Shadow Banks on the Rise: Evidence Across Market Segments[*]

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Abstract

This paper examines the comparative advantages of shadow banks using novel credit bureau data on 653 million formal retail loans in India. Proxying credit demand shocks with weather variation, we show that Fintechs respond more than other lenders in uncollateralized markets. Conversely, non-Fintech shadow banks are more responsive in collateralized markets. Both show stronger responses for borrowers with low credit scores or no credit history. Exploiting the geographic heterogeneity in the adoption of digital payments technology we document the importance of technology for Fintechs. Leveraging four natural experiments across lenders, time, and products, we establish the importance of lax regulation and physical presence for non-Fintech shadow banks. Our results suggest that the dominant comparative advantages of shadow banks differ across market segments.

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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 comparative 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. Second, shadow banks might have an advantage because they are less regulated than traditional banks. It is crucial to distinguish between these drivers 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 lax regulation is the primary driver, consumer benefits may be limited, and shadow bank growth could decline as governments close regulatory gaps.

So far, comparative advantages of shadow banks have been studied in the mortgage market after the financial crisis. Prior research has shown that in this market segment, both laxer regulation and technology play a role in growth, with the former contributing 60% and the latter 30% (Buchak, Matvos, Piskorski, and Seru, 2018). While the post-financial crisis 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 financial commitments, where the benefits of technology – such as convenience and speed – may be less critical to borrowers.

In this paper, we demonstrate that the comparative advantages of shadow banks differ across market segments. Specifically, we document that technology is the comparative advantage in uncollateralized markets, while lax 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 the real economy and policy analysis (Seru, 2020; 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. The data we use has four key advantages. First, we observe all lender types and can distinguish between Fintech shadow banks and non-Fintech shadow banks ("Nontechs"). Fintechs heavily rely on technology, while both Fintechs and Nontechs are subject to lax regulation.[1] While prior research has examined this distinction among shadow banks in mortgage markets, it is yet to consider this issue in non-mortgage lending markets (for a survey, see Thakor (2020)).[2]

Second, we observe all product types, ranging from secured or collateralized loans such as agricultural, gold, and vehicles to unsecured or uncollateralized loans such as business, consumption, and microfinance loans.[3] This allows us to demonstrate that the dominant factor driving shadow bank growth varies by product type. Third, we observe a wide breadth of credit score types. This is wider than what researchers often observe, for instance in mortgage or U.S. unsecured consumer lending data, where borrowers with very low or no scores are often excluded (De Roure, Pelizzon, and Tasca, 2016).

Fourth, the data is not only unique in its breadth but also in its size. We observe 653 million loans, the universe of formal retail loans in India from 2016 to 2021. This is larger by a factor of eight compared to mortgage data (Fuster, Plosser, Schnabl, and Vickery, 2019) and larger by a factor of more than a hundred compared to data on non-mortgage market segments. The latter either observe a random sample of a universe (Di Maggio and Yao, 2021) or data from one specific Fintech lender (Tang, 2019).

The ideal thought experiment to identify the comparative advantages of lenders involves examining their responses to demand shocks. Simply comparing average differences of 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. In contrast, comparative advantage is a dynamic concept that assesses how different lenders can adapt their lending practices in response to changing market conditions. 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 by combining the credit bureau data, which is on the level of year-month $\times$ ZIP $\times$ lender $\times$ product with granular weather data on the level of year-month $\times$ ZIP. Specifically, we utilize the geo-spatial data on the Standardized Precipitation and Evapotranspiration Index (SPEI) index observed at 0.5×0.5 degree to construct local weather shocks. A long-standing literature establishes the exogeneity of these weather shocks as well as how weather shocks increase demand for credit in the agricultural and non-agricultural sector (Dell, Jones, and Olken, 2014).

We employ a granular differences-in-differences strategy. The coefficient of interest is the

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

[2] Di Maggio and Yao (2021) use data of the TransUnion credit bureau in the U.S. on personal loans, but only identify Fintechs, not non-Fintech shadow banks.

[3] It is important to note that business loans 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.

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 $\times$ ZIP $\times$ 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 $\times$ 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 verify this assumption using a pre-trend analysis.

We begin by demonstrating that Fintechs show a substantially stronger response to demand shocks than other lenders. The response is economically meaningful and statistically significant. Specifically, we document that Fintechs issue 1.57% 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 211 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. Additionally, this relative increase in Fintech credit per borrower amounts to 5% of the average monthly income of a casual worker. 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. One key insight of our study is that in collateralized loan segments, Nontechs exhibit a stronger response (1.53%) than Fintechs or traditional banks, particularly in agriculture loans (1.42%) and loans backed by gold (3.25%). Conversely, in uncollateralized loan segments, Fintechs demonstrate a stronger response (1.92%) than Nontechs or traditional banks, especially in business loans (4.49%), consumption loans (1.08%), and microfinance or MFI loans (8.37%). These findings suggest that Nontechs have a comparative advantage in absorbing demand shocks in collateralized markets, whereas Fintechs have a comparative advantage in uncollateralized markets. Overall, this indicates market segmentation in how shadow banks respond to demand shocks.

Lastly, we document another dimension of segmentation of shadow banks. We find that, following a demand shock, both Fintechs and Nontechs increase credit to borrowers with lower credit scores and those new to credit, who are typically subject to the highest levels of information asymmetry. To highlight the importance of these borrower segments: 50% of the credit-eligible population in India is new-to-credit, and 20% is credit underserved due to low credit scores, accounting for a total of 572 million individuals (CIBIL Report, 2022). Moreover, we find that our result is driven by collateralized loans for Nontechs and uncollateralized loans for Fintechs. We also note that this ex-ante risk does not translate into substantial ex-post risk, as measured by default rates. These results suggest that shadow banks not only specialize in specific product segments but also specialize in particular borrower segments.

This market segmentation across the credit score distribution provides evidence of the role of shadow banks in the lending landscape, specifically if they act as complements or substitutes (Tang, 2019; De Roure, Pelizzon, and Thakor, 2022; Gopal and Schnabl, 2022). We find that shadow banks extend credit to individuals with no credit history and high levels of information asymmetry, who may not qualify for loans from traditional banks. Therefore, the increase in credit by shadow banks to new-to-credit borrowers suggests that they may be complementary to traditional banks. We further support this argument, especially for Fintechs, by documenting that Fintechs increase credit more in rural areas where physical banking presence is limited.

While the role of shadow bank lending as a complement to traditional bank lending has been documented previously, we are the first – to the best of our knowledge – to highlight that shadow bank lending may serve as a complement to informal lending. In particular, we find that Fintech lending rises significantly in areas where informal social networks are not well established.

So far, we have documented the existence of comparative advantages of shadow banks in certain market segments. Next, we examine the reasons behind these advantages. We begin by providing more direct evidence that technology plays a key role in the comparative advantage of Fintechs. We utilize two approaches for this. First, we exploit the staggered geographical rollout of the digital payment system in India, which allows Fintechs to access bank transaction data to generate a risk profile of an applicant. Second, we examine data from one of the largest Fintech companies in India to show how alternative data affects the acceptance likelihood of loan applications, the time taken to approve the application, and other lending outcomes.

We begin our analysis by examining the heterogeneity in the effect by geographic variation in the adoption of a key zero-cost digital payment infrastructure in India that facilitates cashless transactions between two bank accounts – Unified Payment Interface (UPI). Crucially, the UPI interface enables data sharing, in particular open banking. A customer who applies for a loan at a Fintech can request her bank to share financial details like income and transactions from the bank to the lender via the open banking framework. Therefore, geographic heterogeneity in UPI should be a strong predictor of Fintechs' ability to access and process data with technology.

However, directly using UPI transaction data may be prone to endogeneity issues, such as unobservable factors that drive credit demand and UPI transactions. Therefore, we construct an index that measures geographic variation in the timing of the adoption of UPI. The UPI index for a ZIP code is defined as the share of total deposits of early adopter banks over the total deposits of all banks. The construction of the index is motivated by the discussion in Dubey and Purnanandam (2024) and is similar to the one employed in Alok, Ghosh, Kulkarni, and Puri (2024). This index exploits two sources of variation. First, it uses the staggered adoption of UPI at the bank level. Second, it relies on geographic variation in bank deposits of early and late adopters. The intuition of this index is that regions where early UPI adopter banks are dominant players are more likely to be extensive adopters of digital transactions due to strong network externalities as documented in Higgins (2022) and Crouzet, Gupta, and Mezzanotti (2023).

We observe an increasing trend in the estimate of the interaction term of Fintech and weather shock as we move from the first to the fourth quartile of the UPI index distribution. The effect starts at 0.66% in the first quartile and increases to 2.33% in the fourth quartile. This upward trend is both economically and statistically significant, with the magnitude of the effect growing consistently across the UPI distribution. This result suggests that the ability of Fintechs to respond to demand shocks increases with the adoption of cashless transactions, as measured by our UPI index. Notably, this effect is primarily driven by the uncollateralized lending segment. In contrast, we do not observe a similar trend for Nontechs. These findings suggest that the technological advantage of Fintechs may be a key factor driving their comparative advantage.

A potential concern with this analysis is that the UPI index might be correlated with other unobserved factors that determine digital adoption, potentially confounding our result. To address this, we perform a placebo test by examining the effect's heterogeneity based on geographic variation in Yono adoption—a digital banking platform from the State Bank of India, the nation's largest bank. Yono also facilitates digital transactions and could be expected to correlate with unobserved factors similar to the UPI index. However, unlike UPI, Yono's transaction data is private and not part of the open banking framework, meaning it cannot be shared with other lenders. We examine the heterogeneity in the effect across the Yono adoption quartiles. We do not observe an increasing trend in the effect across Yono adoption quartiles; instead, the effect remains flat. This suggests that the increasing coefficients across UPI exposure quartiles are likely due to data provision to Fintechs, rather than being driven by unobserved factors.

Furthermore, to provide application-level evidence consistent with the technology advantage of Fintechs, we exploit data from one of India's largest Fintechs, which specializes in lending to small businesses. This company generates a standardized score for each applicant based on their digital transactions, referred to as alternative data. Our objective is to assess how the availability of this alternative data influences loan acceptance decisions after a weather shock at the application level. The results indicate that the score derived from alternative data is positively correlated with loan acceptance following a weather shock, particularly for new-to-credit borrowers. Additionally, applicants with higher alternative data scores, especially those new to credit, tend to receive loans more quickly. This evidence on speed is consistent with the findings of Fuster, Plosser, Schnabl, and Vickery (2019). These findings suggest that technology, specifically the use of alternative data coming from digital transactions, plays a critical role in enabling Fintechs to extend credit, especially to new-to-credit borrowers.

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. First, we exploit the changes in regulatory measures issued by the Reserve Bank of India in November 2023 which raised the risk weight for MFI loans issued by traditional banks from 100% to 125%, while the MFI loans made by shadow banks were exempt from this change. We leverage this regulatory disparity to analyze the importance of the lax regulation channel in creating a comparative advantage for shadow banks, especially for Fintechs who are more responsive in MFI lending. We find that the response of Fintechs to this regulatory change in MFI lending is economically small and statistically insignificant, suggesting that Fintechs are not responding more strongly to demand shocks due to the laxer 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 from 75% to 90%, while leaving the LTV requirements for gold loans issued by shadow banks at 75%. We leverage this regulatory disparity to analyze the importance of the lax regulation channel in creating a comparative advantage for shadow banks, especially for Nontechs who are more responsive in retail lending backed by gold. We find that the response of Nontechs to this regulatory change in lending backed by gold is economically meaningful and statistically significant, suggesting that Nontechs are responding more strongly to demand shocks due to their regulatory advantage.

Overall, the results on regulation indicate that while lax regulation may be a key driver of the comparative advantage for Nontechs, it does not seem to be important for Fintechs. Lastly, these results also suggest that as the regulatory arbitrage gap between traditional and Nontechs closes, the latter may lose its comparative advantage.

An emerging literature has documented the importance of bank lending to shadow banks as an important source of funding (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). The literature conjectures that banks lend to shadow banks to benefit from higher return opportunities that are more likely to be available to shadow banks as they face less strict regulation and are more skilled at using technology to identify lending opportunities. We leverage two natural experiments to examine these channels which can create a funding advantage for shadow banks.

First, we employ the regulatory change in November 2023 that raised the risk weight for bank loans to shadow banks by 25 percentage points, 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 active in agricultural lending. We exploit this regulatory change and document that Nontechs increased their response to demand shocks in the agricultural sector following this change, indicating the role of bank funding in explaining their response.

Second, we exploit an idiosyncratic 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 shockwaves 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 idiosyncratic 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. Since, IL&Fs shock was primarily a funding shock from banks to shadow banks, the different responses across Fintechs and Nontechs indicate that bank lending primarily supports Nontechs. Therefore, these results also suggest that one reason banks extend credit to shadow banks is the relatively lenient regulatory environment that Nontechs operate under. 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 potential consequences for aggregate risk in the economy (Acharya, Schnabl, and Suarez, 2013; Acharya, Cetorelli, and Tuckman, 2024).

Thus far, we have shown that Fintechs' strong responses to demand shocks are likely due to their technological advantages, while lax regulation significantly influences Nontechs' reactions. Next, we explore why Nontechs react more strongly in collateralized markets. We find that the increase in Nontech lending after demand shocks is concentrated in areas where they have a physical presence. In contrast, our measure of physical presence is unrelated to Fintechs' responses to demand shocks. We argue that the presence of a local office is crucial for Nontechs in collateralized markets, as it facilitates effective inspection and seizure of collateral.

Lastly, we present an extensive set of robustness tests. We confirm that a decline in lending from traditional banks does not drive the results. The results are robust to different regression specifications and definitions of the weather shock. Lastly, we employ a placebo test to show that our results are unlikely to be spurious.

The key contribution of this paper is its exploration of how comparative advantages driving shadow bank growth differ across market segments. We present two new findings: First, the rise of non-Fintech shadow banks in the collateralized market may be driven by a combination of lax regulation and local physical presence. Second, the growth of Fintech shadow banks in the uncollateralized market may be attributed to their technological expertise and lack of physical presence. Prior literature that examines the reasons behind the rise of shadow banks has almost exclusively focused on mortgage markets and corporate or small business lending.[4] This focus of the literature on specific sectors 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 score, 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 Seru (2020), 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, we add to the discussion on whether shadow

[4]See Berger (2003), Buchak, Matvos, Piskorski, and Seru (2018), Frame, Wall, and White (2019), 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), 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; Balyuk, Berger, and Hackney, 2022). Alternatively, studies rely on a random subset of credit bureau data but are unable to distinguish between types of shadow banks, as in Di Maggio and Yao (2021).

banks act as complements or substitutes by documenting their complementary role to social networks, while the extant literature has discussed this role with respect to traditional banks (Tang, 2019; De Roure, Pelizzon, and Thakor, 2022; Gopal and Schnabl, 2022).

Second, this paper 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.[5] 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. Moreover, we document the role of different mechanisms across market segments and customer quality types in shaping the response of shadow banks to weather shocks.

Our work also contributes to the emerging literature on cashless transaction technology, which has primarily examined the determinants of technology adoption and the subsequent effect on income, consumption, and production.[6] More recently, this literature has examined the effect of different digital transactions technology on deposits, banking competition, and bank lending (Jiang, Yu, and Zhang, 2022; Whited, Wu, and Xiao, 2022; Koont, 2023; Sarkisyan, 2023; Koont, Santos, and Zingales, 2024; Liang, Sampaio, and Sarkisyan, 2024). We contribute to the literature by providing micro-evidence on how cashless payments affect credit market outcomes, showing that they reduce information asymmetry and enable Fintechs to extend credit after weather shocks. This finding supports the theoretical predictions of Brunnermeier and Payne (2022) and is based on comprehensive data from India's formal credit market, unlike previous studies focused on a single Fintech (Ouyang, 2021; Ghosh, Vallee, and Zeng, 2022). Moreover, our analysis documents the potential benefits of integrating cashless transactions within an open banking framework and informs the theoretical literature examining its welfare implications for consumers (Parlour, Rajan, and Zhu, 2022; Goldstein, Huang, and Yang, 2022; He, Huang, and Zhou, 2023).

Our findings are consistent with Alok, Ghosh, Kulkarni, and Puri (2024), who link UPI adoption to Fintech consumption loans. While we employ UPI to examine the technological comparative advantage of shadow banks, our primary focus is on understanding the broader dynamics of market segmentation among shadow banks in both collateralized and uncollateralized markets. Specifically, we document the importance of both technology and lax

[5]See Morse (2011), Berg and Schrader (2012), Cortés (2014), Chavaz (2016), 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.

[6]See Jack and Suri (2014), Muralidharan, Niehaus, and Sukhtankar (2016), Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020), Higgins (2022), Crouzet, Gupta, and Mezzanotti (2023), Dubey and Purnanandam (2024) and Agarwal, Ghosh, Li, and Ruan (2024) among others.

regulation in explaining the differences in the comparative advantage of Fintechs and Nontechs across market segments. Additionally, we trace the response of Fintechs and Nontechs to weather shocks. This temporal variation generated by random demand shocks not only aids in identification but also improves our ability to examine real effects as discussed in Paravisini, Rappoport, and Schnabl (2023).

This paper proceeds as follows. Section 2 describes the data. Section 3 discusses background information on the credit markets in India and the summary statistics of the data. Section 4 delineates the empirical strategy. Section 5 presents the results, and Section 6 documents the underlying mechanisms. Section 7 concludes.

