R-squared	0.45	0.45	0.44
Observations	20,459,958	9,262,879	8,045,001

Notes: This table presents the relative effects of weather shocks on credit default rate across different types of lenders, based on estimates derived from Equation 2. Default rate$_{ym,z,l,p}$ is the fraction of loans that defaulted within one year of being issued in that given year-month. This variable takes a value between zero and one. The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table 5: Effect on Credit Issuance: Heterogeneity by Geography

	ln(Amount)			
	Panel A: Urban and Rural Regions			
	Metro	Urban	Semi-Urban	Rural
	(1)	(2)	(3)	(4)
Fintech × Shock	0.0025	0.0163***	0.0159***	0.0213***
	(0.0065)	(0.0063)	(0.0038)	(0.0034)
Nontech × Shock	0.0072*	0.0039	0.0050***	0.0004
	(0.0038)	(0.0032)	(0.0019)	(0.0017)
Fintech × Shock = Nontech × Shock	0.49	0.06	0.01	0.00
R-squared	0.86	0.86	0.83	0.80
Wald p-val Fintech (Metro=Rural)	.	.	.	0.04
Wald p-val Nontech (Metro=Rural)	.	.	.	0.18
Observations	1,672,004	2,362,551	7,324,494	9,006,083
	Panel B: Traditional Bank Constraints			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
	(1)	(2)	(3)	(4)
Fintech × Shock	0.0050	0.0056	0.0154***	0.0225***
	(0.0053)	(0.0046)	(0.0046)	(0.0043)
Nontech × Shock	0.0047*	-0.0003	-0.0007	0.0019
	(0.0025)	(0.0023)	(0.0023)	(0.0023)
Fintech × Shock = Nontech × Shock	0.96	0.23	0.00	0.00
R-squared	0.84	0.86	0.86	0.84
Wald p-val Fintech (Q1=Q4)	.	.	.	0.04
Wald p-val Nontech (Q1=Q4)	.	.	.	0.51
Observations	4,420,020	4,439,306	4,434,633	4,448,434
	Panel C: Social Connectedness			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
	(1)	(2)	(3)	(4)
Fintech × Shock	0.0226***	0.0214***	0.0074	0.0087*
	(0.0043)	(0.0046)	(0.0047)	(0.0046)
Nontech × Shock	0.0084***	0.0012	-0.0052**	0.0066***
	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Fintech × Shock = Nontech × Shock	0.00	0.00	0.01	0.66
R-squared	0.85	0.84	0.82	0.82
Wald p-val Fintech (Q1=Q4)	.	.	.	0.07
Wald p-val Nontech (Q1=Q4)	.	.	.	0.63
Observations	5,128,802	5,039,199	5,087,261	5,050,075

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by geography. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 4 describe the geographical unit. Panel A displays results for metro, urban, semi-urban, and rural ZIPs. Panel B displays results by quartiles of lending constraints by traditional banks on the ZIP-year level, calculated as a weighted average of lending shares of each traditional bank, weighted by each bank's total non-performing assets (NPA) ratio. Panel C displays results by quartiles of social connectedness on the district level, measured by the Facebook social connectedness index (SCI). Appendix Section A.1 describes the construction of these variables. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels.

Table 6: UPI Index & Other Observable Characteristics at ZIP Level

	UPI Exposure Index		
	(1)	(2)	(3)
ln(area)	-0.0247***	-0.0095*	-0.0095
	(0.0052)	(0.0052)	(0.0069)
ln(population)	0.0144	0.0040	-0.0115
	(0.0111)	(0.0117)	(0.0150)
% scheduled caste and tribe	0.1581***	0.0942***	-0.0014
	(0.0356)	(0.0356)	(0.0547)
% literate	-0.3585***	-0.0281	-0.0994
	(0.0603)	(0.0679)	(0.1046)
# schools per 1,000 people	0.0198**	0.0169*	-0.0028
	(0.0094)	(0.0099)	(0.0120)
# colleges per 1,000 people	0.0925	-0.0349	0.0317
	(0.1117)	(0.1069)	(0.1226)
# firms per 1,000 people	0.0252*	0.0033	0.0033
	(0.0148)	(0.0132)	(0.0156)
ln(nightlight)	0.0054	0.0104	-0.0051
	(0.0105)	(0.0103)	(0.0143)
ln(employment)	0.0207*	0.0082	0.0160
	(0.0111)	(0.0114)	(0.0145)
% employed in manufacturing	-0.6466***	-0.2203	-0.4151
	(0.2304)	(0.2190)	(0.2743)
% employed in services	-0.4925**	0.2035	0.0629
	(0.1999)	(0.2072)	(0.2563)
State FE		✓	
District FE			✓
R-squared	0.04	0.26	0.46
Observations	3,667	3,667	3,667

Notes: This table presents the correlation between the UPI exposure index and several characteristics including the natural logarithm of geographic area, the natural logarithm of population, the share of the population belonging to scheduled caste and scheduled tribe, the share of the literate population, the number of schools per thousand people, number of colleges per thousand people, number of firms per thousand people, the natural logarithm of nightlights, the natural logarithm of total employment, and the share of population in the manufacturing and services sectors. The numbers on total population, SC/ST population, literate population, number of schools and the number of colleges come from the 2011 Indian Census. Numbers of total employment and number of people employed in the manufacturing and the services sector come from the 2015 Economic Census. Data on the number of firms in 2015 come from Dutta, Ghosh, Sarkar, and Vats (2021). Average nightlight data comes from Agarwal, Desai, Ghosh, and Vats (2024). The UPI exposure index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. Early adopter banks are banks that were providing UPI services as of November 2016. The unit of observation is ZIP code. Robust standard errors are reported in parentheses. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 7: Relationship Between UPI Index & UPI Transactions

	Panel A: ln(UPI Transaction Volume)					
	(1)	(2)	(3)	(4)	(5)	(6)
UPI Exposure Index	0.0136***	0.0148***	0.0150***	0.0150***	0.0150***	0.0150***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Month-year FE		✓	✓			
State FE			✓			
Month-year × State FE				✓	✓	
District FE					✓	
Month-year × District FE						✓
R-squared	0.02	0.78	0.83	0.83	0.86	0.86
Observations	462,414	462,414	462,414	462,414	462,414	462,414

	Panel B: ln(UPI Transaction Value)					
	(1)	(2)	(3)	(4)	(5)	(6)
UPI Exposure Index	0.0140***	0.0152***	0.0159***	0.0160***	0.0160***	0.0160***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Month-year FE		✓	✓			
State FE			✓			
Month-year × State FE				✓	✓	
District FE					✓	
Month-year × District FE						✓
R-squared	0.02	0.76	0.80	0.81	0.84	0.84
Observations	462,414	462,414	462,414	462,414	462,414	462,414

Notes: This table presents the relationship between UPI transactions and the UPI exposure index. Panel A uses the natural logarithm of UPI transaction volume as the dependent variable and Panel B uses the natural logarithm of UPI transaction value as the dependent variable. The UPI exposure index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. Early adopter banks are banks that were providing UPI services as of November 2016. The unit of observation in ZIP code - month-year level. The outcome variables are winsorized at 1% on both ends. Robust standard errors are reported in parentheses. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 8: Role of Technology: Heterogeneity by UPI Exposure

	ln(Amount)			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
	(1)	(2)	(3)	(4)
	Panel A: All Loans			
Fintech × Shock	0.0065	0.0128**	0.0164***	0.0232***
	(0.0053)	(0.0050)	(0.0050)	(0.0050)
Nontech × Shock	-0.0001	0.0018	0.0055**	0.0003
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Fintech × Shock = Nontech × Shock	0.23	0.03	0.04	0.00
R-squared	0.83	0.85	0.85	0.81
Wald p-val Fintech (Q1=Q4)	.	.	.	0.06
Wald p-val Nontech (Q1=Q4)	.	.	.	0.93
Observations	3,974,444	3,973,448	3,974,116	3,973,383
	Panel B: Collateralized Loans			
Fintech × Shock	-0.0800***	0.0201	-0.0547***	-0.0148
	(0.0236)	(0.0174)	(0.0191)	(0.0288)
Nontech × Shock	0.0144***	0.0154***	0.0175***	0.0075**
	(0.0031)	(0.0028)	(0.0028)	(0.0031)
Fintech × Shock = Nontech × Shock	0.00	0.79	0.00	0.44
R-squared	0.84	0.87	0.86	0.81
Wald p-val Fintech (Q1=Q4)	.	.	.	0.17
Wald p-val Nontech (Q1=Q4)	.	.	.	0.21
Observations	1,775,033	1,775,002	1,773,897	1,774,575
	Panel C: Uncollateralized Loans			
Fintech × Shock	0.0094*	0.0134***	0.0260***	0.0241***
	(0.0052)	(0.0052)	(0.0052)	(0.0051)
Nontech × Shock	-0.0079**	-0.0049	-0.0034	0.0010
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.00
R-squared	0.83	0.85	0.85	0.81
Wald p-val Fintech (Q1=Q4)	.	.	.	0.09
Wald p-val Nontech (Q1=Q4)	.	.	.	0.18
Observations	1,566,988	1,566,804	1,566,827	1,566,431

This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by ZIP level UPI exposure. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 4 describe quartiles by the UPI exposure index. The UPI exposure index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. Early adopter banks are banks that were providing UPI services as of November 2016. Panel A displays results for all loans, while Panel B and C display results for collateralized loans (agricultural, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table 9: Role of Technology: Evidence from Application Level Data

	All	New-to-Credit	Not New-to-Credit	All	New-to-Credit	Not New-to-Credit
	(1)	(2)	(3)	(1)	(2)	(3)
	Panel A: Application Accepted (0 or 1)			**Panel B: # Days to Disbursal**		
Transaction-Based Score × Shock	0.0080***	0.0237***	0.0041*	-0.1266***	-0.5521***	-0.1389***
	(0.0021)	(0.0052)	(0.0023)	(0.0489)	(0.1984)	(0.0524)
Transaction-Based Score	0.0621***	0.0564***	0.0789***	-0.4177***	-0.5061***	-0.4543***
	(0.0017)	(0.0035)	(0.0019)	(0.0332)	(0.1358)	(0.0367)
R-squared	0.34	0.34	0.40	0.24	0.32	0.27
Observations	712,049	136,846	534,638	315,478	38,406	251,263
	Panel C: Loan in Default (0 or 1)			**Panel D: Interest Rate**		
Transaction-Based Score × Shock	-0.0029**	-0.0030	-0.0027*	0.0040***	0.0009	0.0022
	(0.0014)	(0.0052)	(0.0016)	(0.0015)	(0.0024)	(0.0014)
Transaction-Based Score	-0.0157***	-0.0096***	-0.0171***	-0.0766***	-0.1633***	-0.0940***
	(0.0010)	(0.0031)	(0.0011)	(0.0010)	(0.0017)	(0.0010)
R-squared	0.25	0.33	0.27	0.32	0.79	0.40
Observations	315,489	38,406	251,273	315,489	38,406	251,273
Year-month × ZIP × Merchant Type FE	✓	✓	✓	✓	✓	✓
Onboarding Channel FE	✓	✓	✓	✓	✓	✓
Swipe Machine FE	✓	✓	✓	✓	✓	✓
Membership in Investment App FE	✓	✓	✓	✓	✓	✓