2 Data

2.1 Lender Types

The Indian lending landscape is divided into two broad types: traditional banks (including public, private, and foreign banks) and shadow banks. Shadow banks are financial institutions that provide loans but do not provide demand deposits, accounts from which funds can be withdrawn at any time without a need to notify (RBI, 2021).[7] 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 on the universe of formal retail loans in India. We obtain data from India's oldest credit bureau - TransUnion CIBIL.[8] 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, as well as repayments, to credit bureaus. Mishra, Prabhala, and Rajan (2022) note that almost all financial institutions report their data to CIBIL, and the bureau extensively cross-checks submissions for integrity. Hence, this credit dataset comprehensively represents the landscape of formal retail loans in India.

The data is recorded at a granular level of year-month × ZIP × lender type × product type.

[7] 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.

[8] 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.

At this level, the data is further divided into credit score categories. We obtain this data from January 2016 until December 2021 for all of India's ZIP codes, approximately 19 thousand. We observe three outcomes: the number of loans issued, total loan amount issued, and the number of defaulted loans that were issued in this year-month × ZIP × lender × product. A loan is defined as defaulted once it reaches 90 days past due (DPD) within one year of being issued. We define the default rate as the proportion of loans issued each month that have surpassed the 90 DPD mark within one year of issuance.

This data has four 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 (public, private, foreign, and other). We can utilize the classification by the Credit Bureau, in contrast to other studies like Buchak, Matvos, Piskorski, and Seru (2018) that rely on a manual lender classification.[9] Being able to systematically distinguish between Fintechs and Nontechs is critical to identifying the comparative advantage of shadow banks relative to traditional banks. While prior research has examined this distinction among shadow banks in mortgage markets, it is yet to consider this issue in non-mortgage lending markets (for a survey, see Thakor (2020)).[10] 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 agriculture, gold[11], and vehicle to unsecured loans such as business, consumption, and MFI.[12] 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 consumer 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. In addition, mortgage lending is only a minuscule part of Fintech lending. 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.[13] New-to-credit borrowers do not yet have a credit score; thus, lenders experience the highest

[9] CIBIL classifies Fintechs based on their market knowledge 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).

[10] Di Maggio and Yao (2021) use data of the TransUnion credit bureau in the U.S. on personal loans but only identify Fintechs, not Nontech shadow banks.

[11] Gold loans are loans for which individuals pledge their gold as collateral.

[12] 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.

[13] 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).

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. Even in the U.S. unsecured consumer lending data, borrowers with very low or no credit score are often excluded (De Roure, Pelizzon, and Tasca, 2016).

Fourth, the data is unique in its size. We observe 653 million loans, the universe of formal retail loans in India from 2016 to 2021. This is larger by a factor of eight compared to mortgage data (Fuster, Plosser, Schnabl, and Vickery, 2019) and larger by a factor of more than a hundred compared to data on non-mortgage market segments. The latter either observe a random sample of a universe (Di Maggio and Yao, 2021) or data from one specific Fintech lender (Tang, 2019).

Finally, we complement our main dataset with a second dataset from CIBIL to get a proxy of credit applications. We rely on inquiry data, 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 public sector 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. To summarize, the CIBIL data is granular and very comprehensive, which is crucial for our empirical strategy.

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 by 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 areas 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 that specific area, starting in 1901.[14] This distribution captures the variability in water balance for a given month throughout the year in a given area. The next key 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 x 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.[15] 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.[16] [17] 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 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 Technology Data

2.4.1 UPI Index

In addition to the credit bureau dataset and the local weather shocks dataset, we employ several other datasets to explore the degree to which technology plays a role in Fintechs' relative comparative advantage. Specifically, we utilize the data on the Unified Payment Interface (UPI). The UPI is an instant payment system developed in 2016 that facilitates transactions between two bank accounts. It was publicly funded by the National Payments Corporation of India (NPCI). Indian lenders can make their apps available on the UPI structure. In 2022,

[14] 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.

[15] Note that the SPEI values are geographically clustered. This geographic clustering can be explained by time-invariant geographic determinants such as elevation (see Appendix Figure A.1). The time-invariant determinants of this geographical clustering of shocks that might be correlated with our outcome, such as elevation, are absorbed with ZIP code fixed effects. Thus, this spatial correlation does not pose a threat to identification.

[16] We show our results are robust to employing alternative definitions of the local shock variable, such as using different cutoffs or directly using the continuous measure. See Section 5.9.

[17] We also show that the binary shock does not show a clear increasing or decreasing trend over time; see Figure C.1.

India has been the global leader for instant payments, accounting for 46% of all global instant payment transactions (Business Wire, 2023). Crucially, the UPI interface enables data sharing, in particular open banking. A customer who applies for a loan at a Fintech can request her bank to share financial details like income and transactions from the bank to the lender. Thus, contemporaneous work has argued that UPI has been a strong driver of the rapid Fintech growth (Alok, Ghosh, Kulkarni, and Puri, 2024). Geographical ZIP-level heterogeneity in UPI should be a strong predictor of Fintechs' ability to access and process data with technology.

Instead of measuring UPI directly, we adopt a methodology similar to Dubey and Purnanandam (2024) and Alok, Ghosh, Kulkarni, and Puri (2024) to construct a UPI index that predicts UPI presence. This empirical strategy rests on two key insights. First, a bank account is required to access the full functionality of UPI. Therefore, when the dominant deposit-supplying bank in a region offers UPI services, its depositors are more inclined to adopt the platform. Second, prior research has demonstrated significant network externalities in the adoption of digital payments (Higgins, 2022; Crouzet, Gupta, and Mezzanotti, 2023). As a result, when the dominant bank's customers adopt UPI, it increases the likelihood of widespread UPI adoption in the region due to network effects.

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. The empirical strategy exploits the staggered adoption of UPI by banks. Following Dubey and Purnanandam (2024), we define early adopters as banks that were providing UPI services as of November 2016. Information on banks that were live on UPI as of November 2016 is provided by the Government of India.[18] 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, which corresponds to 13,313 ZIP codes. We use deposits measured as of March 2016 and create a deposit-weighted index of early adopter banks:

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

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. This is unlikely to be the case. The decision to provide UPI services was made at the bank level – not bank-ZIP level – and driven by aggregate factors and adaptation

[18]Early adopters refer to banks that adopted UPI in November 2016. November 2016 is an important date in the history of digital transaction adoption in India due to the demonetization of old notes. We direct readers to Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020) for more details on the demonetization episode. The adoption dates of UPI by banks are public information and can be accessed here.

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. 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 in Section 6.1.

2.4.2 Fintech Micro Data

We collect detailed data from one of the largest Fintechs in India. The provider (say Fintech ABC) focuses on lending to small businesses. It is a financial technology company based in India 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 UPI, credit/debit cards, and digital wallets. 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. Ultimately, the core of their business model revolves around empowering merchants with digital payment solutions, providing access to finance, and offering business management tools. We observe application-level information including the date of application, ZIP code of the applicant, her credit score (if available) and a proprietary score created by the Fintech based on digital transactions 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.

2.4.3 Facebook Social Connectedness Index

We test whether Fintech or Nontech is a complement or substitute to informal insurance – risk-sharing arrangements within social networks. For this purpose, we utilize as a proxy for the degree of informal insurance the Social Connectedness Index (SCI) from Facebook. SCI measures the strength of connectedness between two locations, represented by Facebook friendship ties. We direct readers to Kuchler and Stroebel (2021) for a discussion on the construction and measurement of SCI. The SCI is computed as follows:

$$\text{Social Connectedness Index}_{i,j} = \frac{\text{Facebook Connections}_{i,j}}{\text{Facebook Users}_i \times \text{Facebook Users}_j} \tag{2}$$

Here, 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. 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, averaging over all districts in India. We then link this district-level data to the ZIP code level.

3 Context and Summary Statistics

3.1 Shadow Banks in the Indian Lending Landscape

Across the world, shadow banks play an increasingly large role in lending markets. Table A.1 presents summary statistics of the Indian lending landscape. Nontechs are already an established player at the beginning of our sample period. In 2016, they issued 26 million loans with 2.59 trillion rupees (38 billion USD). They experienced moderate growth in our sample period. In 2021, Nontechs issued 44 million loans with 3.14 trillion rupees (46 billion USD). As of 2021, Nontechs captured 41% of the market in terms of the number of loans and 24% in terms of loan amount.

In contrast, Fintechs are just starting in our sample period and experiencing very rapid growth. In 2016, Indian Fintechs issued 76 thousand loans with 22 billion rupees (316 million USD). Five years later, in 2021, they issued 8.86 million loans with 228 billion rupees (3.32 billion USD). As of 2021, Fintechs captured 8% of the market in terms of the number of loans and 2% in terms of loan amount. In the product category of consumption loans, Fintechs capture 16% in terms of loan number and 4% in terms of amount. Fintechs have been experiencing the largest growth among all lenders. Between 2016 and 2021, Fintechs' number of loans grew by a multiplier of 117.12, while other lenders experienced a maximum multiplier of 1.72. Fintechs' loan amount multiplied by 10.51, while other lenders experienced a maximum multiplier of 1.30.

What market segments are shadow banks focusing on? Nontechs have a very broad loan portfolio. In 2021, 64% of their loan amount focuses on collateralized products (5% agriculture, 24% gold, 36% vehicles) and 36% on uncollateralized loans (business 8%, consumption 28%, microfinance 0.11%). Agricultural loans are typically secured by land, crops, or other assets. In the case of vehicle loans, the vehicle itself is the collateral. Gold loans are backed by gold jewelry or coins. Business, consumption, and microfinance loans mostly do not have collateral. In contrast to Nontechs, Fintechs have a very strong concentration in uncollateralized markets. 97% of their loan portfolio comes from uncollateralized loans such as business loans (22%) and consumption loans (75%). Considering the loan number instead of amounts, consumption loans make up 98% of Fintechs' loan portfolio (see Table A.1).

In terms of credit score types, both Nontechs (58% of the loan amount) and Fintechs (66% of the loan amount) have a large share of their loan portfolio issued to prime or near-prime borrowers. However, both lender types also issue to sub-prime (13% of the amount for Nontech and 7% of the amount for Fintech), as well as new-to-credit borrowers (14% of the amount for Nontech and 8% of the amount for Fintech).

The median loan size of Nontechs is 106 thousand rupees or 1,550 USD (see Table A.3, median loan amount divided by median number of loans). Fintechs have a much smaller loan size of 21 thousand rupees or 304 USD. The median loan size of both shadow bank types is smaller than that of traditional lender types such as public banks (3,632 USD) and private banks (2,683 USD). Default rates are relatively similar for Nontechs and Fintechs, around 5-8% after one year. Other traditional bank types have slightly lower default rates of 3-4% after one year. We do not observe information on interest rates in our data. Finally, Nontechs and Fintechs have a wide geographical spread comparable to other lenders, as depicted in Figure A.4.

3.2 Granular Summary Statistics

Going more granular, Table A.2 presents the summary statistics at our level of variation – year-month × ZIP × lender × product. The table includes the total number of loans issued, the loan amount, the one-year default rate, and inquiries. To bring inquiries to this level of variation, we divide the annual data by twelve. The summary statistics reflect the very high granularity of our data; the median number of loans issued in a given cell is six, corresponding to a total loan amount of 938k rupees (≈14k USD). This corresponds to a loan size of 156k rupees (≈2k USD). The average number of loans issued in a given cell is 32, relating to a total loan amount of 4m rupees (≈62k USD) and a loan size of 134k rupees (≈2k USD). The average number of loans multiplied by the number of observations in our sample [=32x20,459,958] equals approximately the total number of loans if we sum over the total sample (653m).

The average one-year default rate is 4.25%. The median number of inquiries is two. The ratio of the number of inquiries to the number of loans given is around one third, which is less than one. As noted earlier, this mismatch is because loans can be issued without an inquiry.

Appendix Table A.3 presents these statistics by lender type. A Nontech cell has a median number of ten loans with a total loan amount of 1m rupees (≈16k USD). A Fintech cell has a median number of five loans, corresponding to a total loan amount of 104k rupees (≈1.5k

USD). Table A.4 presents the key statistics by product type. Appendix Table A.5 depicts them by lender type and credit score type, and Table A.6 shows them by lender type and product type.[19]

3.3 Weather Shocks and Credit Demand

We analyze exogenous increases in credit demand by investigating the effect of weather shocks, which influence both agricultural and non-agricultural sectors. Since the seminal paper of Townsend (1994), several works have documented the relationship between weather shocks and agricultural income and output. While the negative effect of weather shocks on the agricultural sector is well understood, the impact of weather shocks extends significantly beyond the agricultural sector, affecting the overall economy in several ways.

First, weather disturbances can disrupt the day-to-day operations of non-agricultural firms. These disruptions can increase their credit demand to meet working capital needs. These disruptions can occur either 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 (Bas and Paunov, 2025). Therefore, firms' credit demand to meet working capital needs is likely to go up following these shocks.

The effect of these weather disturbances is likely to be more pronounced for micro, small, and medium enterprises (MSMEs), for which the working capital constraints tend to be more binding (see Woodruff (2018) for a review). In the Indian context, the effect of weather disturbances on MSMEs is especially important as it employs 23% of the total workforce. It is also worth noting that access to credit during times of unexpected liquidity needs can have strong, positive effects on both the real and financial outcomes of small businesses (Collier, Hartley, Keys, and Ng, 2024; Collier, Howell, and Rendell, 2024).

Second, weather disturbances can result in a loss of income or an 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. Extreme weather events, such as extreme heat, can considerably make it difficult for workers to go to work (Somanathan, Somanathan, Sudarshan, and Tewari, 2021; Dell, Jones, and Olken, 2009; Graff Zivin and Neidell, 2014). Moreover, the incidence of work-related injuries increases with extreme weather (Filomena and Picchio, 2024). As a result workers, especially daily wage earners and non-contractual labor, may suffer a loss of income. Additionally, the negative effects

[19] These tables indicate that Fintechs tend to inquire at a much higher rate than public or private sector banks.

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).

Lastly, we confirm that local economic activity measured using nightlights exhibits a negative relationship with weather shocks in our setting. Specifically, combining Jordà (2005) projection with the average nightlight luminosity measured at the ZIP year-month level, we document that weather shocks negatively affect local economic activity (see Appendix Figure B.1).

4 Empirical Strategy

The objective of this paper is to examine the growth of shadow banks relative to traditional banks in their local area. A key challenge in isolating the growth of shadow banks relative to traditional banks is that the relative growth may be a function of several local characteristics that can vary systematically across regions. For this reason, instead of comparing the credit by shadow banks and traditional banks, our approach is to identify demand shocks that plausibly affect these regions equally and examine changes in lending by shadow and traditional banks around such a shock.

We exploit a differences-in-differences (DID) estimation strategy to examine the effect of credit demand shocks – local weather shocks – on Fintechs' and Nontechs' loan portfolios. Specifically, we examine the lending response of Fintechs and Nontechs relative to traditional lenders following a weather shock using the specification outlined in Equation 3:

$$y_{ym,z,l,p} = \beta \cdot \text{Shock}_{ym,z} \times \text{Fintech}_l + \gamma \cdot \text{Shock}_{ym,z} \times \text{Nontech}_l + \text{FE}_{ym,z,p} + \text{FE}_{z,l,p} + \text{FE}_{ym,l,p} + \epsilon_{ym,z,l,p} \quad (3)$$

$y_{ym,z,l,p}$ refers to the outcome of interest, such as the natural logarithm of the loan amount or delinquency rate, 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 takes a value of one if the ZIP code experienced a weather shock in the given year-month and zero otherwise. Fintech_l is an indicator variable taking a value of 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 the weather shock on the outcome variable for Fintechs and Nontechs relative to traditional providers. If $\beta > 0$, this suggests that the shock has a larger positive effect on the outcome for Fintechs compared to traditional providers. If $\gamma > 0$, this suggests that the shock has a larger positive effect on the outcome for Nontechs compared to traditional providers. We additionally test for the difference between β and γ. We include granular fixed effects: year-month × ZIP × product fixed effect ($FE_{ym,z,p}$), ZIP × lender × product fixed effect ($FE_{z,l,p}$), and year-month × lender × product fixed effect ($FE_{ym,l,p}$). The standard errors for the specification are estimated by clustering at the ZIP level.

An identifying 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). Moreover, the year-month × ZIP × product fixed effect ($FE_{ym,z,p}$) incorporates the year-month × ZIP fixed effect which controls for local vulnerability and resilience developed over time to weather shocks.

Equipped with the exogeneity of the shock, we need to address two potential threats that could bias 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 aggregate investment opportunity set available to lenders in an area à la Drechsler, Savov, and Schnabl (2017).[20]

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

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

where Fintechs, Nontechs, and traditional lenders operate, thereby abstracting away from the confounding factor of non-random matching of lender types to locations.[21]

Finally, the inclusion of the year-month × lender × product fixed effect ($\text{FE}_{ym,l,p}$) 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 lenders. While this assumption is untestable, we will document parallel pre-trends in an event study analysis.[22]

5 Results: Credit, Weather Shocks & Shadow Banks

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 4, estimating our strictest specification in column 4 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 4. 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.

[21] 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.

[22] 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 treatment is permanent and one off, but our setting involves a unit experiencing multiple shocks over time (see Figure C.1). 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.

Column 5 splits shadow banks into its two components – Fintech shadow banks and Nontech shadow banks to estimate our baseline specification, presented in equation 3. The coefficient of interest associated with the interaction terms of Fintech and Nontechs with Shock are both positive and statistically significant. The positive estimate indicates that they increase their lending relative to traditional banks following a weather shock. Specifically, we find that Fintechs issue 1.57% 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 Fintechs. Specifically, they increase credit by 0.31%, and this effect is statistically different from the response of Fintechs.

Overall, our results suggest that shadow banks respond more to weather shocks, relative to traditional banks. Moreover, while both Fintechs and Nontechs respond by increasing credit the response of Nontechs is smaller in magnitude relative to Fintechs. This result highlights the role played by different types of shadow banks in navigating fluctuations in demand due to weather shocks.

5.1 Economic Magnitude of Baseline Effect

This section discusses the economic magnitude of the baseline effect. The average monthly Fintech loan amount within a ZIP code-lender-product cell (the unit of observation in Table 1) is 705k rupees (≈10k USD). This is accompanied by an average of 28.76 loans per cell, resulting in an average loan size of 24,520 rupees (≈358 USD). Furthermore, the point estimates in Column 4 of Table 1 indicate a 1.57% increase in Fintech credit following a weather shock. This translates to an increase of 385 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.7). For households in the bottom 5$^{\text{th}}$ percentile of monthly expenditure, the increase in Fintech credit per borrower represents approximately 19% of 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 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 5.5, 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% [=385/(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 – as documented in Section 5.5 – 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% of that figure.

We also provide back-of-the-envelope calculations to give a brief overview of the overall impact. Specifically, we estimate that the average loan amount across various products and ZIP codes in a given year-month is 190 million USD, and Fintechs issued a total of 13 billion USD in credit during our sample period. Additionally, as shown in Column 5 of Table 1, our findings indicate that Fintechs issue 1.57% more credit after weather shocks compared to traditional lenders within the same year-month, ZIP code, and product category. Consequently, this estimate translates to an aggregate increase of 3 million USD in credit in any given month, totalling 211 million USD over the course of our study period.

5.2 Dynamic Response

Next, we investigate the dynamic response of credit issuance over time. This corresponds to Equation 3 but additionally includes specific dummies for pre- and post-periods. Figure 2 presents the dynamic effects of the loan amount. There are two key takeaways from estimating the dynamic version of Equation 3. First, the results indicate that the pre-trends are unlikely to drive our results and our 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.

5.3 Heterogeneity by Collateralization

This section examines the differences in the baseline effects of shadow banks within collateralized and uncollateralized market segments. This analysis is significant for three main reasons. First, it allows us to assess whether various types of shadow banks have distinct comparative advantages in absorbing weather shocks across these market segments. Second, understanding this heterogeneity is essential for understanding the industrial organization of credit markets. Third, recognizing the differences in comparative advantages across market segments can help better understand the underlying reasons for these advantages. For instance, lax regulation may be a more important factor determining the comparative advantage in collateralized markets, which are more heavily regulated.

Table 2 presents the results examining the heterogeneity in the baseline effects across collateralization. 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 of 1.53% compared to Fintechs and traditional banks. Conversely, in the uncollateralized loan segment, Fintechs demonstrate a stronger response of 1.92% than Nontechs or traditional banks. These findings suggest that Nontechs hold a comparative advantage in collateralized markets, whereas Fintechs are better positioned in uncollateralized markets.

Next, we present a dynamic assessment of the effect for 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. The results indicate that the pre-trends are unlikely to drive our results and our 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 uncollateralized 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. The results 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 (3.25%), and vehicle loans (0.33%). 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 (4.49%), consumption loans (1.08%), and MFI loans (8.37%). 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. The results also suggest that lax regulation may be a critical determinant of Nontech's comparative advantage, as they exhibit greater response in collateralized markets which tend to be more heavily regulated. Section 6.3 discusses this issue in more detail.

5.4 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, product, lender and year level since the inquiry data is available at annual frequency. Appendix Table B.2 presents the results. We find that Fintechs conduct greater 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 uncollateralized 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 reflect loan applications or acceptance rate for two reasons. First, lenders may not necessarily conduct an inquiry in the credit bureau (Mishra, Prabhala, and Rajan, 2022). Second, borrowers may apply for loans with multiple lenders.

5.5 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, which is important for two reasons. First, it may shed light on the factors driving the comparative advantages of shadow banks. For instance, if lax regulation may be the primary factor for their comparative advantage, shadow banks might be more inclined to serve riskier borrowers whom traditional banks cannot assist. Second, 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 evaluating the reasons behind their comparative advantage and their broader welfare implications (Tang, 2019; De Roure, Pelizzon, and Thakor, 2022; Gopal and Schnabl, 2022).

To this end, we estimate our baseline Equation 3 for each credit score category separately. Table 3 presents the results. We find that Fintechs react stronger than Nontechs and traditional banks for prime borrowers (0.75%), near-prime borrowers (1.11%), and sub-prime borrowers (1.74%). This effect is monotonically increasing. The most significant response occurs among new-to-credit borrowers, at 2.67%, 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.

Appendix Tables B.3 and B.4 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, Nontechs 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 1.92%, 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 slight 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 Tables B.5, B.6, and B.7 show results for all loans, collateralized loans, and uncollateralized loans, respectively. 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 from super-prime to prime borrowers. Thus, the inquiry effects among scored borrowers are unlikely to explain the heterogeneity in loan issuance documented in Tables 3, B.3, and B.4.

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 5.2, 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.

5.6 Default Rates

We next analyze default rates on new loans issued by shadow banks following weather shocks. Section 5.5 documents that shadow banks primarily cater 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 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.

5.7 Heterogeneity Across Rural and Urban Areas

In this section, we examine the heterogeneity of the impact across rural and urban areas. Understanding this heterogeneity is important for assessing whether shadow banks effectively address regional disparities in financial services. Generally, rural areas face significant barriers to accessing financial services, while urban areas benefit from a more developed financial infrastructure, including a higher concentration of branches of traditional banks. Therefore, understanding regional disparities in the effect is also important from a welfare perspective as prior research has shown that financial intermediation in rural areas can aid in reducing poverty (Burgess and Pande, 2005; Barboni, Field, and Pande, 2024).

To this end, we split all ZIP codes into one of the four groups – metro, urban, semi-urban, and rural – and estimate our baseline specification for each group. Table B.8 presents the results. We document that Fintechs tend to lend more in rural areas relative to metro areas, following a demand shock. This result indicates that Fintechs can play an active role in smoothing demand shocks, especially in regions where traditional banks may be less prevalent. Furthermore, this result adds to our argument that Fintechs may act as a complement to traditional banks by providing credit to an underserved population that traditional banks are unable to reach.

In contrast to Fintechs, Nontechs tend to increase their lending activities in metro areas relative to rural areas. We posit two key channels to explain this difference across shadow bank responses. First, Nontechs typically respond to demand shocks by increasing lending in collateralized markets. These markets often require a physical presence to inspect or collect the underlying assets, which may explain their greater response in metro areas. Second, the technological advantage of Fintechs may allow them to exploit lending opportunities in remote areas. We will explore both of these channels in detail in Section 6.

5.8 Substitution with Informal Insurance

This section investigates the heterogeneity in the baseline response of shadow banks following demand shock by informal insurance – risk-sharing arrangements within social networks. We posit that the role of shadow banks in providing insurance to these shocks via credit will be lower in regions with a greater degree of informal insurance. This reduction in the role of shadow banks may stem from the fact that the liquidity needs of individuals in affected regions are often met through their social connections, rather than through formal lenders. The lower demand for formal insurance in the presence of a greater degree of informal insurance in India has been documented previously in the context of agricultural insurance by Mobarak and Rosenzweig (2013).

To this end, we use the data on social connections from Facebook as a proxy for informal insurance. Using the social connections of individuals, measured using the social connectedness index (SCI), we split the ZIP codes into four quartiles. Quartile one corresponds to the lowest social connectedness, while quartile four corresponds to the highest social connectedness.

Table 5 presents the results. The effect for Fintechs is statistically stronger in the quartile with the lowest social connectedness (2.27%), compared to the quartile with the highest social connectedness (0.89%). This suggests that Fintech is a complement to informal insurance, i.e., when informal insurance is limited Fintechs provide insurance against these demand shocks via credit. In contrast, we find no such difference for Nontechs. The lack of relationship between social networks and the response of Nontechs may be attributed to the limited role of social networks in collateralized markets. Typically, loans in collateralized markets involve larger sums of money, while borrowing between family and friends generally involves smaller amounts (De Aghion and Morduch, 2005; Karaivanov and Kessler, 2018).

5.9 Robustness and Placebo

This section presents a series of robustness tests to validate our baseline findings. First, our specification in Equation 3 examines the effect of Fintechs and Nontechs compared to traditional banks. A potential concern is that both types of banks may reduce lending after weather shocks, with traditional banks potentially cutting back even more due to deposit withdrawals, which could limit funding (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 public sector banks show a positive response. This suggests that our findings are not driven by shadow banks reducing lending less than traditional banks or by a decline in funding at 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 × ZIP × lender × 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. The estimate for Fintech rises to 4.00%, while the coefficient for Nontech remains small at 0.59%. 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.

Fifth, we discuss a set of robustness tests related to the construction of the weather shock. 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 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 (Appendix Table C.7) and floods (Appendix Table C.8) separately.

Fifth, we examine whether the likelihood of experiencing a weather shock changes over time, as this could indicate shifts in underlying weather patterns. Figure C.1 presents the average probability of weather shock over time for a ZIP code. We note that this within-ZIP probability is mean stationary, and does not suggest distinct upward or downward trends. This indicates that our identification strategy remains robust and our results are unlikely to be driven by long-term climate change patterns.

Finally, we run a placebo test. We replace our weather shock dummy with a dummy 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 100 times. Figure C.2 plots the kernel density of the resulting coefficients. As expected, the distribution of the Fintech coefficients is centred around zero, varying between -0.007 and

0.007. Thus, our main Fintech coefficient in Table 1 Column 4 (0.0157) – indicated in blue in the figure – does not fall within the range of the placebo estimates. Similarly, the Nontech placebo coefficients are centered around zero, varying between -0.003 and 0.003, and the main Nontech coefficient of 0.0031 is to the far right of the distribution. Thus, the results of the placebo test provide further confidence that our results are unlikely to be spurious.

6 What Explains the Comparative Advantage of Shadow Banks?

This section investigates the reasons behind the comparative advantages of shadow banks. Specifically, it looks at why Fintechs tend to respond more strongly in uncollateralized markets, while Nontechs show greater reactions in collateralized markets. We start by analyzing the role of technology, providing two pieces of evidence that highlight its critical role in the stronger responses of Fintechs. In contrast, we find that technology does not significantly impact the responses of Nontechs. Next, we leverage four natural experiments to demonstrate how lax regulation contribute to the comparative advantages of Nontechs. We show that less stringent regulations create direct regulatory arbitrage opportunities for Nontechs and facilitate easier funding from banks. Finally, we highlight the importance of Nontechs' physical presence in determining their response in collateralized markets. We posit that this presence enhances their ability to inspect and seize collateral effectively.

6.1 Technology: UPI Index

We evaluate whether Fintechs' technological advantage facilitates credit extension after a shock, by examining variation in the baseline effect based on differences in UPI adoption. We measure UPi adoption using UPI index discussed in section 2.4.1. The intuition of this test is that The UPI index captures digital financial transactions, providing a proxy for open banking activity. Specifically, when a borrower applies for a Fintech loan, they can share their banking data with the lender more readily if majority of their transactions are done digitally. Therefore, in ZIP codes with a higher UPI index – indicating greater UPI activity – we expect to observe stronger credit responses if technological advantage is the key mechanism.

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 correlation 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 between the two is positive and UPI transaction volume and values 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 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.

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 0.66% and statistically insignificant. In the fourth quartile, the coefficient is 2.33% and statistically significant at 1% level. A Wald test confirms that the coefficients in the first and fourth quartiles are significantly different, with a p-value of 0.03. Additionally, Appendix Table D.1 and D.2 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.

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, the digital banking platform of the State Bank of India, the largest public 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 not a part of the open banking framework as it cannot be 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 D.3 presents the results. The estimate of interest is flat 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 unobservable factors.

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 within an open banking framework. 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.

6.2 Technology: Application-Level Fintech Data

This section provides application-level evidence consistent with the technology advantage of Fintechs. Specifically, we exploit data from one of the largest Fintechs in India that specializes in small business lending. This company generates a standardized score for each applicant based on their digital transactions (see Section 2.4.2 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, etc. at the application level.

Table 9 presents the results, for the entire sample of applicants as well as the split by new-to-credit and not new-to-credit applicants. Moreover, in this section, we define alternative data as the standardized score assigned by the lender to the applicant, based on digital transactions conducted by the merchant. We find that a rise in the alternative data 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 – plays a key role in allowing Fintechs to serve credit after shocks, especially to new-to-credit borrowers.

Additionally, we examine the effect of alternative data on other dimensions of borrowing. We begin by examining the effect on days to disbursal (Appendix Table D.4). This is an important metric, especially in our setting, as timely provision of liquidity for households navigating extreme weather shocks can be critical. Moreover, analysis of this variable can indicate if Fintechs can reduce frictions in credit markets, such as lengthy loan processing. We document that higher alternative data 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).

Next, we examine the relationship of the score or the alternative data with the default on loans given after weather shocks (Appendix Table D.5). We do not observe a significant change in default for new-to-credit borrowers. Finally, in terms of interest rate, we do not find an effect for those new-to-credit or those not new-to-credit consistent with the lender's uniform pricing policy (Appendix Table D.6).

This result indicates that higher alternative data increases the probability of acceptance and reduces the time of disbursal, especially for new-to-credit borrowers. However, it does not materialize as a higher default for these borrowers after weather shocks. This result of a faster speed of disbursal and an insignificant effect on default is consistent with the findings of Fuster, Plosser, Schnabl, and Vickery (2019) and suggests that the technology based lending model for Fintechs can alleviate frictions in credit markets, such as removing information asymmetry and lengthy credit disbursal process, especially in times of need.

6.3 Role of Differences in 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.

6.3.1 Fintech & Regulation

First, we exploit a change in regulatory measure towards consumer lending issued by the Reserve Bank of India in November 2023.[23] Specifically, the regulatory change raised the risk weight for retail loans issued by banks and shadow banks from 100% to 125%. An important distinction of the change was that loans made by shadow banks to MFIs were exempt from this regulatory change, while MFIs receiving loans from banks faced an increased 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.[24]

[23]We refer to the November 16, 2023 RBI circular that can be accessed here.

[24]We want the readers to note that Nov 2023 is outside the range of our baseline sample. Therefore, we collected a more recent wave of data from the credit bureau spanning from July 2021 until June 2024.

We hypothesize that if the lax 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 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 lax regulatory environment.

6.3.2 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%.[25] 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 more lax. 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. This result also indicates that as the regulatory arbitrage gap between traditional and shadow banks closes, the latter may lose its comparative advantage.

[25]We refer to the August 6, 2020 circular that can be accessed here.

6.4 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).[26] 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 laxer 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 would otherwise be unavailable. Thus, we hypothesize that if superior technology (lax 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 an idiosyncratic shock to examine this channel.

6.4.1 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. As argued by Acharya, Khandwala, and Öncü (2013), banks have strong incentives to lend to shadow banks for priority sector lending. Such arrangements help some banks fulfil their regulatory targets for priority sector lending.

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. Consistent with our baseline findings, the interaction term between Nontech 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.

[26] 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 per cent 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).

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.

6.4.2 Idiosyncratic Shock to Funding: IL&FS Crises

Next, we examine an idiosyncratic 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 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 on 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 Non-Banking Financial Company (NBFC), 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 reduced lending to shadow bank borrowers by 5.8 percentage points, equivalent to 48%, after the IL&FS crisis. This chain of events resulted in a substantial and unexpected funding shock to the shadow banking sector.

We exploit the funding shock resulting from the IL&FS crisis to examine its role in the response of shadow banks to demand shocks. Specifically, we investigate how their response to demand shocks changed after the IL&FS collapse. Table 11 presents the findings for total lending as well as lending in collateralized and uncollateralized markets in columns 1, 2, and 3, respectively. 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 their 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 effect the response of Fintechs. Therefore, these results suggest that a reason behind bank lending to shadow banks may be the lax regulation faced by these entities, specifically Nontechs who harness less stringent regulatory burden as their comparative advantage. 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).

6.5 Nontech Effect in Collateralized Markets

Thus far, we have shown that Fintechs' strong responses to demand shocks can likely be attributed to their technological advantages, while lax regulation and funding appear to be significant factors explaining Nontechs' reactions. However, we still need to clarify why the responses of Fintechs and Nontechs differ based on collateralization. In particular, what accounts for the stronger reactions of Nontechs in collateralized markets?

We posit that a distinction between Fintechs and Nontechs is the local physical presence of Nontechs, which likely explains why Nontechs exhibit a greater reaction in collateralized lending. Specifically, we contend that having a local office in the area where loans are disbursed is essential for effectively seizing collateral in the event of default, particularly when the collateral involves politically sensitive assets like agricultural land or smaller items such as vehicles.

This section presents suggestive empirical evidence supporting our hypothesis. We categorize ZIP codes into two groups based on the median per-capita number of shadow bank loans in 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 physical 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. These results indicate that physical presence is likely a key factor contributing to Nontechs' comparative advantage in collateralized lending, as such proximity increases their ability to seize collateral in the event of default.

As a falsification exercise, we examine Fintech responses in above- and below-median ZIP codes. The logic behind this test is that Fintechs should not exhibit significant differences across these regions, as their physical presence is not a critical factor. Conversely, if the Nontech results are influenced by omitted variables, we would expect to see variability in Fintech responses, particularly in uncollateralized markets. The response of Fintech to demand shocks reported in Table 12 does not exhibit variation across these regions. This indicates that the Nontech response in collateralized markets is likely a result of their physical presence which increases their ability to seize collateral.