Notes: This table presents the relationship between digital transactions based score and applications level outcomes after the shock based on detailed application level data from a Fintech in India. Equation 4 describes the regression.

$$y_{app} = \beta_0 \cdot \text{Shock}_{ym,z} \times \text{Transaction-Based Score}_{app} + \beta_1 \text{Transaction-Based Score}_{app} + \text{FE} + \epsilon_{app} \tag{4}$$

The outcome variable in Panel A is Application Accepted which is a binary variable that takes a value of one if the application was accepted and zero otherwise. Panel B uses the Days to Disbursal as the outcome variable. It is a measure of how many days it takes the Fintech to disburse the loan, conditional on the application being accepted. Panel C uses default as the outcome variable which takes a value of one if the loan is in default and zero otherwise. Panel D uses interest rate on the loan as the outcome variable. Transaction-based score refers to a proprietary score created by the Fintech, from the digital transaction history of the merchant. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Columns 1 and 4 describe results for the full sample, Columns 2 and 5 for those new-to-credit, and Columns 3 and 6 for those not new-to-credit. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table 10: Role of Regulation: Exploiting Regulatory Changes

	ln(Amount)		
	MFI	Gold	Agri
	(1)	(2)	(3)
Fintech × Shock	0.0521**	-0.0277	0.2172
	(0.0245)	(0.0353)	(0.1962)
Nontech × Shock	-0.0171	0.0414***	0.0572***
	(0.0128)	(0.0029)	(0.0150)
Fintech × Shock × Post	-0.0077	0.0464	-0.1662
	(0.0590)	(0.0746)	(0.2369)
Nontech × Shock × Post	0.0052	-0.0404***	0.1414***
	(0.0306)	(0.0073)	(0.0324)
Omitted Category	Traditional	Traditional	Traditional
Month-year × ZIP × Product FE	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	14,643	17,959	16,625
Years	4	6	4
R-squared	0.81	0.88	0.77
Observations	670,184	2,144,083	848,813

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, before and after regulations, based on estimates derived from Equation 2. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable, and a Post indicator. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Post$_{ym}$ is a dummy equal to one after November 2023 in Columns 1 and 3 and after August 2020 in Column 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock and post variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. The data ranges in Column 1 and 3 from July 2021 to June 2024, and in Column 2 from January 2016 to March 2021. Column 1 presents results for MFI loans, Column 2 for gold loans, and Column 3 for agricultural loans. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table 11: Role of Regulation & Funding: Exploiting IL&FS Crisis

	ln(Amount)		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0154**	-0.0013	0.0200***
	(0.0073)	(0.0200)	(0.0077)
Nontech × Shock	0.0136***	0.0315***	-0.0069**
	(0.0018)	(0.0022)	(0.0030)
Fintech × Shock × Post	-0.0012	-0.0312	-0.0008
	(0.0076)	(0.0225)	(0.0081)
Nontech × Shock × Post	-0.0170***	-0.0274***	0.0060
	(0.0023)	(0.0027)	(0.0037)
Omitted Category	Traditional	Traditional	Traditional
Year-month × ZIP × Product FE	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,006	19,052
Years	6	6	6
R-squared	0.84	0.85	0.84
Observations	20,459,958	9,262,879	8,045,001

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, before and after the IL&FS corporate loan defaults in August 2018, based on estimates derived from Equation 2. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable, and a Post indicator. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Post$_{ym}$ is a dummy equal to one after August 2018. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock and post variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table 12: Role of Local Presence

	ln(Amount)					
	All		Collateralized		Uncollateralized	
	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech × Shock	0.0089**	0.0138***	0.0500	-0.0293***	0.0167***	0.0193***
	(0.0036)	(0.0029)	(0.0308)	(0.0104)	(0.0036)	(0.0030)
Nontech × Shock	-0.0024	0.0037**	0.0036	0.0148***	-0.0032	-0.0024
	(0.0018)	(0.0014)	(0.0022)	(0.0017)	(0.0029)	(0.0022)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.13	0.00	0.00	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIPs	9,530	9,530	9,476	9,530	9,522	9,530
Years	6	6	6	6	6	6
R-squared	0.80	0.85	0.80	0.86	0.80	0.85
Wald p-val Fintech (Below = Above)	.	0.39	.	0.05	.	0.63
Wald p-val Nontech (Below = Above)	.	0.03	.	0.00	.	0.87
Observations	8,326,747	12,133,122	3,803,554	5,459,265	3,324,118	4,720,865

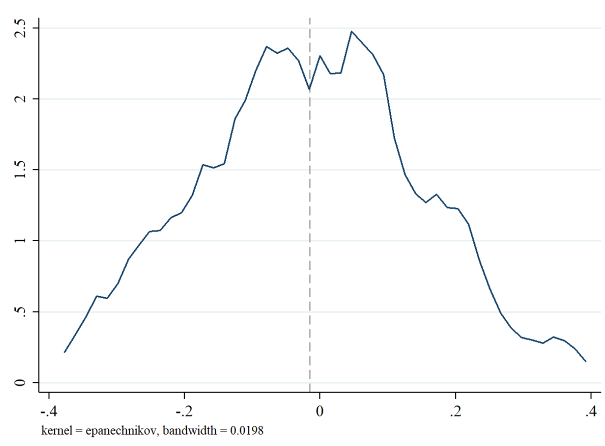
Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by shadow bank local presence. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 2 report results for all loans, Columns 3 to 4 for collateralized loans (agriculture, gold, vehicle), and Columns 5 to 6 for uncollateralized loans (business, consumption, MFI). The samples are split by ZIP level shadow bank local presence, measured by total loan count by shadow banks in the ZIP in January to March 2016, divided by population. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Online Appendix for:

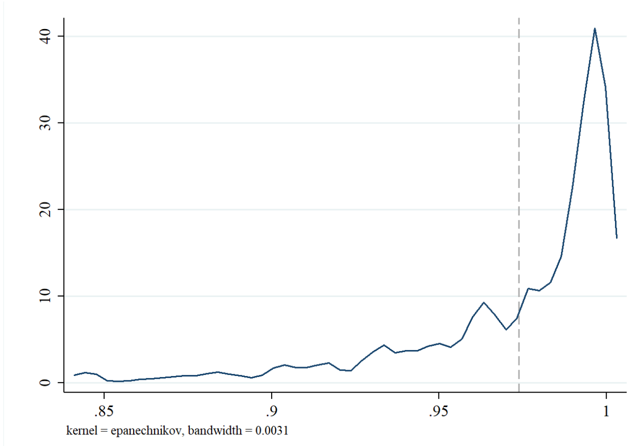
“Shadow Banks on the Rise: Evidence Across Market Segments”

Appendix A Data

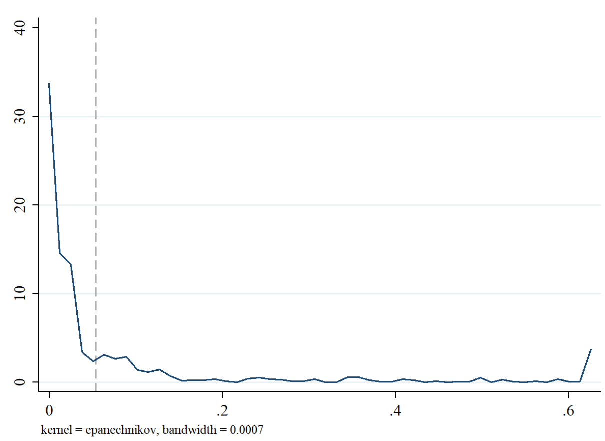
Figure A.1: Properties of Weather Shocks



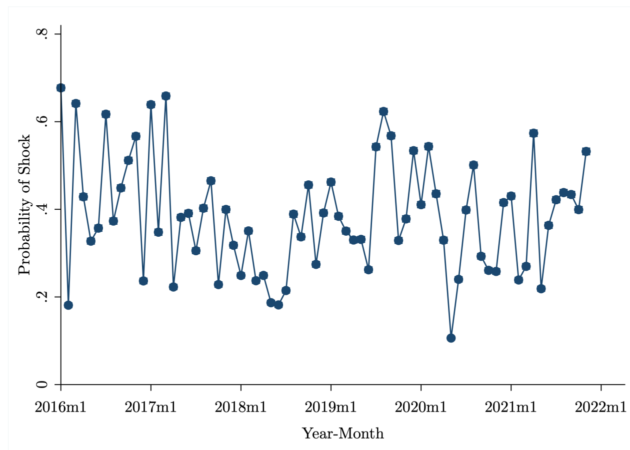
(a) AR(1) Estimate for Weather Shocks



(b) Idiosyncratic Component of Weather Shocks



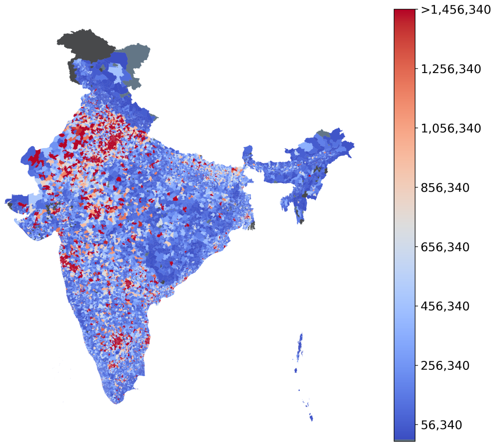
(c) Spatial Correlation (ρ^2) of Weather Shocks



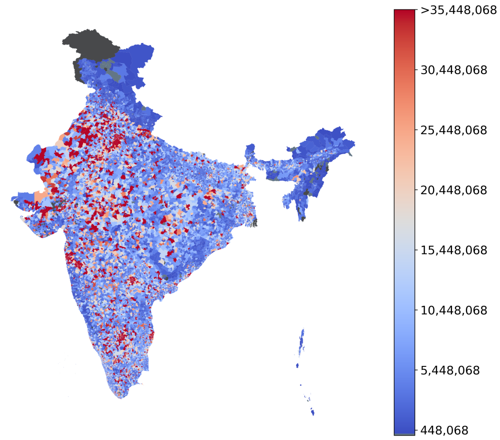
(d) Probability of Weather Shocks over Time

This figure describes the properties of weather shocks, documenting their spatial isolation and temporal non-persistence. Figure A.1a plots the estimated coefficients of the AR(1) term from a ZIP-wise regression. We run time series AR(1) regression for each ZIP and estimate the AR(1) coefficient. The blue line reports the kernel density of AR(1) coefficients obtained from the time series regression. The gray vertical line indicates the average AR(1) value of -0.015. Figure A.1b plots the kernel density of $1 - R^2$ of the AR(1) regression for each ZIP, indicating the unexplained component in the regression. The gray vertical line indicates the average idiosyncratic component value of 0.974. Figure A.1c plots the kernel density of the square of the spatial correlation of weather shocks across ZIPs. The gray vertical line indicates the average squared correlation value of 0.054. All the metrics are calculated using ZIP-level monthly data on weather shocks from January 2013 until December 2015 and winsorized at 1% level. Figure A.1d presents the within ZIP (monthly) probability of incidence of the weather shock over time from 2016 until 2021.