7 Conclusion

In conclusion, our study leverages novel and comprehensive credit bureau data on retail loans in India to disentangle the drivers of comparative advantages of shadow banks across different market segments. Our findings reveal that the factors driving the expansion of shadow banks vary significantly by loan type, emphasizing the importance of both technology and regulation but in different contexts.

We first establish that shadow banks are more likely to smooth fluctuations in credit demand, especially for those facing high levels of information asymmetry. We document this using three key results. First, we show that shadow banks increase credit more than traditional banks in areas affected by weather shocks, suggesting the presence of a comparative advantage in navigating these shocks. Second, we show that Nontechs exhibit a stronger response in collateralized markets, whereas Fintechs demonstrate a stronger response in collateralized markets. Third, 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. This result indicates a market segmentation in the response of shadow banks to demand shocks. Moreover, we show that shadow banks can act as complements to traditional banks by extending credit to borrowers and to regions that are underserved by traditional banks.

The second part of the paper investigates the reasons underlying the comparative advantage of shadow banks across market segments. Exploiting the geographic heterogeneity in the adoption of digital technology, Unified Payment Interface (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 five natural experiments across time and products to establish the importance of lax regulation in explaining the comparative advantage of Nontechs. Moreover, we show that this regulatory advantage for Nontechs may create a funding advantage by incentivizing traditional banks to lend to Nontechs and, therefore, take advantage of opportunities that are unavailable to them. Lastly, we highlight the importance of the physical presence of Nontechs in explaining their dominance in collateralized markets, as physical presence is important for inspecting collateral when giving loans and seizing it in case of default.

Overall, our research contributes to a deeper understanding of the dynamics of shadow banking beyond the heavily studied mortgage market, providing new evidence on how technology and regulation may interact to shape the growth of these institutions across different segments of the credit market. This segmentation in the responses highlights the distinct comparative advantages that different types of shadow banks hold, driven by their respective business models and operational strategies. Moreover, we show that shadow banks can act as a complement to traditional banks by serving borrowers with low credit scores and new-to-credit borrowers, as well as borrowers in rural areas, whom traditional banks are unable to serve.

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Figures

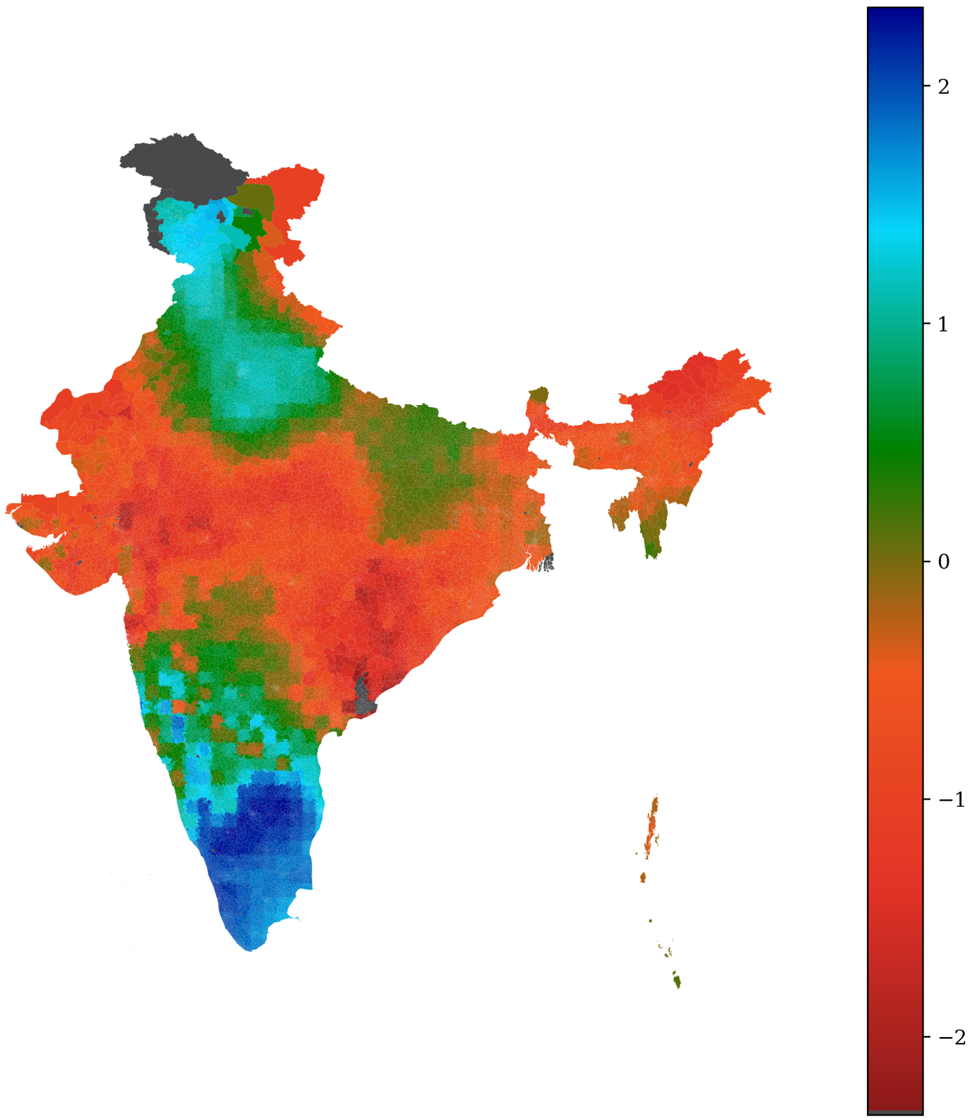


Figure 1: **Continuous Water Balance Variable (SPEI).** The figure presents the geographic ZIP-level distribution of the continuous water balance variable SPEI, for December 2020 as an example. The definition of the SPEI is outlined in Section 2. It has a mean of zero and standard deviation of one. The continuous SPEI forms the basis for our weather shock dummy. Note that the SPEI values are geographically clustered. This geographic clustering can be explained by time-invariant geographic determinants such as elevation (see Appendix Figure A.1). The time-invariant determinants of this geographical clustering of shocks that might be correlated with our outcome, such as elevation, are absorbed with ZIP code fixed effects. Thus, this spatial correlation does not pose a threat to identification.

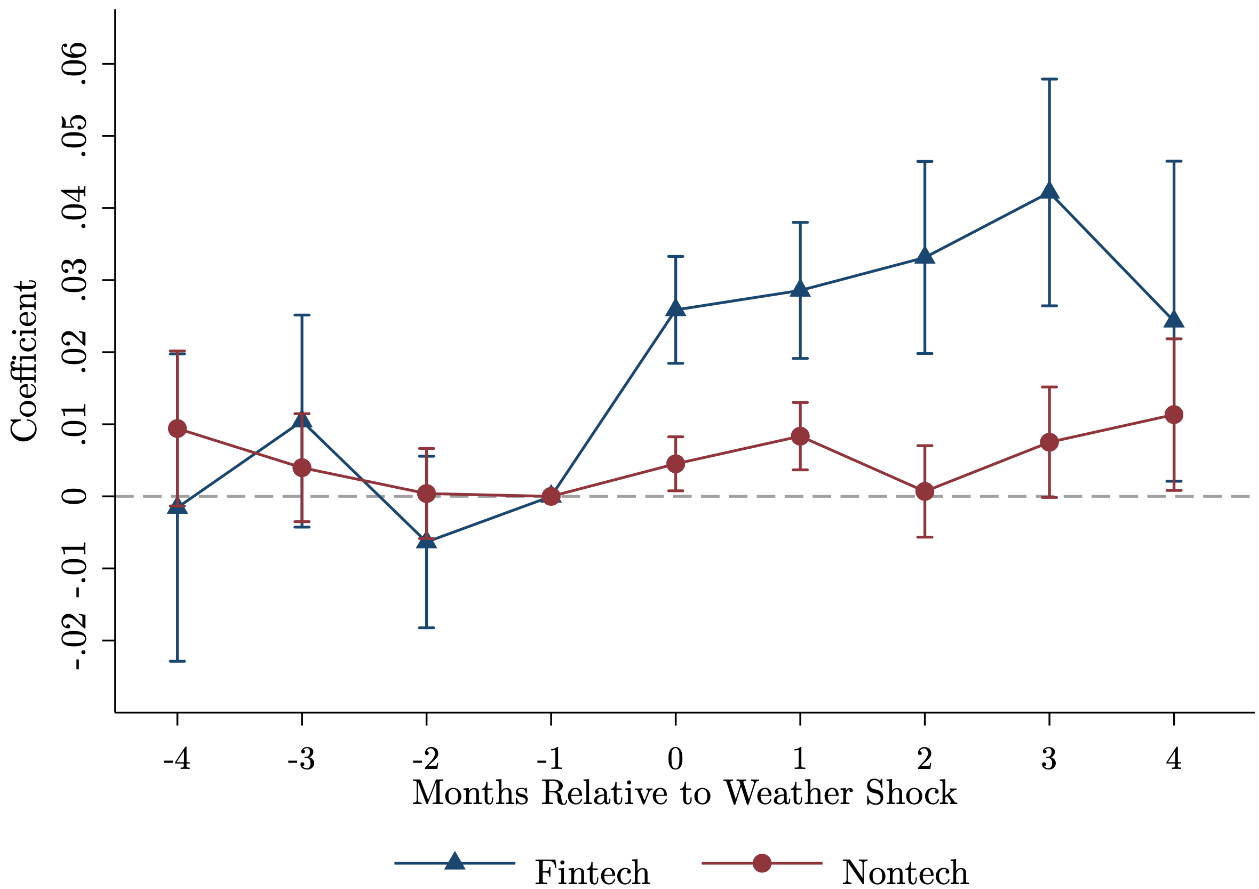
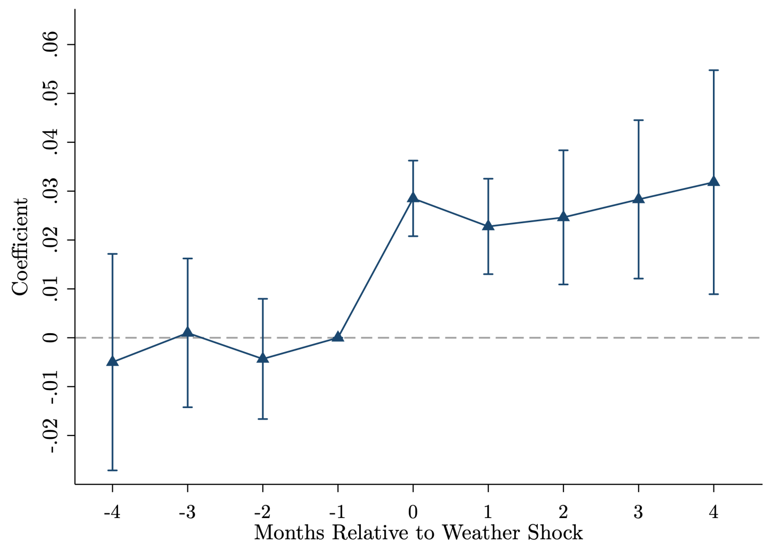
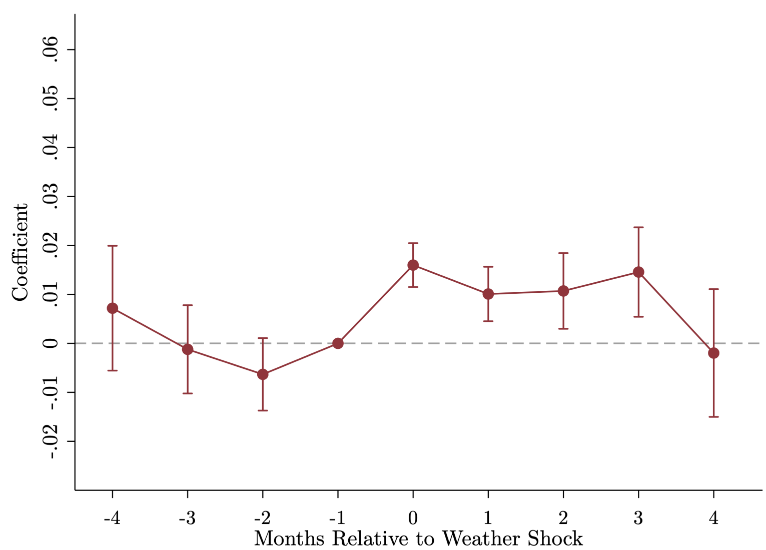


Figure 2: **Fintech and Nontech Credit Issuance, Amount**. This figure presents the dynamic effects of Fintech and Nontech credit issuance in response to a shock, compared to traditional lenders. Equation 4 describes the regression, where t is the year-month relative to the shock and the reference period is t=-1. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. The figure shows 90% and 95% confidence intervals.

$$y_{z,ym,l,p} = \sum_{t=-K}^{T} \beta_t \text{Shock}_{z,ym} \times \text{Fintech}_l + \sum_{t=-K}^{T} \gamma_t \text{Shock}_{z,ym} \times \text{Nontech}_l + \text{FE}_{ym,z,p} + \text{FE}_{ym,l,p} + \text{FE}_{z,l,p} + \epsilon_{z,ym,l,p} \tag{4}$$

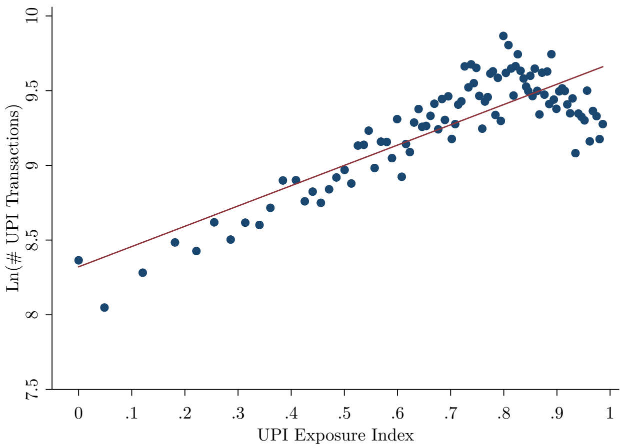


(a) Fintech (Uncollateralized)

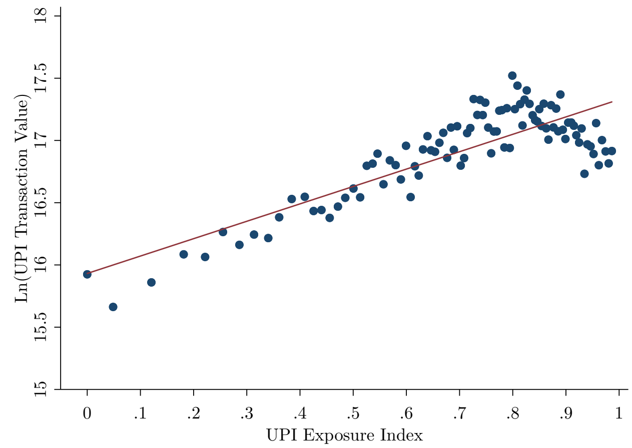


(b) Nontech (Collateralized)

Figure 3: **Fintech and Nontech Credit Issuance, Amount, by Collateralization**. This figure presents the dynamic effects of Fintech (Figure 3a) and Nontech (Figure 3b) credit issuance in response to a shock, compared to traditional lenders, for collateralized loans (agricultural, gold, vehicle) and uncollateralized loans (business, consumption, MFI). Equation 4 describes the regression, where t is the year-month relative to the shock and the reference period is t=-1. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. The figure shows 90% and 95% confidence intervals.



(a) UPI Transaction Volume



(b) UPI Transaction Value

Figure 4: **UPI Transactions & UPI Exposure Index.** The figure presents the binscatter plot of UPI transactions and the UPI exposure index. The unit of observation is at the ZIP code - month-year level from January 2017 until December 2022. 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 X-axis plots 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. All variables are winsorized at the 1st and 99th percentile.