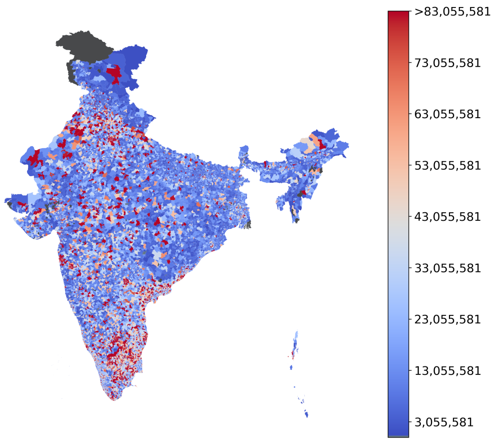
Figure A.2: Spatial Distribution of Credit Issuance



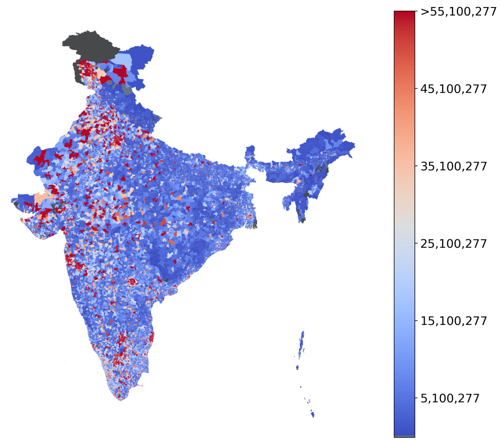
(a) Fintech



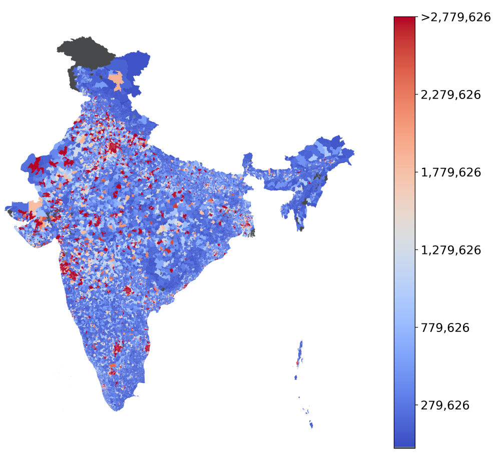
(b) Nontech



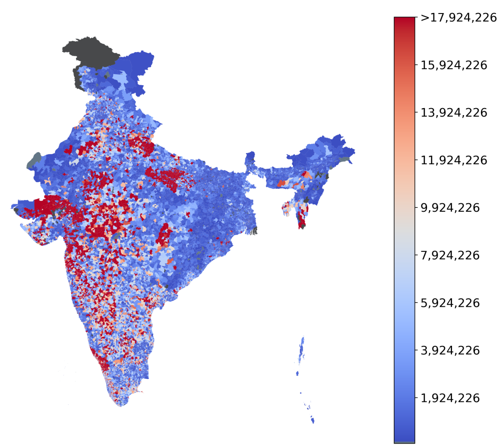
(c) State-Owned



(d) Private



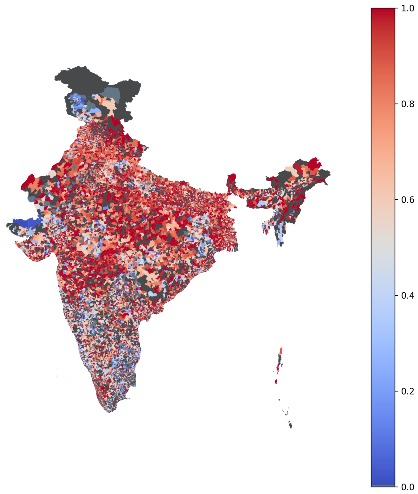
(e) Foreign



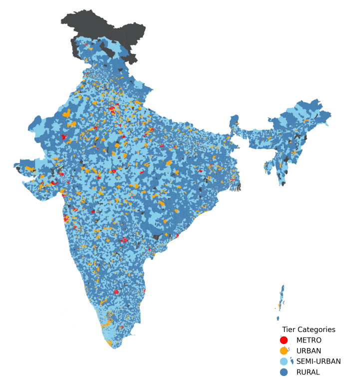
(f) Others

This figure presents the average of the monthly loan amount in rupees over our study period issued in a ZIP code by a lender across products. The maximum number on the legend indicates the 90th percentile of the ZIP-level distribution for a given lender. Light gray indicates zero loan issuance and dark gray indicates missing data.

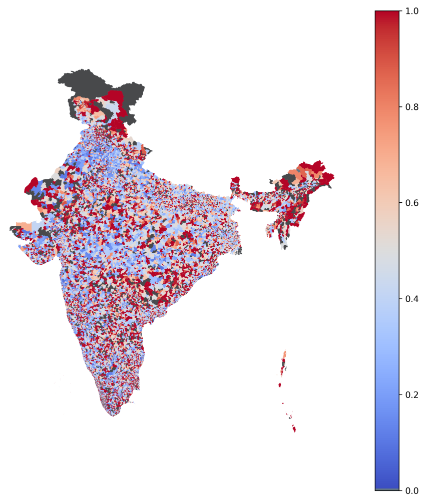
Figure A.3: Spatial Distribution of Key Heterogeneity Variables



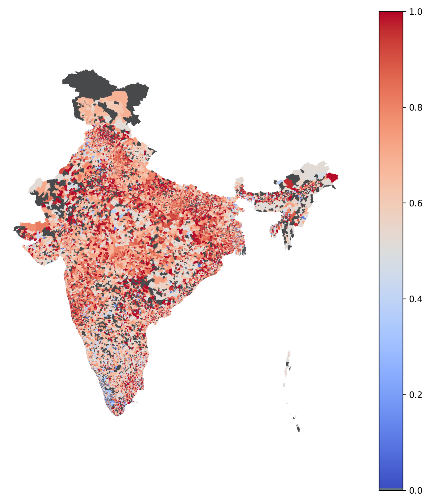
(a) UPI Index



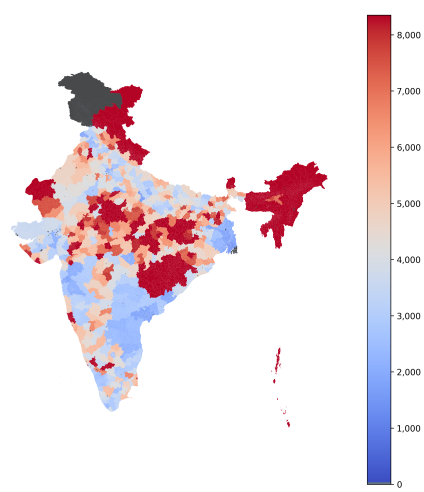
(b) Urban/Rural



(c) HHI (Credit)



(d) Non-Performing Assets



(e) Social Connectedness Index

Figure A.3a reports the ZIP level UPI index. Figure A.3b depicts metro (red), urban (orange), semi-urban (light blue), and rural (navy) ZIPs. Figure A.3c presents the ZIP level HHI measure constructed using credit. Figure A.3d presents the temporal average of the ZIP-year level NPA measure. Finally, Figure A.3e reports the district-level social connectedness index (SCI). Light gray indicates zero, dark gray indicates missing. Section 2 and Appendix Section A.1 describe the data sources and construction of these variables.

Table A.1: Indian Lending Landscape

	2016			2021		
	Fintech	Nontech	Traditional	Fintech	Nontech	Traditional
Loan number						
Total (million)	0.08	25.31	50.85	8.81	43.69	55.16
Total (%)	0.00	0.33	0.67	0.08	0.41	0.51
Agriculture (%)	0.00	0.02	0.98	0.00	0.02	0.98
Gold (%)	0.00	0.62	0.38	0.00	0.59	0.41
Vehicle (%)	0.00	0.52	0.48	0.00	0.61	0.39
Business (%)	0.03	0.44	0.53	0.12	0.44	0.44
Consumption (%)	0.00	0.42	0.58	0.16	0.46	0.38
Microfinance (%)	0.00	0.02	0.98	0.00	0.15	0.85
Other (%)	0.00	0.01	0.98	0.04	0.20	0.76
Super Prime (%)	0.00	0.23	0.77	0.06	0.25	0.68
Prime-Plus (%)	0.00	0.27	0.73	0.07	0.31	0.62
Prime (%)	0.00	0.30	0.70	0.09	0.36	0.55
Near-Prime (%)	0.00	0.41	0.59	0.10	0.45	0.45
Sub-Prime (%)	0.00	0.42	0.58	0.07	0.48	0.45
New-to-Credit (%)	0.00	0.30	0.70	0.07	0.48	0.45
Loan amount						
Total (billion Rs)	21.66	2,587.35	8,557.31	227.71	3,139.30	9,832.87
Total (billion USD)	0.32	37.78	124.94	3.32	45.83	143.56
Total (%)	0.00	0.23	0.77	0.02	0.24	0.74
Agriculture (%)	0.00	0.04	0.96	0.00	0.06	0.94
Gold (%)	0.00	0.49	0.51	0.00	0.40	0.60
Vehicle (%)	0.00	0.44	0.56	0.00	0.42	0.58
Business (%)	0.03	0.30	0.67	0.07	0.37	0.56
Consumption (%)	0.00	0.19	0.81	0.04	0.21	0.75
Microfinance (%)	0.00	0.07	0.93	0.00	0.06	0.94
Other (%)	0.00	0.10	0.90	0.01	0.14	0.85
Super Prime (%)	0.00	0.18	0.82	0.01	0.15	0.84
Prime-Plus (%)	0.00	0.20	0.80	0.02	0.18	0.80
Prime (%)	0.00	0.22	0.78	0.02	0.21	0.77
Near-Prime (%)	0.00	0.29	0.71	0.02	0.27	0.71
Sub-Prime (%)	0.00	0.32	0.68	0.01	0.33	0.66
New-to-Credit (%)	0.00	0.20	0.80	0.01	0.32	0.66

Notes: This table describes the Indian lending landscape. Loan number and loan amount are aggregated over a given year and winsorized at 1% on both ends.

Table A.2: Granular CIBIL Summary Statistics by Lender

	# Obs	p25	p50	p75	Mean	SD
	Panel A: All Lenders					
Loan Number	20,459,958	2.00	6.00	22.00	31.66	78.27
Loan Amount	20,459,958	250,000	938,310	3,250,000	4,285,059	10,536,773
Default Rate	20,459,958	0.00	0.00	0.02	0.04	0.13
# Inquiries	20,459,958	0.58	4.67	18.75	22.51	49.86
	Panel B: State-Owned Banks					
Loan Number	4,612,254	3.00	8.00	28.00	38.12	86.71
Loan Amount	4,612,254	650,000	1,990,000	6,274,334	6,840,465	13,285,471
Default Rate	4,612,254	0.00	0.00	0.00	0.03	0.09
# Inquiries	4,612,254	3.08	7.75	19.58	18.83	33.22
	Panel C: Private Banks					
Loan Number	5,293,364	2.00	6.00	17.00	25.91	68.30
Loan Amount	5,293,364	351,598	1,102,454	3,508,765	4,797,929	11,728,324
Default Rate	5,293,364	0.00	0.00	0.00	0.03	0.11
# Inquiries	5,293,364	1.83	6.75	20.75	24.03	49.63
	Panel D: Foreign Banks					
Loan Number	1,065,930	2.00	4.00	12.00	18.74	52.39
Loan Amount	1,065,930	119,000	348,000	1,128,200	2,137,461	7,127,444
Default Rate	1,065,930	0.00	0.00	0.00	0.04	0.11
# Inquiries	1,065,930	0.00	0.08	0.33	2.32	13.29
	Panel E: Nontech					
Loan Number	5,055,554	3.00	10.00	35.00	44.72	96.42
Loan Amount	5,055,554	300,150	1,061,582	3,447,068	4,136,931	9,701,351
Default Rate	5,055,554	0.00	0.00	0.05	0.05	0.12
# Inquiries	5,055,554	0.42	8.83	37.75	38.14	69.09
	Panel F: Fintech					
Loan Number	1,307,221	2.00	5.00	19.00	28.56	77.56
Loan Amount	1,307,221	26,050	103,995	380,000	705,260	2,765,448
Default Rate	1,307,221	0.00	0.00	0.09	0.08	0.17
# Inquiries	1,307,221	2.17	10.08	31.42	33.77	62.01
	Panel G: Other Financial Institutions					
Loan Number	3,125,635	1.00	4.00	12.00	16.46	44.01
Loan Amount	3,125,635	144,900	500,000	1,590,000	2,114,833	6,231,386
Default Rate	3,125,635	0.00	0.00	0.00	0.06	0.18
# Inquiries	3,125,635	0.00	0.25	1.33	2.29	8.13

Notes: This table describes the summary statistics of the credit bureau (TransUnion-CIBIL) data, by lender. The data is on the year-month × ZIP × lender × product level. To describe inquiries, which are on the year × ZIP × lender × product level, we divide the number by twelve. Loan amount is expressed in rupees. Default rate is the fraction of loans that is more than 90 days past due within one year of being issued. Loan number, loan amount, and inquiries are winsorized at 1% on both ends.

Table A.3: Granular CIBIL Summary Statistics by Product

	# Obs	p25	p50	p75	Mean	SD
	Panel A: Agriculture Loans					
Loan Number	3,269,797	2.00	6.00	25.00	41.73	98.27
Loan Amount	3,269,797	468,000	1,350,000	4,620,000	5,995,254	13,099,331
Default Rate	3,269,797	0.00	0.00	0.00	0.05	0.14
# Inquiries	3,269,797	0.17	1.42	6.17	6.87	17.28
	Panel B: Gold Loans					
Loan Number	2,488,014	4.00	13.00	49.00	50.00	91.53
Loan Amount	2,488,014	237,794	884,500	3,214,600	3,603,942	8,063,012
Default Rate	2,488,014	0.00	0.00	0.00	0.02	0.09
# Inquiries	2,488,014	0.00	0.08	0.83	1.97	7.56
	Panel C: Vehicle Loans					
Loan Number	3,505,068	2.00	6.00	19.00	19.33	41.42
Loan Amount	3,505,068	575,000	1,671,310	4,861,874	5,387,766	11,274,004
Default Rate	3,505,068	0.00	0.00	0.03	0.03	0.09
# Inquiries	3,505,068	5.00	14.42	37.00	34.38	54.25
	Panel D: Business Loans					
Loan Number	1,590,155	1.00	2.00	5.00	5.58	15.71
Loan Amount	1,590,155	180,000	645,449	2,260,000	3,165,503	8,880,988
Default Rate	1,590,155	0.00	0.00	0.00	0.05	0.18
# Inquiries	1,590,155	2.33	7.08	19.50	18.04	32.31
	Panel E: Consumer Loans					
Loan Number	6,069,098	3.00	9.00	29.00	41.85	97.05
Loan Amount	6,069,098	160,288	660,000	2,403,431	3,579,160	9,876,105
Default Rate	6,069,098	0.00	0.00	0.04	0.05	0.12
# Inquiries	6,069,098	1.67	9.00	33.33	37.91	70.10
	Panel F: Microfinance Loans					
Loan Number	385,748	1.00	3.00	8.00	8.38	19.37
Loan Amount	385,748	40,000	169,000	593,000	708,747	2,960,381
Default Rate	385,748	0.00	0.00	0.00	0.06	0.18
# Inquiries	385,748	0.08	0.75	4.50	7.20	22.63

Notes: This table describes the summary statistics of the credit bureau (TransUnion-CIBIL) data, by product. The data is on the year-month × ZIP × lender × product level. To describe inquiries, which are on the year × ZIP × lender × product level, we divide the number by twelve. Loan amount is expressed in rupees. Default rate is the fraction of loans that is more than 90 days past due within one year of being issued. Loan number, loan amount, and inquiries are winsorized at 1% on both ends.

Table A.4: Granular CIBIL Summary Statistics by Lender and Credit Score

	Loan Number				Loan Amount				Default Rate				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Panel A: State-Owned Banks																
Super Prime	4,612,254	0.00	1.45	4.31	4,612,254	0	331,522	1,090,052	4,612,254	0.00	0.00	0.00	4,612,254	0.17	0.58	1.30
Prime-Plus	4,612,254	1.00	4.23	11.52	4,612,254	50,000	848,565	2,128,117	4,612,254	0.00	0.00	0.03	4,612,254	0.58	1.93	3.88
Prime	4,612,254	2.00	13.64	33.70	4,612,254	600,000	2,465,045	5,182,036	4,612,254	0.00	0.01	0.07	4,612,254	2.00	5.41	10.17
Near-Prime	4,612,254	1.00	7.58	18.22	4,612,254	280,000	1,298,842	2,679,420	4,612,254	0.00	0.02	0.09	4,612,254	1.33	3.42	6.34
Sub-Prime	4,612,254	1.00	3.53	8.30	4,612,254	23,022	560,553	1,241,402	4,612,254	0.00	0.03	0.13	4,612,254	0.83	2.14	4.08
New-To-credit	4,612,254	1.00	6.56	14.18	4,612,254	256,800	1,021,837	1,979,203	4,612,254	0.00	0.02	0.09	4,612,254	2.17	5.18	8.92
Panel B: Private Banks																
Super Prime	5,293,364	0.00	1.18	3.76	5,293,364	0	304,082	1,112,410	5,293,364	0.00	0.00	0.00	5,293,364	0.08	0.69	1.61
Prime-Plus	5,293,364	1.00	3.88	11.10	5,293,364	15,500	759,193	2,192,696	5,293,364	0.00	0.00	0.03	5,293,364	0.58	2.37	5.09
Prime	5,293,364	2.00	9.15	26.45	5,293,364	250,000	1,697,857	4,527,153	5,293,364	0.00	0.02	0.07	5,293,364	1.58	6.64	14.51
Near-Prime	5,293,364	1.00	4.41	12.89	5,293,364	70,000	865,803	2,307,698	5,293,364	0.00	0.02	0.10	5,293,364	1.17	4.54	9.68
Sub-Prime	5,293,364	0.00	1.72	5.11	5,293,364	0	316,017	959,521	5,293,364	0.00	0.03	0.13	5,293,364	0.75	2.82	6.23
New-To-credit	5,293,364	1.00	5.07	12.00	5,293,364	111,600	599,154	1,414,476	5,293,364	0.00	0.02	0.10	5,293,364	1.75	6.69	13.38
Panel C: Foreign Banks																
Super Prime	1,065,930	0.00	1.08	3.40	1,065,930	0	220,878	907,380	1,065,930	0.00	0.00	0.00	1,065,930	0.00	0.16	0.81
Prime-Plus	1,065,930	1.00	3.99	10.67	1,065,930	32,000	520,809	1,729,184	1,065,930	0.00	0.01	0.05	1,065,930	0.00	0.41	2.06
Prime	1,065,930	2.00	7.48	21.65	1,065,930	100,000	803,778	2,767,256	1,065,930	0.00	0.03	0.09	1,065,930	0.00	0.85	4.51
Near-Prime	1,065,930	0.00	1.99	6.65	1,065,930	0	207,968	885,951	1,065,930	0.00	0.02	0.11	1,065,930	0.00	0.45	2.49
Sub-Prime	1,065,930	0.00	0.35	1.47	1,065,930	0	38,378	273,278	1,065,930	0.00	0.01	0.10	1,065,930	0.00	0.21	1.31
New-To-credit	1,065,930	1.00	3.26	7.80	1,065,930	25,000	243,987	696,676	1,065,930	0.00	0.02	0.09	1,065,930	0.00	0.17	1.77
Panel D: Nontech																
Super Prime	5,055,554	0.00	0.92	3.09	5,055,554	0	132,314	650,286	5,055,554	0.00	0.00	0.00	5,055,554	0.08	0.63	1.59
Prime-Plus	5,055,554	0.00	4.21	12.15	5,055,554	0	426,545	1,442,954	5,055,554	0.00	0.01	0.04	5,055,554	0.33	2.60	5.80
Prime	5,055,554	2.00	13.33	34.27	5,055,554	196,000	1,278,117	3,522,925	5,055,554	0.00	0.02	0.09	5,055,554	1.58	9.40	19.07
Near-Prime	5,055,554	2.00	10.14	22.75	5,055,554	150,000	936,922	2,211,486	5,055,554	0.00	0.04	0.12	5,055,554	1.67	7.55	13.82
Sub-Prime	5,055,554	1.00	4.67	10.04	5,055,554	37,537	472,094	1,138,134	5,055,554	0.00	0.06	0.17	5,055,554	1.08	5.16	9.35
New-To-credit	5,055,554	2.00	9.95	18.58	5,055,554	124,998	652,825	1,393,164	5,055,554	0.00	0.04	0.13	5,055,554	3.08	12.41	20.58
Panel E: Fintech																
Super Prime	1,307,221	0.00	0.48	2.13	1,307,221	0	21,398	214,354	1,307,221	0.00	0.00	0.00	1,307,221	0.08	0.38	1.06
Prime-Plus	1,307,221	0.00	1.85	6.81	1,307,221	0	75,132	465,162	1,307,221	0.00	0.01	0.05	1,307,221	0.42	1.71	4.18
Prime	1,307,221	1.00	9.71	28.79	1,307,221	21,433	291,614	1,266,751	1,307,221	0.00	0.04	0.12	1,307,221	2.17	8.47	16.97
Near-Prime	1,307,221	1.00	8.35	21.11	1,307,221	12,000	176,447	754,930	1,307,221	0.00	0.06	0.16	1,307,221	2.33	7.57	13.25
Sub-Prime	1,307,221	0.00	2.69	7.74	1,307,221	0	54,635	288,765	1,307,221	0.00	0.06	0.19	1,307,221	1.67	5.52	9.35
New-To-credit	1,307,221	1.00	4.78	12.12	1,307,221	3,748	70,559	296,329	1,307,221	0.00	0.05	0.16	1,307,221	2.75	9.36	17.03

Notes: This table describes the summary statistics of the credit bureau (TransUnion-CIBIL) data, by lender and credit score. The data is on the year-month $\times$ ZIP $\times$ lender $\times$ product level. To describe inquiries, which are on the year $\times$ ZIP $\times$ lender $\times$ product level, we divide the number by twelve. Loan amount is expressed in rupees. Default rate is the fraction of loans that is more than 90 days past due within one year of being issued. Loan number, loan amount, and inquiries are winsorized at 1% on both ends.