Table 1: **Baseline Results: Effect on Credit Issuance**

	ln(Amount)				
	(1)	(2)	(3)	(4)	(5)
Shadow × Shock	0.0026*	0.0023*	0.0030**	0.0055***	
	(0.0015)	(0.0014)	(0.0014)	(0.0011)	
Shock	0.0215***	0.0016**			
	(0.0018)	(0.0007)			
Fintech × Shock					0.0157***
					(0.0023)
Nontech × Shock					0.0031***
					(0.0011)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	.	.	.	.	0.00
Lender FE	✓	✓	✓		
Month-year FE		✓			
ZIP 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	19,060
Years	6	6	6	6	6
R-squared	0.14	0.36	0.39	0.84	0.84
Observations	20,459,958	20,459,958	20,459,958	20,459,958	20,459,958

Notes: This table presents shadow bank credit issuance after the shock, compared to traditional lenders. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. ln(Amount)$_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Shadow$_l$ is a dummy equal to one if the lender is either a Fintech or a Nontech and zero otherwise. Fintech$_l$ is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech$_l$ is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. 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. Standard errors 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	0.0157***	-0.0235**	0.0192***
	(0.0023)	(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
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 Fintech and Nontech credit issuance after the shock, compared to traditional lenders, for collateralized loans (agricultural, gold, vehicle) and uncollateralized loans (business, consumption, MFI). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors 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)
Fintech × Shock	0.0157***	-0.0047	-0.0017	0.0075***	0.0111***	0.0174***	0.0267***
	(0.0023)	(0.0074)	(0.0043)	(0.0028)	(0.0030)	(0.0042)	(0.0034)
Nontech × Shock	0.0031***	0.0017	-0.0034	-0.0043***	0.0021	-0.0014	0.0115***
	(0.0011)	(0.0036)	(0.0021)	(0.0015)	(0.0017)	(0.0022)	(0.0016)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
FinTech × Shock = Nontech × Shock	0.00	0.40	0.71	0.00	0.00	0.00	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,060	15,468	18,821	19,007	18,940	18,601	18,968
Years	6	6	6	6	6	6	6
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

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, by credit score type. New-to-credit are borrowers who do not yet have a credit score. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 4: **Default Rate for Loans Issued Following Weather Shocks**

	Default Rate		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech $\times$ Shock	0.0003	0.0018	0.0007*
	(0.0003)	(0.0019)	(0.0003)
Nontech $\times$ Shock	0.0001	-0.0004**	0.0009***
	(0.0001)	(0.0002)	(0.0002)
Omitted Category	Traditional	Traditional	Traditional
Fintech $\times$ Shock = Nontech $\times$ Shock	0.54	0.24	0.60
Year-month $\times$ ZIP $\times$ Product FE	✓	✓	✓
Year-month $\times$ Lender $\times$ Product FE	✓	✓	✓
ZIP $\times$ Lender $\times$ 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 default rates for loans issued by Fintech and Nontech after the shock, compared to traditional lenders, for collateralized loans (agricultural, gold, vehicle) and uncollateralized loans (business, consumption, MFI). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. 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. Fintech$_l$ is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech$_l$ is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. 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. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 5: **Substitution with Informal Insurance**

	ln(Amount)			
	SCI Quartile 1 (1)	SCI Quartile 2 (2)	SCI Quartile 3 (3)	SCI Quartile 4 (4)
Fintech × Shock	0.0227***	0.0215***	0.0076	0.0089*
	(0.0043)	(0.0046)	(0.0047)	(0.0047)
Nontech × Shock	0.0084***	0.0012	-0.0053**	0.0065***
	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Month-year × ZIP × Product FE	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓
ZIPs	4,188	4,377	4,738	5,564
Years	6	6	6	6
R-squared	0.85	0.84	0.82	0.82
Wald p-val Fintech (Q1=Q4)	.	.	.	0.03
Wald p-val Nontech (Q1=Q4)	.	.	.	0.56
Observations	5,128,802	5,039,199	5,087,261	5,050,075

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, separately by district code level social connectedness index quartiles described in Section 2. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. ln(Amount)$_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech$_l$ is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech$_l$ is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. 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. Standard errors 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)
employment manufacturing (%)	-0.6466***	-0.2203	-0.4151
	(0.2304)	(0.2190)	(0.2743)
employment 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 UPI exposure 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, the share of population in manufacturing and services sector. 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 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. Robust standard errors are reported in parentheses. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 7: **Relationship Between UPI Index & UPI Transactions**

	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

	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 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. Robust standard errors are reported in parentheses. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 8: **Role of Technology: Exploiting Heterogeneity by UPI Exposure**

	ln(Amount)			
	UPI Exposure in ZIP Code Quartile 1 (1)	UPI Exposure in ZIP Code Quartile 2 (2)	UPI Exposure in ZIP Code Quartile 3 (3)	UPI Exposure in ZIP Code Quartile 4 (4)
FinTech × Shock	0.0066	0.0128**	0.0166***	0.0233***
	(0.0053)	(0.0050)	(0.0050)	(0.0051)
Nontech × Shock	-0.0001	0.0017	0.0055**	0.0002
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.22	0.04	0.04	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓
ZIPs	3,406	2,952	2,997	3,834
Years	6	6	6	6
R-squared	0.83	0.85	0.85	0.81
Wald p-val Fintech (Q1=Q4)	.	.	.	0.03
Wald p-val Nontech (Q1=Q4)	.	.	.	0.92
Observations	3,974,444	3,973,448	3,974,116	3,973,383

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, separately by ZIP code level UPI index quartiles. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors 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**

	Application Accepted (0 or 1)		
	All (1)	New-to-Credit (2)	Not New-to-Credit (3)
Alternative Data × Shock	0.0080***	0.0237***	0.0041*
	(0.0021)	(0.0052)	(0.0023)
Alternative Data	0.0621***	0.0564***	0.0789***
	(0.0017)	(0.0035)	(0.0019)
Year-month × ZIP × Merchant Type FE	✓	✓	✓
Onboarding Channel FE	✓	✓	✓
Swipe Machine FE	✓	✓	✓
Membership in Investment App FE	✓	✓	✓
ZIPs	8,138	4,934	7,687
Years	2	2	2
R-squared	0.34	0.34	0.40
Observations	712,049	136,846	534,638

Notes: This table presents Fintech acceptance rates after the shock. Equation 5 describes the regression. The data is on the application level. Application Accepted is a binary indicator equal to one if the application is approved. Alternative Data 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. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

$$y_{app} = \beta_0 \cdot \text{Shock}_{ym,z} \times \text{Alternative Data}_{app} + \beta_1 \text{Alternative Data}_{app} + \text{FE} + \epsilon_{app} \tag{5}$$

Table 10: **Role of Lax Regulation: Exploiting Regulatory Changes**

	ln(Amount)		
	MFI (1)	Gold (2)	Agri (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	0.0465	-0.1662
	(0.0590)	(0.0746)	(0.2369)
Nontech × Shock × Post	0.0052	-0.0405***	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 Fintech and Nontech credit issuance after the shock, after the regulations, compared to traditional lenders. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level, and in Column 1 and 3 ranges from July 2021 to June 2024, in Column 2 from January 2016 to March 2021. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Post_{ym} is a dummy equal to one after November 2023 in Columns 1 and 3 and after August 2020 in Column 2. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

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

	ln(Amount)		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0155**	-0.0025	0.0202***
	(0.0074)	(0.0200)	(0.0078)
Nontech × Shock	0.0137***	0.0315***	-0.0069**
	(0.0018)	(0.0022)	(0.0030)
Fintech × Shock × Post	-0.0011	-0.0300	-0.0007
	(0.0077)	(0.0225)	(0.0081)
Nontech × Shock × Post	-0.0171***	-0.0275***	0.0058
	(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 Fintech and Nontech credit issuance after the shock, compared to traditional lenders, before and after the IL&FS corporate loan defaults in August 2018. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Post_{ym} is a dummy equal to one after August 2018. Standard errors 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	0.0105***	0.0131***	0.0346	-0.0287***	0.0170***	0.0194***
	(0.0036)	(0.0029)	(0.0303)	(0.0104)	(0.0036)	(0.0030)
Nontech × Shock	-0.0016	0.0030**	0.0048**	0.0138***	-0.0025	-0.0028
	(0.0018)	(0.0014)	(0.0022)	(0.0017)	(0.0029)	(0.0022)
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIPs	9,412	9,648	9,358	9,648	9,404	9,648
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)		0.60		0.06		0.73
Wald p-val Nontech (Below = Above)		0.06		0.00		0.85
Observations	8,293,865	12,166,006	3,805,232	5,457,588	3,308,363	4,736,619

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, separately by ZIP code local presence. Local presence is measured by total loan amount by shadow banks in the ZIP divided by population in January to March 2016. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors 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

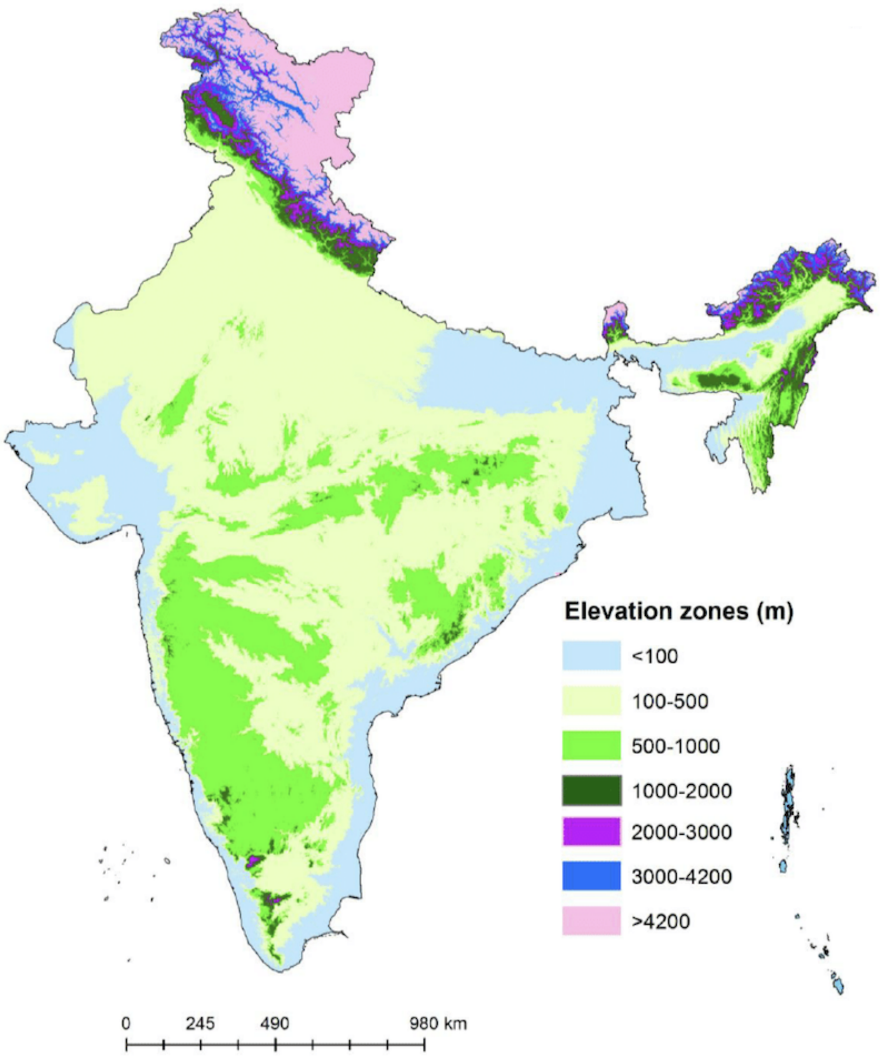


Figure A.1: **Elevation.** The Figure presents the geographic distribution of the elevation profile of India, an important determinant of the weather, sourced from Chintala, Jha, Diwakar, and Dadhwal (2015).

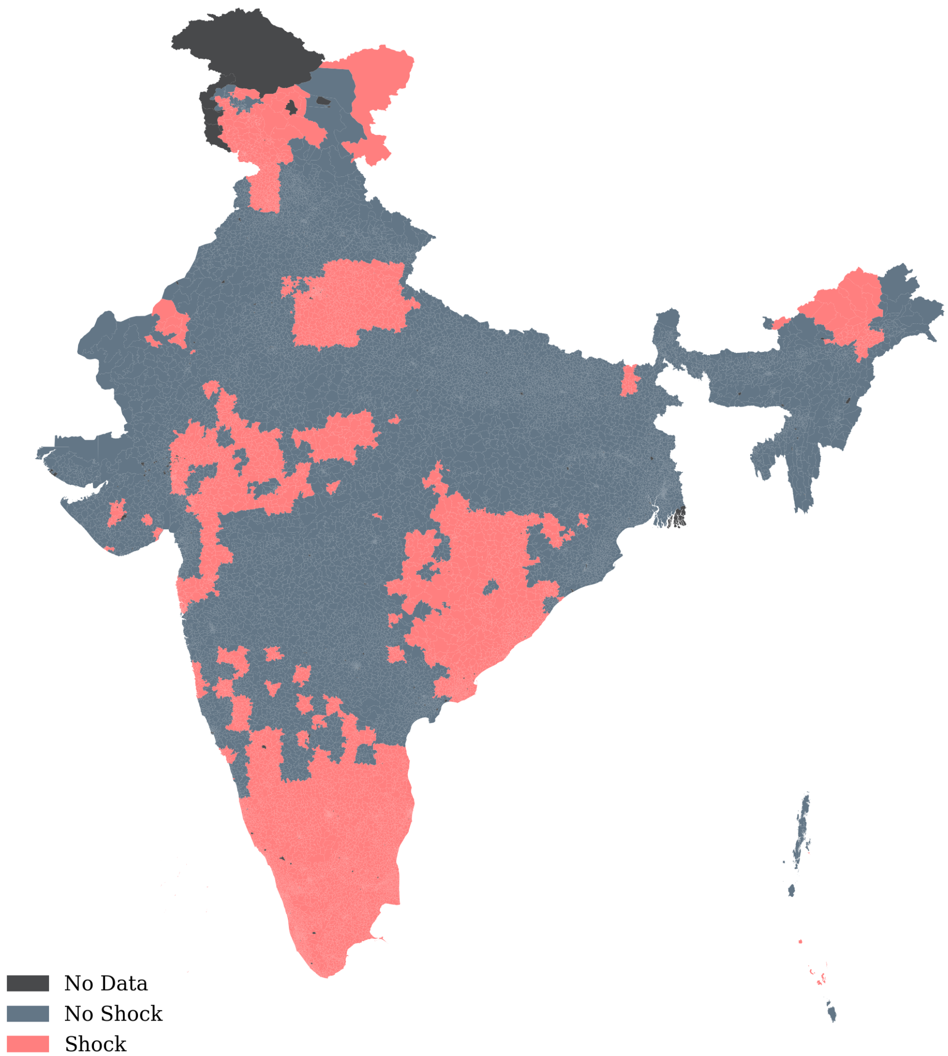
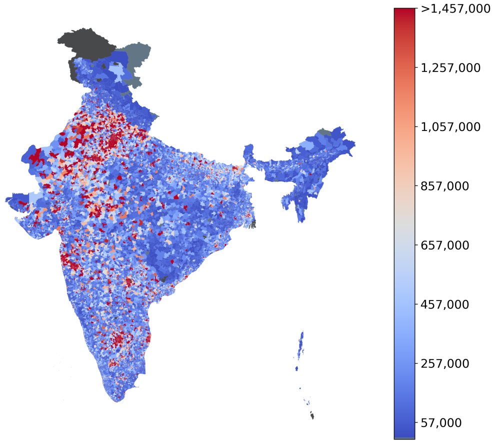
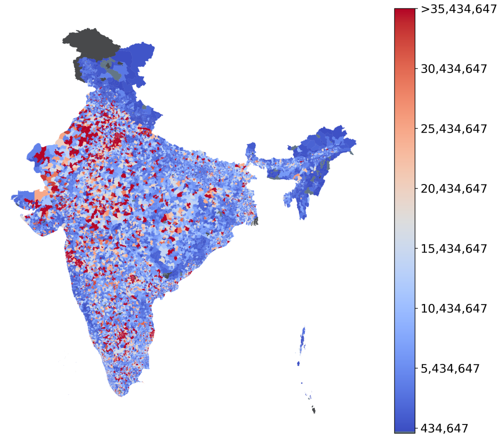


Figure A.2: Weather Shock

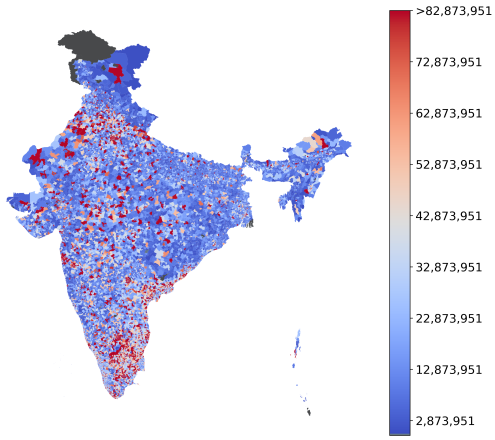
Figure A.3: **Weather Shock Dummies.** This figure refers to December 2020 as an example. The figure shows the ZIP codes in which the SPEI is lower and higher than the 20th percentile 80th percentile of the historical SPEI distribution in that ZIP code. Note that the weather shock dummies are geographically clustered. This geographic clustering can be explained by time-invariant geographic determinants such as elevation (see Appendix Figure A.1). The time-invariant determinants of this geographical clustering of shocks that might be correlated with our outcome, such as elevation, are absorbed with ZIP code fixed effects. Thus, this spatial correlation does not pose a threat to identification.



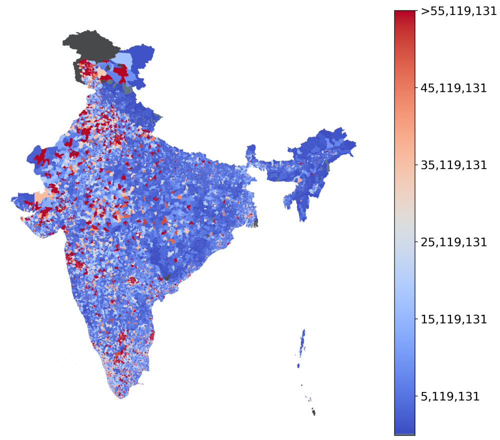
(a) Fintech



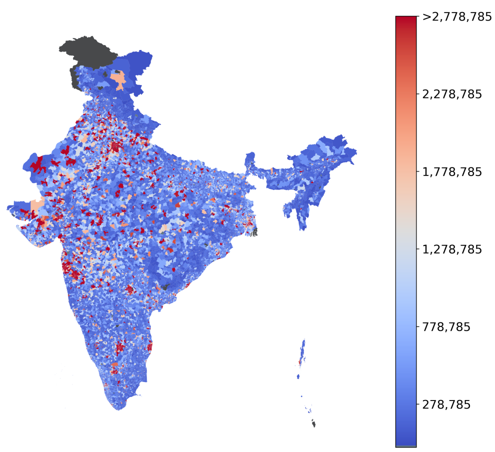
(b) Nontech



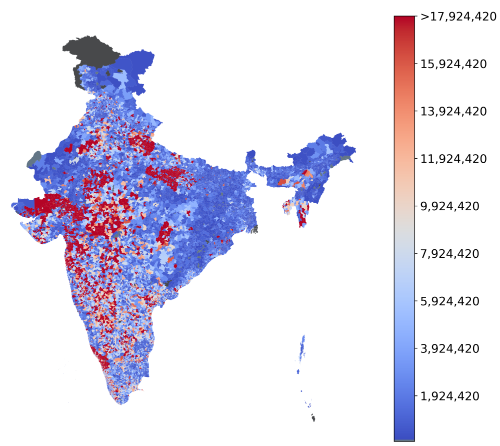
(c) Public



(d) Private



(e) Foreign



(f) Others

Figure A.4: **Credit Issuance.** This is the average year-monthly loan amount over our study period issued in a ZIP code by a lender across products. The data is in rupees. The maximum number presented indicates the 90th percentile of the ZIP-level distribution for a given lender. Light gray indicates zero loan issuance and dark gray indicates missing.

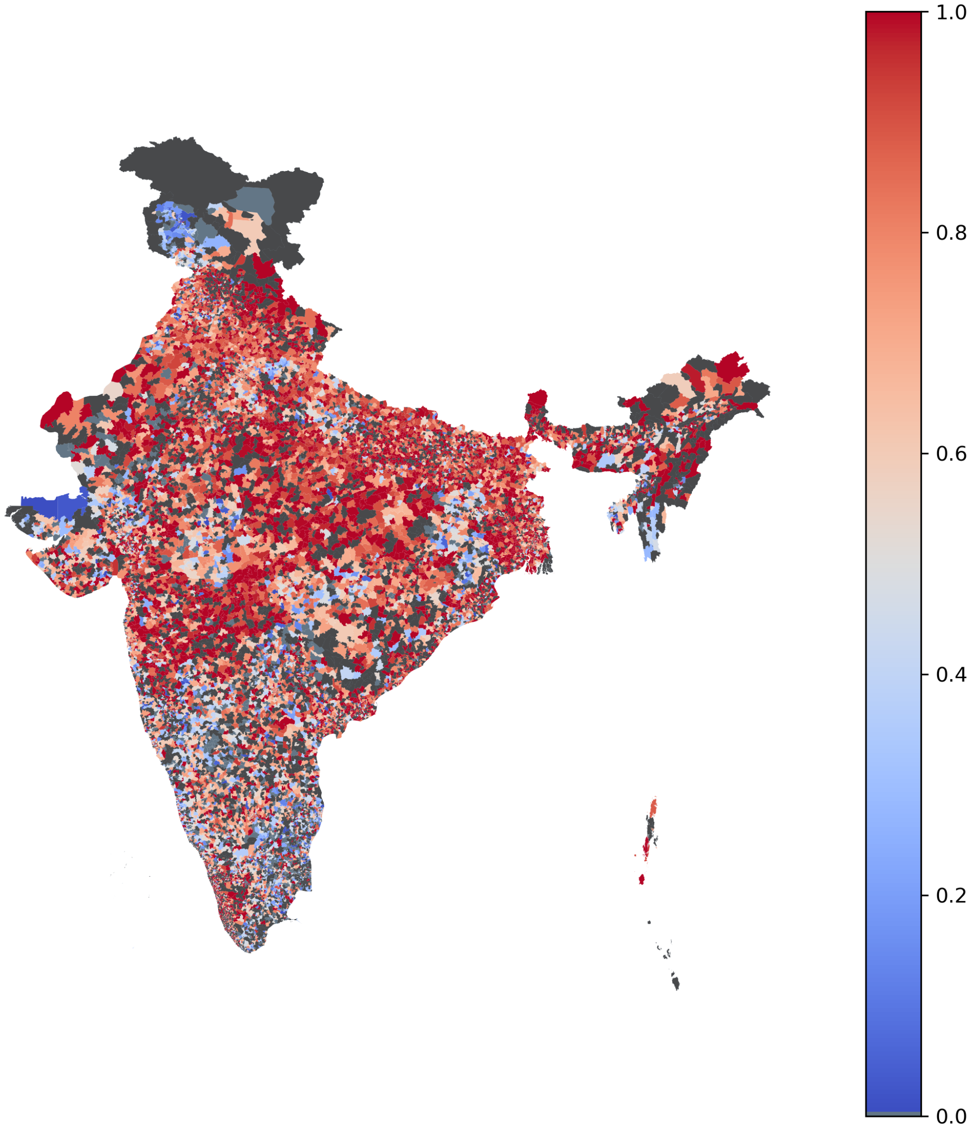


Figure A.5: **UPI Index.** This figure reports the cross-sectional UPI index on the ZIP-level, constructed as described in Section 2. Light gray indicates zero, dark gray indicates missing.

Table A.1: **Indian Lending Landscape**

	Public	Private	Foreign	Nontech	Fintech	Other	Total	% Fintech	% Nontech
Loan number (2021) - in thousands									
	Public	Private	Foreign	Nontech	Fintech	Other	Total	% Fintech	% Nontech
Total	22,956	22,489	2,586	44,048	8,856	7,427	108,362	8.17%	40.65%
Loan amount (2021) - in billion rupees									
	Public	Private	Foreign	Nontech	Fintech	Other	Total	% Fintech	% Nontech
Total	4,612	3,973	218	3,137	228	1,015	13,183	1.73%	23.79%
Loan number (2021) - in thousands									
	Public	Private	Foreign	Nontech	Fintech	Other	Total	% Fintech	% Nontech
Agriculture	14,350	608	0	375	2	1,305	16,640	0.01%	2.25%
Gold	0	5,443	0	13,557	5	3,855	22,860	0.02%	59.29%
Vehicle	579	2,304	0	4,647	13	86	7,629	0.17%	60.90%
Business	112	237	2	473	135	121	1,080	12.50%	43.80%
Consumption	3,572	12,826	2,579	23,176	8,338	319	50,810	16.41%	45.62%
Microfinance	73	425	0	96	0	45	639	0.00%	15.02%
Loan amount (2021) - in billion rupees									
	Public	Private	Foreign	Nontech	Fintech	Other	Total	% Fintech	% Nontech
Agriculture	1,964	269	0	145	1	243	2,622	0.04%	5.53%
Gold	0	699	0	673	1	321	1,694	0.06%	39.73%
Vehicle	389	961	0	1,017	4	38	2,409	0.17%	42.21%
Business	78	202	8	222	44	49	603	7.30%	36.82%
Consumption	1,161	1,361	200	794	152	90	3,758	4.04%	21.13%
Microfinance	8	36	0	3	0	9	56	0.00%	5.36%
Loan number (2021) - in thousands									
	Public	Private	Foreign	Nontech	Fintech	Other	Total	% Fintech	% Nontech
Super Prime	949	1,177	130	943	232	311	3,742	6.20%	25.20%
Prime-Plus	3,015	3,625	549	4,049	844	783	12,865	6.56%	31.46%
Prime	8,847	8,187	1,051	13,489	3,402	2,209	37,185	9.15%	36.27%
Near-Prime	4,459	3,932	239	10,229	2,279	1,552	22,690	10.04%	45.10%
Sub-Prime	2,214	1,624	44	5,175	764	938	10,759	7.10%	48.08%
New-To-Credit	2,357	3,254	526	8,105	1,206	1,404	16,852	7.16%	48.11%
Loan amount (2021) - in billion rupees									
	Public	Private	Foreign	Nontech	Fintech	Other	Total	% Fintech	% Nontech
Super Prime	248	286	20	107	10	42	712	1.37%	15.03%
Prime-Plus	674	693	56	347	32	107	1,908	1.70%	18.18%
Prime	1,874	1,462	86	1,023	99	293	4,836	2.04%	21.15%
Near-Prime	887	718	18	701	50	208	2,582	1.94%	27.14%
Sub-Prime	357	258	3	371	15	122	1,127	1.36%	32.92%
New-To-Credit	353	313	27	414	19	152	1,278	1.47%	32.40%

Notes: This table describes the Indian lending landscape. Loan number and loan amount are winsorized at the 1st and 99th percentile.

Table A.2: **Granular CIBIL Summary Statistics**

	# Obs	p25	p50	p75	Mean	SD
Loan Number	20,459,958	2.00	6.00	22.00	31.91	79.84
Loan Amount	20,459,958	250,000	938,310	3,250,000	4,283,915	10,528,424
12-month Default Rate	20,459,958	0.0000	0.0000	0.0175	0.0425	0.1282
# Inquiries	20,459,958	0.08	2.08	12.33	18.13	46.53

Notes: This table reports the key summary statistics of the credit bureau (TransUnion-CIBIL) data. The credit issuance dataset corresponds to a unique combination of year-month × ZIP × lender × product. The inquiry dataset corresponds to a unique combination of year × ZIP × lender × product. For comparability, we divide the number of inquires by twelve to indicate monthly inquiries.

Table A.3: **Granular CIBIL Summary Statistics by Lender**

	# Obs	p25	p50	p75	Mean	SD
Panel A: Public Sector Banks						
Loan number	4,612,254	3	8	28	38.43	88.4
Loan Amount	4,612,254	650,000	1,990,000	6,274,334	6,839,081.72	13,277,819.09
12-month Default Rate	4,612,254	0	0	0	0.0259	0.0922
# Inquiries	4,612,254	1.5	4.83	14.08	14.56	29.82
Panel B: Private Sector Banks						
	# Obs	p25	p50	p75	Mean	SD
Loan Number	5,293,364	2	6	17	26.1	69.66
Loan Amount	5,293,364	351,598	1,102,453.5	3,508,765	4,795,975.85	11,715,634.43
12-month Default Rate	5,293,364	0	0	0	0.0318	0.1055
# Inquiries	5,293,364	0.58	3.58	14	18.81	45.66
Panel C: Foreign Banks						
	# Obs	p25	p50	p75	Mean	SD
Loan Number	1,065,930	2	4	12	18.82	53.1
Loan Amount	1,065,930	119,000	348,000	1,128,200	2,137,123.93	7,123,484.05
12-month Default Rate	1,065,930	0	0	0	0.0357	0.1125
# Inquiries	1,065,930	0	0	0.17	1.05	7.35
Panel D: Nontech						
	# Obs	p25	p50	p75	Mean	SD
Loan Number	5,055,554	3	10	35	45.15	98.57
Loan Amount	5,055,554	300,150	1,061,582.5	3,447,068	4,135,903.4	9,693,066.12
12-month Default Rate	5,055,554	0	0	0.0541	0.0518	0.1239
# Inquiries	5,055,554	0.08	3.92	27.83	32.4	66.14
Panel E: Fintech						
	# Obs	p25	p50	p75	Mean	SD
Loan Number	1,307,221	2	5	19	28.76	79.03
Loan Amount	1,307,221	26,050	103,995	380,000	705,198.36	2,763,901.72
12-month Default Rate	1,307,221	0	0	0.087	0.0787	0.1692
# Inquiries	1,307,221	0.17	4.5	22.75	27.26	58.5
Panel F: Other Financial Institutions						
	# Obs	p25	p50	p75	Mean	SD
Loan Number	3,125,635	1	4	12	16.5	44.48
Loan Amount	3,125,635	144,900	500,000	1,590,000	2,114,495.08	6,227,082.97
12-month Default Rate	3,125,635	0	0	0	0.0573	0.1834
# Inquiries	3,125,635	0	0.08	0.5	1.15	5.36

Notes: This table reports the key summary statistics of the credit bureau (TransUnion-CIBIL) data, by lender. The credit issuance dataset corresponds to a unique combination of year-month × ZIP × lender × product. The inquiry dataset corresponds to a unique combination of year × ZIP × lender × product. For comparability, we divide the number of inquires by twelve to indicate monthly inquiries.

Table A.4: **Granular CIBIL Summary Statistics by Product**

	# Obs	p25	p50	p75	Mean	SD
Panel A: Agriculture Loans						
Loan Number	3,269,797	2	6	25	42.17	100.36
Loan Amount	3,269,797	468,000	1,350,000	4,620,000	5,993,857.02	13,091,405.32
12-month Default Rate	3,269,797	0	0	0.0033	0.0452	0.1392
# Inquiries	3,269,797	0	0.67	3.83	4.99	14.48
Panel B: Gold Loans						
Loan Number	2,488,014	4	13	49	50.27	92.83
Loan Amount	2,488,014	237,794	884,500	3,214,600	3,603,792.97	8,061,805.13
12-month Default Rate	2,488,014	0	0	0	0.0247	0.0901
# Inquiries	2,488,014	0	0	0.42	1.39	6.38
Panel C: Vehicle Loans						
Loan Number	3,505,068	2	6	19	19.36	41.79
Loan Amount	3,505,068	575,000	1,671,310	4,861,874	5,386,249.19	11,263,563.74
12-month Default Rate	3,505,068	0	0	0.0299	0.0345	0.0933
# Inquiries	3,505,068	2.08	9.75	29.67	28.57	50.99
Panel D: Business Loans						
Loan Number	1,590,155	1	2	5	5.59	15.83
Loan Amount	1,590,155	180,000	645,449	2,260,000	3,164,580.21	8,872,734.77
12-month Default Rate	1,590,155	0	0	0	0.0546	0.1751
# Inquiries	1,590,155	0.33	1.58	5.5	6.94	19.03
Panel E: Consumption Loans						
Loan Number	6,069,098	3	9	29	42.31	99.41
Loan Amount	6,069,098	160,288	660,000	2,403,431	3,577,856.09	9,865,923.66
12-month Default Rate	6,069,098	0	0	0.0448	0.047	0.1237
# Inquiries	6,069,098	0.42	6.5	27.75	34.06	67.75
Panel F: Microfinance Loans						
Loan Number	385,748	1	3	8	8.38	19.44
Loan Amount	385,748	40,000	169,000	593,000	708,686.67	2,958,832.10
12-month Default Rate	385,748	0	0	0	0.0558	0.1759
# Inquiries	385,748	0	0.08	0.75	2.44	12.71
Panel G: Other						
Loan Number	3,152,078	2	5	14	16.87	39.73
Loan Amount	3,152,078	185,000	825,000	3,040,891	4,182,848.87	10,640,875.77
12-month Default Rate	3,152,078	0	0	0	0.0464	0.1461
# Inquiries	3,152,078	0.25	1.92	7.92	10.23	26.54

Notes: This table reports the key summary statistics of the credit bureau (TransUnion-CIBIL) data, by product. The credit issuance dataset corresponds to a unique combination of year-month × ZIP × lender × product. The inquiry dataset corresponds to a unique combination of year × ZIP × lender × product. For comparability, we divide the number of inquires by twelve to indicate monthly inquiries.

Table A.5: **Granular CIBIL Summary Statistics by Lender and Credit Score**

Panel A: Public Sector Banks

	Loan Number				Loan Amount				Default Rate 1 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Super Prime	4,612,254	0.00	1.48	4.51	4,612,254	-	323,230	1,030,994	4,612,254	0.00	0.00	0.00	4,612,254	0.08	0.42	1.12
Prime-Plus	4,612,254	1.00	4.29	11.84	4,612,254	50,000	843,275	2,094,086	4,612,254	0.00	0.00	0.03	4,612,254	0.33	1.48	3.45
Prime	4,612,254	2.00	13.78	34.45	4,612,254	600,000	2,467,786	5,198,599	4,612,254	0.00	0.01	0.07	4,612,254	1.17	4.19	9.18
Near-Prime	4,612,254	1.00	7.64	18.53	4,612,254	280,000	1,304,912	2,712,170	4,612,254	0.00	0.02	0.09	4,612,254	0.83	2.65	5.71
Sub-Prime	4,612,254	1.00	3.56	8.46	4,612,254	23,022	562,708	1,252,835	4,612,254	0.00	0.03	0.13	4,612,254	0.50	1.64	3.65
New-To-Credit	4,612,254	1.00	6.59	14.37	4,612,254	256,800	1,028,841	2,018,218	4,612,254	0.00	0.02	0.09	4,612,254	1.42	4.05	8.01

Panel B: Private Sector Banks

	Loan Number				Loan Amount				Default Rate 1 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Super Prime	5,293,364	0.00	1.21	3.93	5,293,364	-	293,760	1,040,295	5,293,364	0.00	0.00	0.00	5,293,364	0.00	0.51	1.41
Prime-Plus	5,293,364	1.00	3.93	11.42	5,293,364	15,500	751,615	2,145,385	5,293,364	0.00	0.00	0.03	5,293,364	0.25	1.83	4.63
Prime	5,293,364	2.00	9.22	27.02	5,293,364	250,000	1,699,735	4,540,603	5,293,364	0.00	0.02	0.07	5,293,364	0.83	5.20	13.36
Near-Prime	5,293,364	1.00	4.44	13.11	5,293,364	70,000	870,697	2,339,577	5,293,364	0.00	0.02	0.10	5,293,364	0.67	3.57	8.95
Sub-Prime	5,293,364	0.00	1.73	5.19	5,293,364	-	317,316	968,813	5,293,364	0.00	0.03	0.13	5,293,364	0.33	2.23	5.75
New-To-Credit	5,293,364	1.00	5.10	12.20	5,293,364	111,600	602,608	1,441,138	5,293,364	0.00	0.02	0.10	5,293,364	0.92	5.27	12.21