Table A.5: Granular CIBIL Summary Statistics by Lender and Product

	Loan Number				Loan Amount				Default Rate				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Panel A: State-Owned Banks																
Agriculture	1,079,217	37.00	105.36	146.11	1,079,217	5,623,150	13,516,777	19,013,746	1,079,217	0.00	0.03	0.08	1,079,217	5.08	11.73	20.55
Gold	0	.	.	.	0	.	.	.	0	.	.	.	0	.	.	.
Vehicle	837,653	2.00	6.46	14.81	837,653	1,200,000	3,458,911	7,418,911	837,653	0.00	0.01	0.06	837,653	5.58	16.84	33.71
Business	362,406	2.00	5.70	23.88	362,406	418,000	2,653,454	9,206,663	362,406	0.00	0.05	0.17	362,406	7.83	17.33	29.65
Consumer	1,221,811	7.00	17.10	33.59	1,221,811	2,000,000	4,931,767	9,131,007	1,221,811	0.00	0.01	0.06	1,221,811	11.67	25.70	40.67
Microfinance	82,437	1.00	4.59	17.00	82,437	250,000	668,531	1,922,484	82,437	0.00	0.07	0.20	82,437	4.08	7.87	12.39
Panel B: Private Banks																
Agriculture	772,447	3.00	9.68	25.46	772,447	1,000,000	2,750,392	6,087,713	772,447	0.00	0.04	0.14	772,447	3.08	9.97	22.54
Gold	948,659	10.00	39.86	77.97	948,659	1,043,000	4,343,152	9,463,210	948,659	0.00	0.01	0.06	948,659	1.00	4.59	11.46
Vehicle	1,160,737	6.00	18.26	40.68	1,160,737	1,502,652	6,020,409	13,256,126	1,160,737	0.00	0.03	0.09	1,160,737	17.08	37.99	56.18
Business	328,882	2.00	4.23	7.33	328,882	1,102,931	4,601,443	10,934,409	328,882	0.00	0.02	0.10	328,882	11.50	23.83	36.36
Consumer	1,262,296	11.00	49.49	107.68	1,262,296	1,302,766	6,238,678	14,947,945	1,262,296	0.00	0.04	0.08	1,262,296	9.58	36.89	68.27
Microfinance	138,127	5.00	12.35	22.98	138,127	376,000	1,013,247	2,181,165	138,127	0.00	0.02	0.09	138,127	1.00	12.58	34.23
Panel C: Foreign Banks																
Agriculture	802	1.00	2.15	2.47	802	2,000,000	4,026,712	6,375,499	802	0.00	0.00	0.02	802	0.00	0.12	0.53
Gold	0	.	.	.	0	.	.	.	0	.	.	.	0	.	.	.
Vehicle	0	.	.	.	0	.	.	.	0	.	.	.	0	.	.	.
Business	33,169	1.00	1.85	2.14	33,169	3,100,000	5,859,741	9,503,595	33,169	0.00	0.01	0.08	33,169	0.33	1.60	3.23
Consumer	1,009,479	4.00	19.66	53.68	1,009,479	324,000	1,983,630	6,884,930	1,009,479	0.00	0.04	0.11	1,009,479	0.08	1.53	9.53
Microfinance	0	.	.	.	0	.	.	.	0	.	.	.	0	.	.	.
Panel D: Nontech																
Agriculture	671,101	2.00	4.23	6.56	671,101	880,000	1,563,390	2,379,000	671,101	0.00	0.07	0.19	671,101	0.17	1.30	5.37
Gold	960,958	20.00	66.49	110.59	960,958	819,626	3,352,202	7,871,625	960,958	0.00	0.03	0.09	960,958	0.00	0.51	2.65
Vehicle	1,203,029	17.00	33.41	53.39	1,203,029	3,149,254	7,227,685	12,247,093	1,203,029	0.03	0.06	0.09	1,203,029	27.33	50.89	63.07
Business	439,955	3.00	7.21	12.88	439,955	1,000,000	3,701,185	8,952,686	439,955	0.00	0.05	0.16	439,955	8.83	21.08	35.35
Consumer	1,256,034	27.00	89.38	143.59	1,256,034	657,611	3,678,085	9,863,942	1,256,034	0.02	0.04	0.08	1,256,034	40.17	87.20	98.82
Microfinance	66,735	3.00	7.46	15.62	66,735	44,000	206,014	1,540,691	66,735	0.00	0.11	0.23	66,735	0.17	2.19	8.17
Panel E: Fintech																
Agriculture	2,704	1.00	1.42	1.05	2,704	400,000	654,253	781,746	2,704	0.00	0.05	0.20	2,704	2.33	12.40	22.22
Gold	7,417	1.00	2.04	2.91	7,417	75,655	238,521	1,297,587	7,417	0.00	0.12	0.30	7,417	0.00	0.02	0.10
Vehicle	44,640	2.00	3.25	5.65	44,640	115,000	320,767	809,645	44,640	0.00	0.05	0.16	44,640	0.42	2.15	5.57
Business	242,551	2.00	5.28	14.50	242,551	300,000	1,402,529	3,851,668	242,551	0.00	0.09	0.23	242,551	5.50	17.36	33.73
Consumer	818,990	11.00	42.77	94.68	818,990	105,438	621,765	2,600,191	818,990	0.04	0.08	0.13	818,990	18.83	48.10	72.09
Microfinance	39,960	2.00	5.53	13.22	39,960	10,000	23,984	98,628	39,960	0.00	0.00	0.01	39,960	0.00	1.61	7.75

Notes: This table describes the summary statistics of the credit bureau (TransUnion-CIBIL) data, by lender and product. The data is on the year-month × ZIP × lender × product level. To describe inquiries, which are on the year × ZIP × lender × product level, we divide the number by twelve. Loan amount is expressed in rupees. Default rate is the fraction of loans that is more than 90 days past due within one year of being issued. Loan number, loan amount, and inquiries are winsorized at 1% on both ends.

Table A.6: Economic Magnitude

	Monthly Expenditure (in Rupees)		Estimated Increase in Fintech Credit	
Percentile Range	Rural	Urban	Rural	Urban
0-5%	1,373	2,001	28%	19%
5-10%	1,782	2,607	21%	15%
10-20%	2,112	3,157	18%	12%
20-30%	2,454	3,762	16%	10%
30-40%	2,768	4,348	14%	9%
40-50%	3,094	4,963	12%	8%
50-60%	3,455	5,662	11%	7%
60-70%	3,887	6,524	10%	6%
70-80%	4,458	7,673	9%	5%
80-90%	5,356	9,582	7%	4%
90-95%	6,638	12,399	6%	3%
95-100%	10,501	20,824	4%	2%

Notes: This table presents the economic magnitude of the estimates in Column 4 of Table 1, using the average monthly expenditure per capita data from the Household Consumption Expenditure Survey available from the Ministry of Statistics and Program Implementation (MoSPI), Government of India, website https://www.mospi.gov.in/.

A.1 Other Data Sources

This section describes other datasets that we utilize in the paper.

YONO Transactions. We collect data on monthly ZIP-level digital transactions made using YONO from the State Bank of India (SBI) to conduct a falsification text to our UPI Analysis. YONO (You Only Need One) is a comprehensive digital banking platform offered by the State Bank of India (SBI). It integrates banking services with everyday activities, enabling users to manage their accounts, transfer funds, and pay bills in one convenient application. In addition to banking, YONO offers features for shopping, travel bookings, and accessing discounts on lifestyle services, making it a versatile tool for personal finance and lifestyle management. The platform also provides investment opportunities like mutual funds and insurance. Overall, YONO aims to streamline banking. The data is available from April 2018 until the end of our sample.

Region Type Classification. The classification of all ZIP codes into metro, urban, semi-urban, and rural categories comes from the CIBIL database. This classification allows us to examine responses of shadow banks across different region types, particularly investigating whether shadow banks act as complements or substitutes for traditional banks. Appendix Figure A.3b illustrates the geographic distribution of these regional classifications throughout India.

Measures of Banking Competition. We use data on the number of branches, credit and deposits to construct ZIP-level measures of banking competitiveness. We employ these measures to examine if shadow banks complement or substitute traditional banks. We use detailed data on credit, deposits and the number of branches for each bank in a ZIP from the Basic Statistical Returns (BSR) database maintained by the Reserve Bank of India (RBI) for the year 2015. Specifically, we construct measures of banking competitiveness at the ZIP (z) level using the Herfindahl-Hirschman Index (HHI_z) according to the following equation:

$$HHI_z = \sum_b \text{Share}^2_{b,z,2015}$$

where $\text{Share}_{b,z}$ refers to the share of credit, deposits, or number of branches of bank b in ZIP z in 2015. Appendix Figure A.3c presents the spatial distribution of HHI constructed based on the share of credit.

Lending Constraints of Traditional Banks. We construct a ZIP-level metric to assess the loan supply constraints experienced by a ZIP code, which result from the balance sheet constraints of the primary lender in that area. This measure is constructed as a weighted average of lending shares of each traditional bank, weighted by each bank's total non-performing assets (NPA) ratio based on the following equation:

$$\text{Non-Performing Assets Ratio}_{z,fy} = \sum_b \text{NPA}_{b,fy} \times \frac{\text{Credit}_{b,z,2015}}{\sum_b \text{Credit}_{b,z,2015}}$$

where $\text{Credit}_{b,z,2015}$ refers to the credit extended by bank b in ZIP z during 2015. This information is sourced from the Basic Statistical Returns (BSR) database maintained by the Reserve Bank of India (RBI) for the year 2015. We weigh the share of credit extended by each bank b in ZIP z by its non-performing assets ratio in financial year fy, starting in March. Specifically, $\text{NPA}_{b,fy}$ refers to the ratio of non-performing assets to total assets of bank b in financial year fy based on the bank balance sheet data between 2016 and 2021 from RBI. This measure is similar to a shift-share instrument. Appendix Figure A.3d presents the spatial distribution of the average Non-Performing Assets $\text{Ratio}_{z,fy}$ during our sample period.