Panel C: Foreign Banks

	Loan Number				Loan Amount				Default Rate 1 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Super Prime	1,065,930	0.00	1.10	3.54	1,065,930	-	214,050	850,520	1,065,930	0.00	0.00	0.00	1,065,930	0.00	0.06	0.43
Prime-Plus	1,065,930	1.00	4.04	10.94	1,065,930	32,000	516,342	1,694,734	1,065,930	0.00	0.01	0.05	1,065,930	0.00	0.19	1.21
Prime	1,065,930	2.00	7.52	21.98	1,065,930	100,000	803,966	2,769,893	1,065,930	0.00	0.03	0.09	1,065,930	0.00	0.41	2.75
Near-Prime	1,065,930	0.00	2.00	6.71	1,065,930	-	208,384	893,281	1,065,930	0.00	0.02	0.11	1,065,930	0.00	0.22	1.51
Sub-Prime	1,065,930	0.00	0.35	1.48	1,065,930	-	38,446	275,084	1,065,930	0.00	0.01	0.10	1,065,930	0.00	0.10	0.68
New-To-Credit	1,065,930	1.00	3.27	7.85	1,065,930	25,000	244,375	703,148	1,065,930	0.00	0.02	0.09	1,065,930	0.00	0.05	0.49

Panel D: Nontech

	Loan Number				Loan Amount				Default Rate 1 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Super Prime	5,055,554	0.00	0.93	3.20	5,055,554	-	129,302	614,513	5,055,554	0.00	0.00	0.00	5,055,554	0.00	0.52	1.49
Prime-Plus	5,055,554	0.00	4.28	12.54	5,055,554	-	424,222	1,420,795	5,055,554	0.00	0.01	0.04	5,055,554	0.17	2.20	5.52
Prime	5,055,554	2.00	13.49	35.12	5,055,554	196,000	1,278,733	3,528,824	5,055,554	0.00	0.02	0.09	5,055,554	0.67	7.97	18.21
Near-Prime	5,055,554	2.00	10.26	23.27	5,055,554	150,000	940,646	2,236,570	5,055,554	0.00	0.04	0.12	5,055,554	0.75	6.39	13.21
Sub-Prime	5,055,554	1.00	4.72	10.26	5,055,554	37,537	473,903	1,148,843	5,055,554	0.00	0.06	0.17	5,055,554	0.50	4.38	8.93
New-To-Credit	5,055,554	2.00	10.03	18.92	5,055,554	124,998	655,454	1,412,827	5,055,554	0.00	0.04	0.13	5,055,554	1.42	10.61	19.71

Panel E: Fintech

	Loan Number				Loan Amount				Default Rate 1 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Super Prime	1,307,221	0.00	0.49	2.19	1,307,221	-	21,184	206,324	1,307,221	0.00	0.00	0.01	1,307,221	0.00	0.29	0.98
Prime-Plus	1,307,221	0.00	1.86	6.92	1,307,221	-	74,978	460,344	1,307,221	0.00	0.01	0.05	1,307,221	0.17	1.34	3.88
Prime	1,307,221	1.00	9.78	29.35	1,307,221	21,433	291,682	1,268,498	1,307,221	0.00	0.04	0.12	1,307,221	0.92	6.65	15.78
Near-Prime	1,307,221	1.00	8.43	21.55	1,307,221	12,000	176,673	759,758	1,307,221	0.00	0.06	0.16	1,307,221	1.00	6.01	12.43
Sub-Prime	1,307,221	0.00	2.72	7.91	1,307,221	-	54,703	290,457	1,307,221	0.00	0.06	0.19	1,307,221	0.75	4.43	8.82
New-To-Credit	1,307,221	1.00	4.80	12.30	1,307,221	3,748	70,622	298,481	1,307,221	0.00	0.05	0.16	1,307,221	1.33	7.91	16.29

Panel F: Other Financial Institutions

	Loan Number				Loan Amount				Default Rate 1 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Super Prime	3,125,635	0.00	0.56	2.55	3,125,635	-	76,450	416,021	3,125,635	0.00	0.00	0.00	3,125,635	0.00	0.02	0.17
Prime-Plus	3,125,635	0.00	1.39	5.47	3,125,635	-	186,149	794,908	3,125,635	0.00	0.00	0.04	3,125,635	0.00	0.08	0.48
Prime	3,125,635	1.00	4.35	14.51	3,125,635	43,000	536,757	1,852,461	3,125,635	0.00	0.02	0.11	3,125,635	0.00	0.22	1.18
Near-Prime	3,125,635	1.00	2.98	8.88	3,125,635	6,000	370,487	1,171,400	3,125,635	0.00	0.03	0.15	3,125,635	0.00	0.18	0.90
Sub-Prime	3,125,635	0.00	1.59	4.47	3,125,635	-	209,489	670,767	3,125,635	0.00	0.04	0.17	3,125,635	0.00	0.14	0.74
New-To-Credit	3,125,635	1.00	4.77	11.77	3,125,635	80,500	511,360	1,302,033	3,125,635	0.00	0.03	0.14	3,125,635	0.00	0.49	2.61

Notes: This table reports the key summary statistics of the credit bureau (TransUnion-CIBIL) data, by lender and credit score. The credit issuance dataset corresponds to a unique combination of year-month × ZIP × lender × product. The inquiry dataset corresponds to a unique combination of year × ZIP × lender × product. For comparability, we divide the number of inquires by twelve to indicate monthly inquiries.

Table A.6: **Granular CIBIL Summary Statistics by Lender and Product**

Panel A: Public Sector Banks

	Loan Number				Loan Amount				Default Rate 1 yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Agriculture	1,079,217	37.00	106.62	149.64	1,079,217	5,623,150	13,513,274	19,001,482	1,079,217	0.00	0.03	0.08	1,079,217	3.58	9.55	18.61
Gold	-				-				-				-			
Vehicle	837,653	2.00	6.46	14.83	837,653	1,200,000	3,458,578	7,415,434	837,653	0.00	0.01	0.06	837,653	2.83	10.77	27.02
Business	362,406	2.00	5.71	24.17	362,406	418,000	2,652,363	9,197,013	362,406	0.00	0.05	0.17	362,406	1.83	6.63	17.31
Consumption	1,221,811	7.00	17.11	33.79	1,221,811	2,000,000	4,931,249	9,126,944	1,221,811	0.00	0.01	0.06	1,221,811	9.58	22.77	39.03
Microfinance	82,437	1.00	4.59	17.12	82,437	250,000	668,521	1,921,983	82,437	0.00	0.07	0.20	82,437	0.67	2.25	5.00
Other	1,028,730	13.00	32.47	55.04	1,028,730	2,182,000	6,825,251	12,971,803	1,028,730	0.00	0.04	0.10	1,028,730	6.25	16.90	30.90

Panel B: Private Sector Banks

	Loan Number				Loan Amount				Default Rate 1 yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Agriculture	772,447	3.00	9.69	25.64	772,447	1,000,000	2,750,187	6,085,020	772,447	0.00	0.04	0.14	772,447	1.25	6.10	17.33
Gold	948,659	10.00	40.00	78.82	948,659	1,043,000	4,343,199	9,463,885	948,659	0.00	0.01	0.06	948,659	0.42	3.25	9.78
Vehicle	1,160,737	6.00	18.30	41.08	1,160,737	1,502,652	6,017,819	13,241,212	1,160,737	0.00	0.03	0.09	1,160,737	13.08	32.08	52.90
Business	328,882	2.00	4.23	7.33	328,882	1,102,931	4,599,839	10,923,242	328,882	0.00	0.02	0.10	328,882	3.00	9.25	20.90
Consumption	1,262,296	11.00	50.13	110.50	1,262,296	1,302,766	6,234,298	14,926,099	1,262,296	0.00	0.04	0.08	1,262,296	8.00	33.85	66.32
Microfinance	138,127	5.00	12.35	23.04	138,127	376,000	1,013,258	2,181,601	138,127	0.00	0.02	0.09	138,127	0.08	4.73	20.12
Other	682,216	3.00	7.50	17.56	682,216	702,414	3,862,208	10,691,829	682,216	0.00	0.05	0.16	682,216	2.25	11.91	33.80

Panel C: Foreign Banks

	Loan Number				Loan Amount				Default Rate 1 yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Agriculture	802	1.00	2.15	2.47	802	2,000,000	4,026,395	6,371,506	802	0.00	0.00	0.02	802	0.00	0.01	0.05
Gold	-				-				-				-			
Vehicle	-				-				-				-			
Business	33,169	1.00	1.85	2.14	33,169	3,100,000	5,860,115	9,505,956	33,169	0.00	0.01	0.08	33,169	0.00	0.13	0.96
Consumption	1,009,479	4.00	19.74	54.41	1,009,479	324,000	1,983,294	6,880,854	1,009,479	0.00	0.04	0.11	1,009,479	0.00	1.06	7.34
Microfinance	-				-				-				-			
Other	22,480	1.00	3.28	6.36	22,480	463,400	3,484,335	11,035,711	22,480	0.00	0.00	0.05	22,480	0.08	1.91	11.73

Panel D: Nontech

	Loan Number				Loan Amount				Default Rate 1 yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Agriculture	671,101	2.00	4.23	6.57	671,101	880,000	1,563,361	2,378,086	671,101	0.00	0.07	0.19	671,101	0.08	0.77	4.18
Gold	960,958	20.00	66.98	112.50	960,958	819,626	3,351,774	7,867,607	960,958	0.00	0.03	0.09	960,958	0.00	0.35	2.26
Vehicle	1,203,029	17.00	33.46	53.90	1,203,029	3,149,254	7,226,000	12,236,490	1,203,029	0.03	0.06	0.09	1,203,029	22.42	44.51	60.71
Business	439,955	3.00	7.21	12.89	439,955	1,000,000	3,700,271	8,944,553	439,955	0.00	0.05	0.16	439,955	2.50	9.20	22.98
Consumption	1,256,034	27.00	90.69	147.63	1,256,034	657,611	3,677,001	9,855,374	1,256,034	0.02	0.04	0.08	1,256,034	32.58	79.72	97.68
Microfinance	66,735	3.00	7.46	15.69	66,735	44,000	205,987	1,539,283	66,735	0.00	0.11	0.23	66,735	0.00	0.52	3.73
Other	457,742	2.00	7.09	22.45	457,742	423,900	3,683,234	11,084,695	457,742	0.00	0.06	0.17	457,742	3.42	11.32	25.42

Panel E: Fintech

	Loan Number				Loan Amount				Default Rate 1 yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
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	0.00	0.31	2.20
Gold	7,417	1.00	2.04	2.91	7,417	75,655	238,411	1,291,139	7,417	0.00	0.12	0.30	7,417	0.00	0.00	0.01
Vehicle	44,640	2.00	3.25	5.65	44,640	115,000	320,767	809,646	44,640	0.00	0.05	0.16	44,640	0.00	0.17	1.38
Business	242,551	2.00	5.28	14.56	242,551	300,000	1,402,465	3,850,383	242,551	0.00	0.09	0.23	242,551	0.92	5.18	17.52
Consumption	818,990	11.00	43.10	96.55	818,990	105,439	621,704	2,598,574	818,990	0.04	0.08	0.13	818,990	14.33	41.85	69.25
Microfinance	39,960	2.00	5.53	13.29	39,960	10,000	23,981	98,628	39,960	0.00	0.00	0.01	39,960	0.00	0.30	2.06
Other	150,959	1.00	4.23	11.60	150,959	28,470	355,702	2,070,807	150,959	0.00	0.08	0.23	150,959	0.00	0.58	3.53

Panel F: Other Financial Institutions

	Loan Number				Loan Amount				Default Rate 1 yr				# Inquiries			
	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD	# Obs	Median	Mean	SD
Agriculture	743,526	5.00	16.78	44.62	743,526	575,500	2,469,847	7,922,645	743,526	0.00	0.04	0.15	743,526	0.08	1.06	5.33
Gold	570,980	12.00	39.82	71.67	570,980	792,000	2,843,166	5,334,309	570,980	0.00	0.03	0.12	570,980	0.00	0.05	0.40
Vehicle	259,009	1.00	3.19	9.18	259,009	500,000	1,117,990	2,354,033	259,009	0.00	0.04	0.16	259,009	0.17	1.21	4.85
Business	183,192	2.00	4.96	15.16	183,192	300,000	2,159,703	7,895,796	183,192	0.00	0.09	0.23	183,192	0.17	1.52	5.24
Consumption	500,488	2.00	6.97	22.04	500,488	350,000	1,378,802	4,268,254	500,488	0.00	0.13	0.28	500,488	0.17	1.44	6.25
Microfinance	58,489	2.00	7.36	18.92	58,489	200,000	1,087,392	6,132,706	58,489	0.00	0.09	0.24	58,489	0.00	0.95	5.72
Other	809,951	4.00	13.22	35.20	809,951	490,000	2,111,819	6,394,978	809,951	0.00	0.04	0.15	809,951	0.17	1.74	6.57

Notes: This table reports the key summary statistics of the credit bureau (TransUnion-CIBIL) data, by lender and product. The credit issuance dataset corresponds to a unique combination of year-month × ZIP × lender × product. The inquiry dataset corresponds to a unique combination of year × ZIP × lender × product. For comparability, we divide the number of inquires by twelve to indicate monthly inquiries.

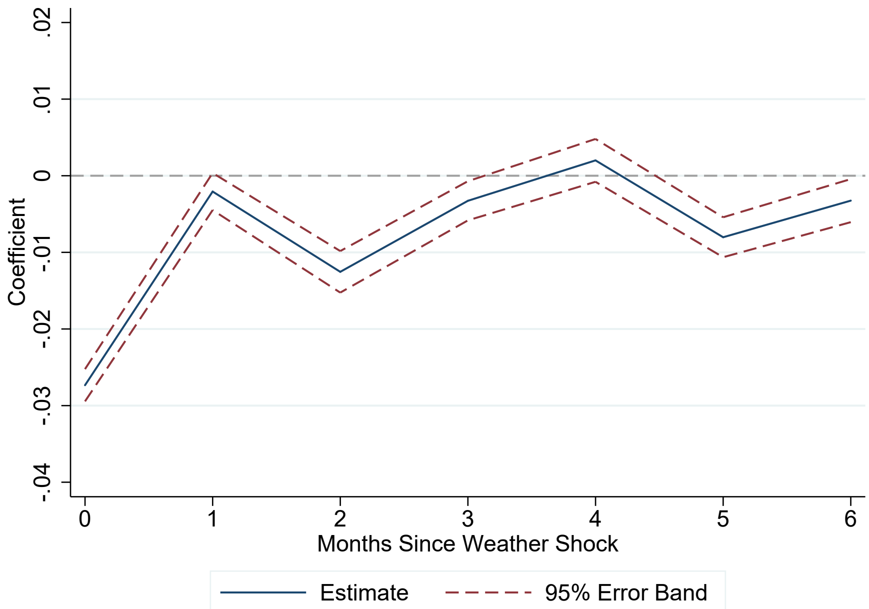
Table A.7: **Economic Magnitudes**

	Monthly expenditure (in INR)		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	22%	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 in Table 1 using the average monthly expenditure per capita data using the Household Consumption Expenditure Survey Data available from the Ministry of Statistics and Program Implementation (MoSPI), Government of India website https://www.mospi.gov.in/.

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 Jordà (2005) style projection regression until 6 steps. The specification is as follows and h takes an integer value between 0 and 6.

$$log(NL_{i,t+h}) - log(NL_{i,t-1}) = \beta_h^0 \cdot Shock_{i,t} + \alpha_i + \theta_t + \nu_{it}$$

where i denotes ZIP code and t is the year-month. α_i denotes ZIP code fixed effects, and θ_t denotes year-month fixed effects. $log(NL_{i,t})$ denotes the natural logarithm of average nighlight luminosity across all pixels within the ZIP i during the month t. 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	0.0157***	-0.0392	-0.0289	-0.0251**	0.0449***	0.0108***	0.0837***
	(0.0023)	(0.0557)	(0.0278)	(0.0108)	(0.0080)	(0.0022)	(0.0132)
Nontech × Shock	0.0031***	0.0142***	0.0325***	0.0033*	-0.0166***	0.0003	0.0183
	(0.0011)	(0.0027)	(0.0024)	(0.0019)	(0.0053)	(0.0018)	(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
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Year-month × 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 Fintech and Nontech credit issuance after the shock, compared to traditional lenders, for collateralized loans (agricultural, gold, vehicle) and uncollateralized loans (business, consumption, MFI). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table B.2: **Effect on Credit Inquiries**

	# Applications		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	8.5038***	-1.5626	9.3533***
	(1.3125)	(1.3215)	(1.6875)
Nontech × Shock	0.6529	8.8431***	-9.8261***
	(0.7330)	(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	3,002,434	851,198	1,279,083

Notes: This table presents Fintech and Nontech inquiries after the shock, compared to traditional lenders, for collateralized loans (agriculture, gold, vehicle) and uncollateralized loans (business, consumption, MFI). Equation 3 describes the regression, except that the data is at Year as opposed to Year-month level. The data is on the year-ZIP-lender-product level. $\text{Inquiries}_{y,z,l,p}$ describes the number of loan applications. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{y,z}$ is a dummy equal to one if the average monthly SPEI in a given year is below the 20th or above the 80th percentile of its historical distribution in that ZIP code. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table B.3: **Effect on Credit Issuance for Collateralized Loans: Heterogeneity by Credit Score Type**

	ln(Amount)						
	Total	Super-Prime	Prime-Plus	Prime	Near-Prime	Sub-Prime	New-to-Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fintech × Shock	-0.0235**	0.1532*	-0.0179	-0.0113	-0.0120	-0.0001	-0.0232
	(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**	0.0162***
	(0.0013)	(0.0054)	(0.0031)	(0.0021)	(0.0022)	(0.0026)	(0.0018)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.09	0.54	0.22	0.26	0.82	0.01
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,006	11,949	17,436	18,716	18,580	18,120	18,773
Year-Months	6	6	6	6	6	6	6
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

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, by credit score type for collateralized product types (agriculture, gold, vehicle). New-to-credit are borrowers who do not yet have a credit score. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