Social Connectedness. We employ the Social Connectedness Index (SCI) constructed using Facebook data based on the methodology presented in Kuchler and Stroebel (2021) to proxy for the degree of informal risk-sharing arrangements, such as informal lending, available to households in a ZIP code. We use this measure to examine if shadow banks complement or substitute informal risk-sharing arrangements. The SCI is computed as follows:

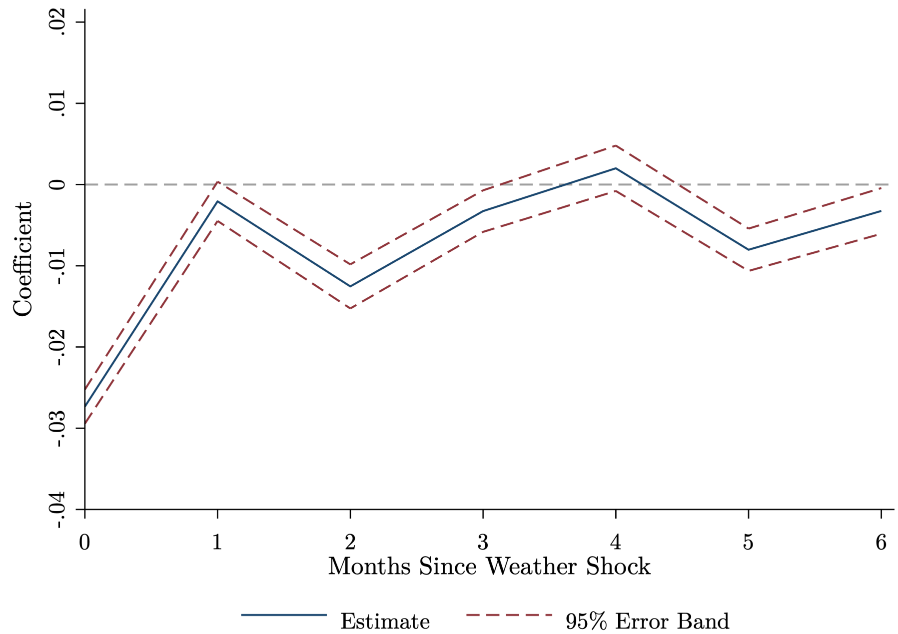
$$\text{Social Connectedness Index}_{i,j} = \frac{\text{Facebook Connections}_{i,j}}{\text{Facebook Users}_i \times \text{Facebook Users}_j}$$

where, Facebook Users_i and Facebook Users_j are the number of Facebook users in locations i and j, respectively, and Facebook Users $\text{Connections}_{i,j}$ is the total number of Facebook friendship connections between individuals in the two locations as of 2021. The index is at the district-pair level. We transform it to the district level by taking the mean of the index for a given district (i), averaging over all other districts, j. We then link this district-level data to the ZIP code level. Appendix Figure A.3e presents the spatial distribution of the SCI measure.

Nightlights. Finally, we employ monthly ZIP-level nightlight luminosity data from 2016 until 2019 to explore the impact of weather shocks on local economic activity and examine real effects. This data comes from Agarwal, Desai, Ghosh, and Vats (2024).

Appendix B Supplementary Results

Figure B.1: Dynamics of Response of Nightlights to Weather Shocks: Jordà (2005) Projection



This figure plots the dynamics of the coefficient of weather shocks over time. We estimate a Jordà (2005) style projection regression until six steps. The specification is as follows, with h taking an integer value between zero and six:

$$ln(\text{NL}_{z,ym+h}) - ln(\text{NL}_{z,ym-1}) = \beta_h^0 \cdot \text{Shock}_{z,ym} + \alpha_z + \theta_{ym} + \nu_{z,ym}$$

where z denotes ZIP code and ym is the year-month. α_z denotes ZIP code fixed effects, and θ_{ym} denotes year-month fixed effects. $ln(\text{NL}_{z,ym})$ denotes the natural logarithm of average nightlight luminosity across all pixels within the ZIP z during the month ym. The main independent variable is the weather shock variable. The unit of observation in each regression is a ZIP year-month pair. The 95% error bands are estimated by clustering the standard errors at the ZIP level.

Table B.1: Effect on Credit Issuance: Heterogeneity by Product Type

	ln(Amount)						
		Collateralized			Uncollateralized		
	All	Agric	Gold	Vehicle	Busi	Cons	MFI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fintech × Shock	0.0155***	-0.0391	-0.0289	-0.0246**	0.0441***	0.0106***	0.0833***
	(0.0022)	(0.0557)	(0.0278)	(0.0108)	(0.0079)	(0.0022)	(0.0131)
Nontech × Shock	0.0031***	0.0142***	0.0324***	0.0032*	-0.0163***	0.0003	0.0188
	(0.0011)	(0.0027)	(0.0024)	(0.0019)	(0.0053)	(0.0017)	(0.0130)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.34	0.03	0.01	0.00	0.00	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,060	18,711	18,078	18,962	16,549	19,052	11,716
Years	6	6	6	6	6	6	6
R-squared	0.84	0.82	0.88	0.84	0.72	0.86	0.84
Observations	20,459,958	3,269,797	2,488,014	3,505,068	1,590,155	6,069,098	385,748

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by product types. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 to 4 and 5 to 7 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table B.2: Effect on Credit Inquiries

	# Inquiries		
	All	Collaterized	Uncollaterized
	(1)	(2)	(3)
Fintech × Shock	9.1161***	-1.5626	9.3533***
	(1.3874)	(1.3215)	(1.6875)
Nontech × Shock	0.0408	8.8431***	-9.8261***
	(0.7962)	(0.7307)	(1.4226)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00
Year × ZIP × Product FE	✓	✓	✓
Year × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,080	19,064	19,077
Years	6	6	6
R-squared	0.94	0.97	0.92
Observations	2,626,226	851,198	1,279,083

Notes: This table presents the relative effects of weather shocks on credit inquiries across different types of lenders, based on estimates derived from Equation 2. # Inquiries$_{y,z,l,p}$ represents the number of inquiries by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year (y). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{y,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year, defined as the average monthly SPEI in a given year in a given ZIP being below the 20th or above the 80th percentile of its historical distribution. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table B.3: Effect on Credit Inquiries: Heterogeneity by Credit Score Type

	# Inquiries						
	Total (1)	Super-Prime (2)	Prime-Plus (3)	Prime (4)	Near-Prime (5)	Sub-Prime (6)	New-to-Credit (7)
	Panel A: All Loans						
Fintech × Shock	9.1161***	0.2572***	0.7654***	1.9803***	1.1373***	0.4833**	3.9542***
	(1.3874)	(0.0255)	(0.0992)	(0.3923)	(0.2902)	(0.1998)	(0.4071)
Nontech × Shock	0.0408	-0.0175	-0.1635***	-0.9742***	-0.4749***	-0.1193	1.6521***
	(0.7962)	(0.0181)	(0.0586)	(0.2174)	(0.1702)	(0.1153)	(0.2724)
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.00	0.00	0.01	0.00
R-squared	0.94	0.93	0.95	0.94	0.93	0.93	0.91
Observations	2,626,226	2,626,226	2,626,226	2,626,226	2,626,226	2,626,226	2,626,226
	Panel B: Collateralized Loans						
Fintech × Shock	-1.5626	-0.1742***	-0.5749***	-0.1080	-0.3315	-0.7329***	-0.1545
	(1.3215)	(0.0580)	(0.1494)	(0.4260)	(0.3075)	(0.2031)	(0.5335)
Nontech × Shock	8.8431***	0.0732***	0.3485***	0.7813***	1.1546***	0.7364***	5.7772***
	(0.7307)	(0.0233)	(0.0595)	(0.1879)	(0.1797)	(0.1241)	(0.3085)
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.06	0.00	0.00	0.00
R-squared	0.97	0.95	0.97	0.97	0.96	0.96	0.95
Observations	851,198	851,198	851,198	851,198	851,198	851,198	851,198
	Panel C: Uncollateralized Loans						
Fintech × Shock	9.3533***	0.2888***	0.7834***	1.9085***	1.0050***	0.5705**	4.3143***
	(1.6875)	(0.0300)	(0.1232)	(0.4842)	(0.3546)	(0.2422)	(0.4862)
Nontech × Shock	-9.8261***	-0.1788***	-0.9710***	-3.4317***	-2.5980***	-1.1741***	-1.4453***
	(1.4226)	(0.0298)	(0.1036)	(0.3951)	(0.2926)	(0.1960)	(0.4745)
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.92	0.93	0.94	0.93	0.92	0.92	0.89
Observations	1,279,083	1,279,083	1,279,083	1,279,083	1,279,083	1,279,083	1,279,083

Notes: This table presents the relative effects of weather shocks on credit inquiries across different types of lenders, based on estimates derived from Equation 2, by credit score types. # Inquiries$_{y,z,l,p}$ represents the number of inquiries by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year (y). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{y,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year, defined as the average monthly SPEI in a given year in a given ZIP being below the 20th or above the 80th percentile of its historical distribution. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-ZIP-lender-product level. Panel A displays results for all loans, while Panel B and C display results for collateralized loans (agricultural, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Column 1 presents results for all types of loans, while Columns 2 to 7 focus on different credit score types. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table B.4: Effect on Default Rate: Heterogeneity by Geography

	Default Rate			
	Panel A: Urban and Rural Region Types			
	Metro (1)	Urban (2)	Semi-Urban (3)	Rural (4)
Fintech × Shock	-0.0018**	0.0010	0.0007	-0.0001
	(0.0009)	(0.0009)	(0.0006)	(0.0005)
Nontech × Shock	-0.0006	0.0001	-0.0000	0.0005**
	(0.0004)	(0.0004)	(0.0002)	(0.0002)
Fintech × Shock = Nontech × Shock	0.20	0.32	0.23	0.31
R-squared	0.48	0.46	0.44	0.45
Wald p-val Fintech (Q1=Q4)	.	.	.	0.18
Wald p-val Nontech (Q1=Q4)	.	.	.	0.05
Observations	1,672,004	2,362,551	7,324,494	9,006,083
	Panel B: Traditional Bank Constraints			
	Quartile 1 (1)	Quartile 2 (2)	Quartile 3 (3)	Quartile 4 (4)
Fintech × Shock	0.0009	0.0011	0.0001	-0.0015**
	(0.0008)	(0.0007)	(0.0007)	(0.0007)
Nontech × Shock	-0.0008***	0.0005	0.0006*	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Fintech × Shock = Nontech × Shock	0.03	0.38	0.50	0.02
R-squared	0.47	0.49	0.51	0.49
Wald p-val Fintech (Q1=Q4)	.	.	.	0.06
Wald p-val Nontech (Q1=Q4)	.	.	.	0.07
Observations	4,420,020	4,439,306	4,434,633	4,448,434
	Panel C: Social Connectedness			
	Quartile 1 (1)	Quartile 2 (2)	Quartile 3 (3)	Quartile 4 (4)
Fintech × Shock	0.0008	0.0016**	-0.0007	0.0002
	(0.0006)	(0.0007)	(0.0007)	(0.0007)
Nontech × Shock	-0.0000	0.0005	0.0009***	-0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Fintech × Shock = Nontech × Shock	0.21	0.09	0.02	0.73
R-squared	0.47	0.45	0.44	0.44
Wald p-val Fintech (Q1=Q4)	.	.	.	0.64
Wald p-val Nontech (Q1=Q4)	.	.	.	1.00
Observations	5,128,802	5,039,199	5,087,261	5,050,075

Notes: This table presents the relative effects of weather shocks on default rate across different types of lenders, based on estimates derived from Equation 2, by geography. Default rate$_{ym,z,l,p}$ is the fraction of loans that defaulted within one year of being issued in that given year-month. This variable takes a value between zero and one. The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 to 4 describe the geographical unit. Panel A displays results for metro, urban, semi-urban, and rural ZIPs. Panel B displays results by quartiles of lending constraints by traditional banks on the ZIP-year level, calculated as a weighted average of lending shares of each traditional bank, weighted by each bank's total non-performing assets (NPA) ratio. Panel C displays results by quartiles of social connectedness on the district level, measured by the Facebook social connectedness index (SCI). Appendix Section A.1 describes the construction of these variables. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

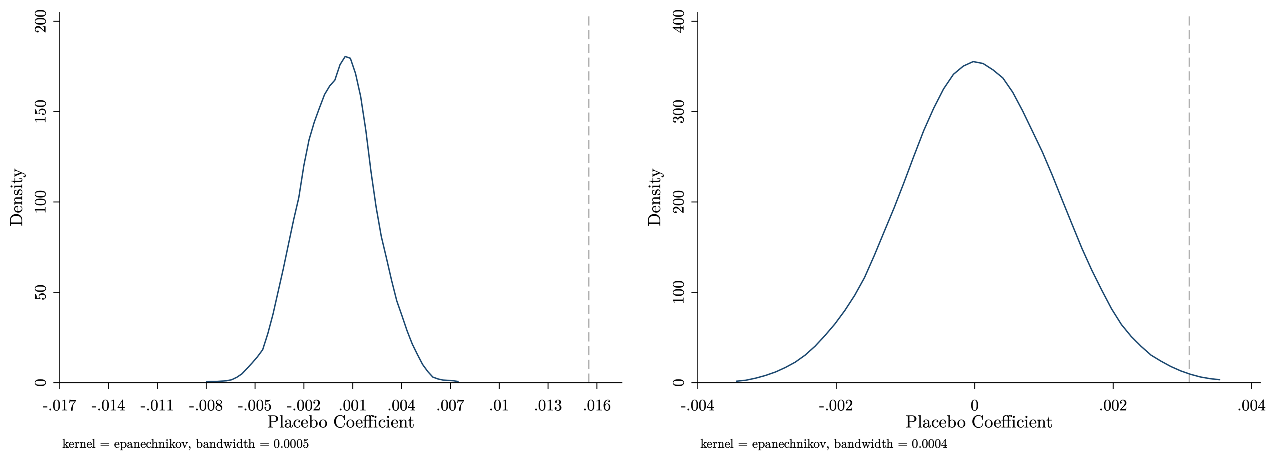
Table B.5: Effect on Credit Issuance & Default Rate: Heterogeneity by HHI

	HHI Branch		HHI Credit		HHI Deposit	
	Below Median (1)	Above Median (2)	Below Median (3)	Above Median (4)	Below Median (5)	Above Median (6)
	Panel A: ln(Amount)					
Fintech × Shock	0.0120***	0.0200***	0.0110***	0.0201***	0.0115***	0.0196***
	(0.0031)	(0.0034)	(0.0032)	(0.0033)	(0.0032)	(0.0033)
Nontech × Shock	0.0042***	0.0014	0.0041**	0.0015	0.0039**	0.0016
	(0.0016)	(0.0017)	(0.0016)	(0.0017)	(0.0016)	(0.0017)
Fintech × Shock = Nontech × Shock	0.02	0.00	0.04	0.00	0.03	0.00
R-squared	0.85	0.80	0.85	0.80	0.85	0.80
Wald p-val Fintech (Above=Below)		0.16		0.11		0.15
Wald p-val Nontech (Above=Below)		0.32		0.36		0.41
Observations	9,989,314	8,722,945	9,356,495	9,355,753	9,356,984	9,355,270
	Panel B: Default Rate					
Fintech × Shock	0.0003	-0.0001	0.0003	-0.0000	0.0002	0.0002
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Nontech × Shock	-0.0001	0.0002	-0.0001	0.0002	-0.0000	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Fintech × Shock = Nontech × Shock	0.44	0.64	0.44	0.65	0.68	0.97
R-squared	0.44	0.45	0.44	0.45	0.44	0.45
Wald p-val Fintech (Q1=Q4)	.	0.69	.	0.71	.	0.97
Wald p-val Nontech (Q1=Q4)	.	0.46	.	0.40	.	0.55
Observations	9,989,314	8,722,945	9,356,495	9,355,753	9,356,984	9,355,270

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by traditional banks' branch-based, credit-based, and deposit-based HHI. A higher HHI corresponds to a higher market concentration. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym) (Panel A). Default rate$_{ym,z,l,p}$ is the fraction of loans that defaulted within one year of being issued in that given year-month. This variable takes a value between zero and one (Panel B). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 2 describe HHI by bank branches, Columns 3 to 4 describe HHI by bank credit, and Columns 5 to 6 describe HHI by bank deposit. Odd columns report results below median, odd columns above median. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. The outcome variable loan amount is winsorized at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Appendix C Robustness and Supplementary Mechanism Results

Figure C.1: Placebo Test



(a) Fintech × Placebo Shock (b) Nontech × Placebo Shock

	Min	p1	p5	p25	p50	p75	p95	p99	Max	Mean	SD
Fintech × Placebo Shock	-0.0075	-0.0049	-0.0034	-0.0014	0.0001	0.0015	0.0035	0.0049	0.0070	0.0000	0.0021
Nontech × Placebo Shock	-0.0030	-0.0024	-0.0017	-0.0007	0.0000	0.0008	0.0017	0.0025	0.0031	0.0001	0.0010

This figure presents the results of a placebo test, based on Equation 2. The weather shock dummy is replaced with a dummy variable that is randomly set to one for 40% of the year-month-ZIPs. The 40% is in alignment with the summary statistics of the weather shock variable, which is a binary variable that takes a value of one if the SPEI observation at the year-month-ZIP level is below the 20th or above the 80th percentile of its historical distribution. We refer to the randomly generated dummy variable as Placebo Shcock. We run the regression 1,000 times and plot the kernel density of the resulting coefficients. Figure C.1a plots the kernel density of the coefficients associated with the interaction term of Fintech and placebo shock. Figure C.1b plots the kernel density of the coefficients associated with the interaction term of Fintech and placebo shock. The grey lines indicate our baseline coefficients from Column 4 in Table 1.

Table C.1: Robustness: Effect for Each Lender

	ln(Amount)				
	Fintech	Nontech	State-Owned	Private	Foreign
	(1)	(2)	(3)	(4)	(5)
Shock	0.0084***	0.0047***	0.0022**	0.0004	-0.0011
	(0.0020)	(0.0009)	(0.0009)	(0.0010)	(0.0020)
Year-month × Product FE	✓	✓	✓	✓	✓
ZIP × Product FE	✓	✓	✓	✓	✓
ZIPs	19,021	19,052	19,051	19,051	19,015
Years	6	6	6	6	6
R-squared	0.71	0.76	0.74	0.70	0.71
Observations	1,307,221	5,055,554	4,612,254	5,293,364	1,065,930

Notes: This table presents the effects of weather shocks on credit issuance by lender types, based on estimates derived from Equation C.1.

$$y_{ym,z,p} = \beta \cdot \text{Shock}_{ym,z} + \text{FE}_{ym,p} + \text{FE}_{z,p} + \epsilon_{ym,z,p} \tag{C.1}$$

The dependent variable, $\ln(\text{Amount})_{ym,z,p}$, represents the natural logarithm of the loan amount in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The primary independent variable is $\text{Shock}_{ym,z}$, a dummy that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. The data is conditional on lender type, and the unit of observation for each regression is at the year-month-ZIP-product level. Column 1 presents results for Fintechs, Column 2 for Nontechs, Column 3 for state-owned traditional banks, Column 4 for private traditional banks, and Column 5 for foreign traditional banks. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.2: Robustness: Effect on Credit Issuance on Extensive Margin

	# Loans		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.1855**	-0.7730***	0.1686*
	(0.0815)	(0.1981)	(0.0960)
Nontech × Shock	-0.0296	0.3862***	-0.2827***
	(0.0404)	(0.0512)	(0.0773)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.01	0.00	0.00
Month-year × ZIP × Product FE	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,006	19,052
Years	6	6	6
R-squared	0.91	0.92	0.91
Observations	20,459,958	9,262,879	8,045,001

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, on the extensive margin. # Loans$_{ym,z,l,p}$ represents the number of loans issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.3: Robustness: Using Poisson Regression

	Amount		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0395***	0.0353	0.0404***
	(0.0037)	(0.0229)	(0.0038)
Nontech × Shock	0.0053***	0.0118***	-0.0002
	(0.0012)	(0.0013)	(0.0018)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.30	0.00
ZIP × Year-month × Product FE	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,083	19,076	19,081
Year-months	6	6	6
R-squared	0.93	0.94	0.93
Observations	35,991,285	14,325,273	14,974,489

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, using poisson regressions. The dependent variable, $\text{Amount}_{ym,z,l,p}$, represents the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. $\text{Shock}_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.4: Robustness: Excluding Covid Period

	ln(Amount)		
	All (1)	Collateralized (2)	Uncollateralized (3)
Fintech × Shock	0.0284***	-0.0011	0.0336***
	(0.0032)	(0.0117)	(0.0033)
Nontech × Shock	0.0155***	0.0243***	0.0056***
	(0.0013)	(0.0016)	(0.0021)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.03	0.00
Month-year × ZIP × Product FE	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,049	18,978	19,036
Years	4	4	4
R-squared	0.84	0.86	0.84
Observations	13,343,960	6,294,980	5,096,339

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, excluding the Covid period (2020 and 2021). The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.5: Robustness: Continuous Water Balance Measure

	ln(Amount)		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0097***	-0.0059	0.0102***
	(0.0020)	(0.0083)	(0.0020)
Nontech × Shock	-0.0000	0.0164***	-0.0106***
	(0.0010)	(0.0012)	(0.0016)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.01	0.00
Year-month × ZIP × Product FE	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,006	19,052
Years	6	6	6
R-squared	0.84	0.85	0.84
Observations	22,455,950	9,262,879	8,045,001

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, utilizing the continuous SPEI water balance measure instead of weather shock dummies. The dependent variable, $\ln(\text{Amount})_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. $\text{Shock}_{ym,z}$ is a continuous water balance measure, the SPEI, during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.6: Robustness: Using More Severe Weather Shocks

	ln(Amount)		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0159***	-0.0359***	0.0163***
	(0.0028)	(0.0121)	(0.0029)
Nontech × Shock	0.0013	0.0226***	-0.0150***
	(0.0014)	(0.0017)	(0.0022)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00
Year-month × ZIP × Product FE	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,006	19,052
Years	6	6	6
R-squared	0.84	0.85	0.84
Observations	20,459,958	9,262,879	8,045,001