Table B.4: **Effect on Credit Issuance for Uncollateralized Loans: Heterogeneity by Credit Score Type**

	ln(Amount)						
	Total	Super-Prime	Prime-Plus	Prime	Near-Prime	Sub-Prime	New-to-Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fintech × Shock	0.0192***	-0.0049	0.0012	0.0062**	0.0103***	0.0104**	0.0250***
	(0.0023)	(0.0075)	(0.0044)	(0.0029)	(0.0031)	(0.0045)	(0.0036)
Nontech × Shock	-0.0031*	0.0070	-0.0029	-0.0085***	-0.0018	-0.0046	0.0049*
	(0.0018)	(0.0046)	(0.0027)	(0.0022)	(0.0027)	(0.0038)	(0.0026)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.13	0.38	0.00	0.00	0.00	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,052	14,899	18,802	18,999	18,895	18,339	18,915
Year-Months	6	6	6	6	6	6	6
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 Fintech and Nontech credit issuance after the shock, compared to traditional lenders, by credit score type for uncollateralized product types (business, consumption, MFI). New-to-credit are borrowers who do not yet have a credit score. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. ln(Amount)$_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech$_l$ is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech$_l$ is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. 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. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table B.5: **Effect on Credit Inquiries: Heterogeneity by Credit Score Type**

	# Applications						
	Total	Super-Prime	Prime-Plus	Prime	Near-Prime	Sub-Prime	New-to-Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fintech × Shock	8.5038***	0.2530***	0.7317***	1.8824***	1.0610***	0.4200**	3.7156***
	(1.3125)	(0.0251)	(0.0936)	(0.3698)	(0.2746)	(0.1898)	(0.3876)
Nontech × Shock	0.6529	0.0095	-0.0806	-0.7252***	-0.3292**	-0.0451	1.7156***
	(0.7330)	(0.0177)	(0.0565)	(0.2023)	(0.1552)	(0.1039)	(0.2466)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
FinTech × Shock = Nontech × Shock	0.00	0.00	0.00	0.00	0.00	0.03	0.00
Year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,080	19,080	19,080	19,080	19,080	19,080	19,080
Years	6	6	6	6	6	6	6
R-squared	0.94	0.94	0.95	0.94	0.93	0.93	0.91
Observations	3,002,434	3,002,434	3,002,434	3,002,434	3,002,434	3,002,434	3,002,434

Notes: This table presents Fintech and Nontech inquiries after the shock, compared to traditional lenders, by credit score types. Equation 3 describes the regression, except that the data is at Year as opposed to Year-month level. The data is on the year-ZIP-lender-product level. Inquiries$_{y,z,l,p}$ describes the number of loan applications. The outcome is winsorized at the 1st and 99th percentile. Fintech$_l$ is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech$_l$ is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. Shock$_{y,z}$ is a dummy equal to one if the average monthly SPEI in a given year is below the 20th or above the 80th percentile of its historical distribution in that ZIP code. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

Table B.6: **Effect on Credit Inquiries for Collateralized Loans: Heterogeneity by Credit Score Type**

	# Applications						
	Total	Super-Prime	Prime-Plus	Prime	Near-Prime	Sub-Prime	New-to-Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.06	0.00	0.00	0.00
Year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,064	19,064	19,064	19,064	19,064	19,064	19,064
Years	6	6	6	6	6	6	6
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

Notes: This table presents Fintech and Nontech inquiries after the shock, compared to traditional lenders, by credit score types for collateralized loans (agriculture, gold, vehicle). Equation 3 describes the regression, except that the data is at Year as opposed to Year-month level. The data is on the year-ZIP-lender-product level. $\text{Inquiries}_{y,z,l,p}$ describes the number of loan applications. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{y,z}$ is a dummy equal to one if the average monthly SPEI in a given year is below the 20th or above the 80th percentile of its historical distribution in that ZIP code. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table B.7: **Effect on Credit Inquiries for Un collateralized Loans: Heterogeneity by Credit Score Type**

	# Applications						
	Total (1)	Super-Prime (2)	Prime-Plus (3)	Prime (4)	Near-Prime (5)	Sub-Prime (6)	New-to-Credit (7)
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)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,077	19,077	19,077	19,077	19,077	19,077	19,077
Years	6	6	6	6	6	6	6
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 Fintech and Nontech inquiries after the shock, compared to traditional lenders, by credit score types for uncollateralized loans (business, consumption, MFI). Equation 3 describes the regression, except that the data is at Year as opposed to Year-month level. The data is on the year-ZIP-lender-product level. $\text{Inquiries}_{y,z,l,p}$ describes the number of loan applications. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{y,z}$ is a dummy equal to one if the average monthly SPEI in a given year is below the 20th or above the 80th percentile of its historical distribution in that ZIP code. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table B.8: **Effect on Credit Issuance: Heterogeneity by Region Type**

	ln(Amount)			
	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)
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.49	0.06	0.01	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓
ZIPs	1,020	1,822	6,718	9,176
Years	6	6	6	6
R-squared	0.86	0.86	0.83	0.80
Wald p-val Fintech (Q1=Q4)	.	.	.	0.01
Wald p-val Nontech (Q1=Q4)	.	.	.	0.11
Observations	1,672,004	2,362,551	7,324,494	9,006,083

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, separated by metro, urban, semi-urban, and rural. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Appendix C Robustness and Placebo

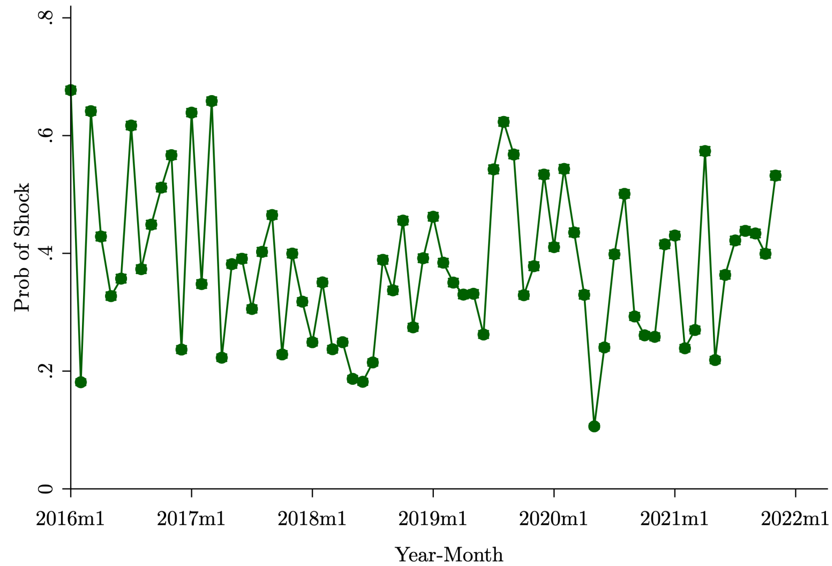
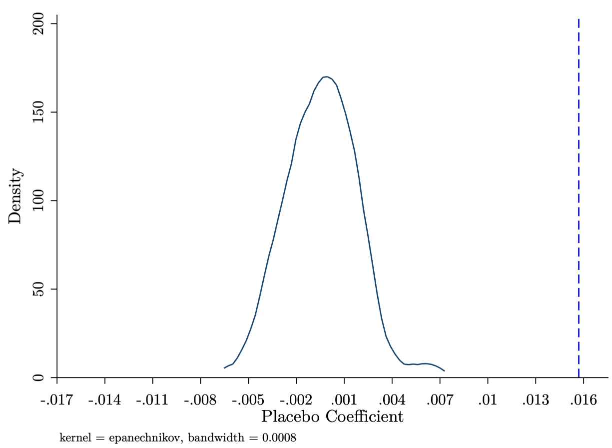
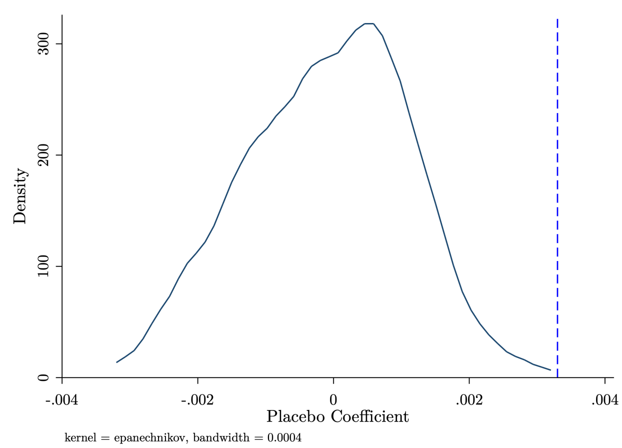


Figure C.1: **Probability of Weather Shocks Over Time.** This figure plots the coefficients of regressing the weather shock on year-month dummies, including ZIP code fixed effects and clustering standard errors at the ZIP code.



(a) Fintech



(b) Nontech

Figure C.2: **Placebo Test.** This figure presents the results of a placebo test. We run our regression Equation 3, corresponding to Table 2, but replace our weather shock dummy with a dummy variable that is randomly set to one for 40% of the year-month-ZIPs. We choose the 40% in alignment with the definition of the weather shock variable, which is based on the 20th and 80th percentile. We run the regression 50 times and plot a kernel density of the resulting coefficients. The blue line indicates our baseline coefficient from Column 4 in Table 1.

Table C.1: **Robustness: Effect for each Lender**

	ln(Amount)					
	Fintech	Nontech	Public	Private	Foreign	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.0127***	0.0044***	0.0025***	-0.0010	-0.0011	-0.0035**
	(0.0022)	(0.0009)	(0.0009)	(0.0009)	(0.0020)	(0.0014)
Year-month × Product FE	✓	✓	✓	✓	✓	✓
ZIP × Product FE	✓	✓	✓	✓	✓	✓
ZIPs	19,037	19,080	19,075	19,077	19,040	18,966
Years	6	6	6	6	6	6
R-squared	0.69	0.76	0.74	0.71	0.71	0.58
Observations	1,353,361	5,452,802	5,221,176	5,694,793	1,069,670	3,281,583

Notes: This table presents the absolute effect on credit issuance by lender. Equation C.1 describes the regression. The data is on the ZIP-year-month-product level, conditional on the specific lender. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

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

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

	# Loans		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.1953**	-0.7917***	0.1786*
	(0.0837)	(0.2020)	(0.0987)
Nontech × Shock	-0.0307	0.3917***	-0.2916***
	(0.0412)	(0.0522)	(0.0795)
Omitted Category	Traditional	Traditional	Traditional
FinTech × Shock = Nontech × Shock	0.01	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	0.91	0.92	0.91
Observations	20,459,958	9,262,879	8,045,001

Notes: This table presents Fintech and Nontech loan number issued after the shock, compared to traditional lenders, for collateralized loans (agricultural, gold, vehicle) and uncollateralized loans (business, consumption, MFI). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. Loan number$_{ym,z,l,p}$ describes the number of loans issued. The outcome is winsorized at the 1st and 99th percentile. Fintech$_l$ is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech$_l$ is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. 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. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table C.3: **Robustness: Using Poisson Regression**

	# Loans		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0400***	0.0332	0.0411***
	(0.0039)	(0.0229)	(0.0039)
Nontech × Shock	0.0059***	0.0126***	0.0005
	(0.0013)	(0.0014)	(0.0019)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.37	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 robustness for our results in Table 2, using Poisson regression. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\text{Amount}_{ym,z,l,p}$ is the loan amount. The outcome is winsorized at the 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors 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	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0288***	-0.0016	0.0340***
	(0.0033)	(0.0117)	(0.0034)
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
Year-month × ZIP × Product FE	✓	✓	✓
Year-month × 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 Fintech and Nontech credit issuance after the shock, compared to traditional lenders, excluding the Covid period (2020 and 2021). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table C.5: **Robustness: Using Continuous Water Balance Measure**

	ln(Amount)		
	All	Collateralized	Uncollateralized
	(1)	(2)	(3)
Fintech × Shock	0.0097***	-0.0061	0.0104***
	(0.0020)	(0.0083)	(0.0020)
Nontech × Shock	-0.0001	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
Lender FE	✓	✓	✓
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 robustness for our results in Table 2 based on the continuous SPEI water balance measure instead of weather shock dummies. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{SPEI}_{ym,z}$ is the standardized continuous water balance measure described in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table C.6: **Robustness: Using Different Shock Severity**

	ln(Amount)					
	>80th or <20th Pct			>90th or <10th Pct		
	All	Collateralized	Uncollateralized	All	Collateralized	Uncollateralized
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech × Shock	0.0157***	-0.0235**	0.0192***	0.0161***	-0.0364***	0.0166***
	(0.0023)	(0.0099)	(0.0023)	(0.0028)	(0.0122)	(0.0029)
Nontech × Shock	0.0031***	0.0153***	-0.0031*	0.0013	0.0226***	-0.0151***
	(0.0011)	(0.0013)	(0.0018)	(0.0014)	(0.0017)	(0.0022)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	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	19,060	19,006	19,052
Years	6.00	6.00	6.00	6.00	6.00	6.00
R-squared	0.84	0.85	0.84	0.84	0.85	0.84
Observations	20,459,958	9,262,879	8,045,001	20,459,958	9,262,879	8,045,001

Notes: This table presents robustness for our results in Table 2 by different severity of the shock as defined by percentiles (see Section 2). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors 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 for Drought by Product Type**

	ln(Amount)					
	Collateralized			Uncollateralized		
	Agri	Gold	Vehicle	Business	Consumer	MFI
	(1)	(2)	(3)	(4)	(5)	(6)
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)
Nontech × 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)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.72	0.01	0.00	0.11	0.00	0.00
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIPs	18,711	18,078	18,962	16,549	19,052	11,716
Years	6.00	6.00	6.00	6.00	6.00	6.00
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

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table C.8: **Robustness: Effect on Credit Issuance for Flood by Product Type**

	ln(Amount)					
	Collateralized			Uncollateralized		
	Agri (1)	Gold (2)	Vehicle (3)	Business (4)	Consumer (5)	MFI (6)
Fintech × Shock	-0.0577	-0.0115	0.0434***	0.0793***	-0.0209***	0.0675***
	(0.0702)	(0.0350)	(0.0150)	(0.0096)	(0.0026)	(0.0146)
Nontech × Shock	-0.0056*	0.0060**	0.0011	-0.0179***	-0.0281***	0.0309**
	(0.0034)	(0.0029)	(0.0024)	(0.0066)	(0.0022)	(0.0151)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.46	0.62	0.00	0.00	0.01	0.04
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIPs	18,711	18,078	18,962	16,549	19,052	11,716
Years	6.00	6.00	6.00	6.00	6.00	6.00
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

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Appendix D Supplementary Results: Mechanism

Table D.1: **Role of Technology: Exploiting Heterogeneity by UPI Exposure in Uncollateralized Markets**

	ln(Amount)			
	UPI Exposure in ZIP Code Quartile 1	UPI Exposure in ZIP Code Quartile 2	UPI Exposure in ZIP Code Quartile 3	UPI Exposure in ZIP Code Quartile 4
	(1)	(2)	(3)	(4)
FinTech × Shock	0.0097*	0.0134**	0.0263***	0.0243***
	(0.0053)	(0.0052)	(0.0052)	(0.0051)
Nontech × Shock	-0.0079**	-0.0049	-0.0034	0.0009
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Omitted Category	Traditional	Traidiitional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓
ZIPs	3,546	2,893	2,931	3,819
Years	6	6	6	6
R-squared	0.83	0.85	0.85	0.81
Wald p-val Fintech (Q1=Q4)	.	.	.	0.05
Wald p-val Nontech (Q1=Q4)	.	.	.	0.11
Observations	1,566,988	1,566,804	1,566,827	1,566,431

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, separately by ZIP code level UPI index quartiles, for uncollateralized loans (business, consumption, MFI). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table D.2: **Role of Technology: Exploiting Heterogeneity by UPI Exposure in Collateralized Markets**

	ln(Amount)			
	UPI Exposure in ZIP Code Quartile 1 (1)	UPI Exposure in ZIP Code Quartile 2 (2)	UPI Exposure in ZIP Code Quartile 3 (3)	UPI Exposure in ZIP Code Quartile 4 (4)
FinTech × Shock	-0.0811***	0.0198	-0.0548***	-0.0153
	(0.0237)	(0.0174)	(0.0192)	(0.0289)
Nontech × Shock	0.0144***	0.0154***	0.0175***	0.0075**
	(0.0031)	(0.0028)	(0.0028)	(0.0031)
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.80	0.00	0.43
Month-year × ZIP × Product FE	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓
ZIPs	3,288	3,035	3,092	3,774
Years	6	6	6	6
R-squared	0.84	0.86	0.86	0.81
Wald p-val Fintech (Q1=Q4)	.	.	.	0.08
Wald p-val Nontech (Q1=Q4)	.	.	.	0.12
Observations	1,775,033	1,775,002	1,773,897	1,774,575

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, separately by ZIP code level UPI index quartiles, for collateralized loans (agriculture, gold, vehicle). Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table D.3: **Role of Technology: Falsification Test Exploiting Heterogeneity by Yono**

	ln(Amount)			
	Yono Exposure in ZIP Code Quartile 1	Yono Exposure in ZIP Code Quartile 2	Yono Exposure in ZIP Code Quartile 3	Yono Exposure in ZIP Code Quartile 4
	(1)	(2)	(3)	(4)
Fintech × Shock	0.0100	0.0109*	0.0060	0.0042
	(0.0062)	(0.0057)	(0.0056)	(0.0053)
Nontech × Shock	-0.0056*	0.0007	-0.0087***	-0.0144***
	(