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, using more severe weather shocks. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, but in contrast to our baseline weather shock, it is defined as one if the SPEI is below the 10th or above the 90th percentile of its historical distribution in that ZIP. Note that in our baseline specfciation, the shock is defined as one if the SPEI is below the 20th or above the 10th percentile of its historical distribution in that ZIP. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Column 1 presents results for all types of loans, while Columns 2 and 3 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.7: Robustness: Effect on Credit Issuance by Product Type

	ln(Amount)					
	Collateralized			Uncollateralized		
	Agri	Gold	Vehicle	Business	Consumer	MFI
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Low Water Balance (Drought)					
Fintech × Shock	0.0046	-0.0556	-0.1060***	-0.0274**	0.0546***	0.0981***
	(0.0861)	(0.0422)	(0.0170)	(0.0114)	(0.0035)	(0.0246)
Shadow × Shock	0.0358***	0.0549***	0.0047*	-0.0086	0.0375***	-0.0111
	(0.0039)	(0.0033)	(0.0027)	(0.0072)	(0.0025)	(0.0210)
Fintech × Shock = Nontech × Shock	0.72	0.01	0.00	0.11	0.00	0.00
R-squared	0.82	0.88	0.84	0.72	0.86	0.84
Observations	3,269,797	2,488,014	3,505,068	1,590,155	6,069,098	385,748
	Panel B: High Water Balance (Flood)					
Fintech × Shock	-0.0576	-0.0115	0.0438***	0.0778***	-0.0209***	0.0671***
	(0.0702)	(0.0350)	(0.0150)	(0.0095)	(0.0026)	(0.0145)
Nontech × Shock	-0.0056*	0.0060**	0.0011	-0.0176***	-0.0280***	0.0312**
	(0.0034)	(0.0029)	(0.0024)	(0.0066)	(0.0022)	(0.0151)
Fintech × Shock = Nontech × Shock	0.46	0.62	0.00	0.00	0.01	0.04
R-squared	0.82	0.88	0.84	0.72	0.86	0.84
Observations	3,269,797	2,488,014	3,505,068	1,590,155	6,069,098	385,748

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by product types. The dependent variable, $\ln(\text{Amount})_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. $\text{Shock}_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, defined as one if the SPEI is below the 20th percentile (Panel A) or above the 80th percentile (Panel B) of its historical distribution in that ZIP. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 3 and 4 to 6 focus on collateralized loans (agriculture, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.8: Role of Technology: Heterogeneity by UPI Exposure (Default Rate)

	Default Rate			
	Quartile 1 (1)	Quartile 2 (2)	Quartile 3 (3)	Quartile 4 (4)
	Panel A: All Loans			
Fintech × Shock	-0.0011	0.0007	0.0005	0.0011
	(0.0008)	(0.0007)	(0.0007)	(0.0008)
Nontech × Shock	-0.0001	0.0008***	0.0000	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Fintech × Shock = Nontech × Shock	0.24	0.92	0.53	0.26
R-squared	0.45	0.44	0.44	0.45
Wald p-val Fintech (Q1=Q4)	.	.	.	0.11
Wald p-val Nontech (Q1=Q4)	.	.	.	0.56
Observations	3,974,444	3,973,448	3,974,116	3,973,383
	Panel B: Collateralized Loans			
Fintech × Shock	0.0089**	0.0001	-0.0008	0.0101*
	(0.0041)	(0.0033)	(0.0038)	(0.0060)
Nontech × Shock	-0.0006	0.0006	-0.0006	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Fintech × Shock = Nontech × Shock	0.02	0.87	0.95	0.08
R-squared	0.46	0.44	0.43	0.45
Wald p-val Fintech (Q1=Q4)	.	.	.	0.90
Wald p-val Nontech (Q1=Q4)	.	.	.	0.80
Observations	1,775,033	1,775,002	1,773,897	1,774,575
	Panel C: Uncollateralized Loans			
Fintech × Shock	-0.0011	0.0012	0.0017**	0.0005
	(0.0008)	(0.0007)	(0.0007)	(0.0008)
Nontech × Shock	-0.0005	0.0016***	0.0011**	0.0009*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Fintech × Shock = Nontech × Shock	0.43	0.61	0.41	0.62
R-squared	0.44	0.45	0.46	0.45
Wald p-val Fintech (Q1=Q4)	.	.	.	0.20
Wald p-val Nontech (Q1=Q4)	.	.	.	0.08
Observations	1,566,988	1,566,804	1,566,827	1,566,431

Notes: This table presents the relative effects of weather shocks on default rate across different types of lenders, based on estimates derived from Equation 2, by ZIP level UPI exposure. Default rate$_{ym,z,l,p}$ is the fraction of loans that defaulted within one year of being issued in that given year-month. This variable takes a value between zero and one. The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 4 describe quartiles by the UPI exposure index. The UPI exposure index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. Early adopter banks are banks that were providing UPI services as of November 2016. Panel A displays results for all loans, while Panel B and C display results for collateralized loans (agricultural, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.9: Role of Technology: Falsification Test Using Heterogeneity by YONO

	ln(Amount)			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
	(1)	(2)	(3)	(4)
	Panel A: All Loans			
Fintech × Shock	0.0091	0.0102*	0.0046	0.0046
	(0.0062)	(0.0056)	(0.0056)	(0.0052)
Nontech × Shock	-0.0062*	0.0009	-0.0089***	-0.0142***
	(0.0033)	(0.0033)	(0.0033)	(0.0034)
Fintech × Shock = Nontech × Shock	0.02	0.12	0.02	0.00
R-squared	0.85	0.87	0.88	0.88
Wald p-val Fintech (Q1=Q4)	.	.	.	0.66
Wald p-val Nontech (Q1=Q4)	.	.	.	0.18
Observations	2,159,865	2,161,724	2,161,484	2,165,672
	Panel B: Collateralized Loans			
Fintech × Shock	-0.0315	0.0028	-0.0568**	0.0058
	(0.0286)	(0.0268)	(0.0264)	(0.0196)
Nontech × Shock	-0.0140***	0.0069*	-0.0032	0.0038
	(0.0040)	(0.0037)	(0.0037)	(0.0038)
Fintech × Shock = Nontech × Shock	0.54	0.88	0.04	0.92
R-squared	0.86	0.88	0.89	0.89
Wald p-val Fintech (Q1=Q4)	.	.	.	0.40
Wald p-val Nontech (Q1=Q4)	.	.	.	0.01
Observations	910,815	911,968	911,384	910,841
	Panel C: Uncollateralized Loans			
Fintech × Shock	0.0121*	0.0108*	0.0067	0.0071
	(0.0064)	(0.0058)	(0.0057)	(0.0055)
Nontech × Shock	-0.0011	0.0012	-0.0077	-0.0165***
	(0.0052)	(0.0051)	(0.0050)	(0.0052)
Fintech × Shock = Nontech × Shock	0.06	0.15	0.02	0.00
R-squared	0.86	0.88	0.88	0.88
Wald p-val Fintech (Q1=Q4)	.	.	.	0.62
Wald p-val Nontech (Q1=Q4)	.	.	.	0.08
Observations	901,360	900,974	900,924	904,880

Notes: This table presents the relative effects of weather shocks on credit issuance across different types of lenders, based on estimates derived from Equation 2, by ZIP level YONO (You Only Need One) exposure. YONO is a digital banking platform of the State Bank of India. YONO transaction data cannot be readily shared with other lenders. The dependent variable, ln(Amount)$_{ym,z,l,p}$, represents the natural logarithm of the loan amount issued by lender type (l) in a specific ZIP code (z) for a certain product (p) in a given year-month (ym). The lender types included in the analysis are Fintechs, Nontechs, and traditional banks. The primary independent variables are interactions of Fintechs and Nontechs with the Shock variable. Shock$_{ym,z}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. Traditional banks serve as the omitted baseline category, meaning all estimates are relative to their interactions with the shock variable. The unit of observation for each regression is at the year-month-ZIP-lender-product level. Columns 1 to 4 describe quartiles by YONO exposure, which is measured by total YONO transaction value, scaled by a ZIP's population. Panel A displays results for all loans, while Panel B and C display results for collateralized loans (agricultural, gold, and vehicle loans) and uncollateralized loans (business, consumption, and microfinance loans), respectively. The regressions include month-year × ZIP × product, month-year × lender × product, and ZIP × lender × product fixed effects. Fintech × Shock = Nontech × Shock reports the p-value of the t-test of the equality of the coefficients. The Wald statistics report the p-value of the t-test of the equality of the coefficients. The outcome variable is winsorised at 1% on both ends. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.

Table C.10: Real Effects: Effect on Economic Activity

	Second Stage	First Stage	
	ln(Nightlight)	Fintech Amount Per Capita × Shock	Fintech Amount Per Capita
	(1)	(2)	(3)
Fintech Amount Per Capita × Shock	0.0323***		
	(0.0125)		
Fintech Amount Per Capita	-0.0211		
	(0.0173)		
Shock	-0.0033	0.0533***	-0.0069
	(0.0105)	(0.0190)	(0.0055)
UPI Exposure Index × Shock		0.0563**	0.0041
		(0.0271)	(0.0078)
ZIP FE	✓	✓	✓
Month-year × Population-Bin FE	✓	✓	✓
Observations	357,974	357,974	357,974

Notes: This table presents the two-stage least squares (2SLS) from the following set of equations:
Second Stage Regression (Column 1):

$$\begin{aligned}\ln(\text{Nightlight})_{z,ym} &= \beta_1 \cdot \widehat{\text{Fintech Amount Per Capita}}_{z,ym} \times \text{Shock}_{z,ym} \\ &+ \beta_2 \cdot \widehat{\text{Fintech Amount Per Capita}}_{z,ym} \\ &+ \beta_3 \cdot \text{Shock}_{z,ym} + \theta_z + \theta_{ym} \cdot \text{Pop Bin}_z + \varepsilon_{z,ym}\end{aligned}$$

First Stage Regressions (Columns 2 & 3):

$$\begin{aligned}\text{Fintech Amount Per Capita}_{z,ym} \times \text{Shock}_{z,ym} = \alpha_1 \cdot \text{UPI Index} \times \text{Shock}_{z,ym} + \alpha_2 \text{Shock}_{z,ym} \\ + \theta_z + \theta_{ym} \cdot \text{Pop Bin}_z + \mu_{z,ym}\end{aligned}$$

$$\begin{aligned}\text{Fintech Amount Per Capita}_{z,ym} &= \gamma_1 \cdot \text{UPI Index} \times \text{Shock}_{z,ym} \\ &+ \gamma_2 \text{Shock}_{z,ym} + \theta_z + \theta_{ym} \cdot \text{Pop Bin}_z + \eta_{z,ym}\end{aligned}$$

where, $\ln(\text{Nightlight})_{z,ym}$ denotes the natural logarithm of nightlights for ZIP z for year-month ym. Fintech Amount Per $\text{Capita}_{z,ym}$ denotes the total amount of Fintech lending in ZIP z at time ym, divided by the total population of ZIP. The UPI exposure index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. Early adopter banks are banks that were providing UPI services as of November 2016. $\text{Shock}_{z,ym}$ is a dummy variable that equals one if the ZIP code experienced a weather shock during a specific year-month, as defined in Section 2. θ_z denotes ZIP fixed effects and $\theta_{ym} \cdot \text{Pop Bin}_z$ denotes Year-Month × Population bin fixed effects. All ZIPs are divided into 100 bins based on the total population value of each ZIP in the sample. Standard errors reported in parentheses are clustered at the ZIP code level. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels.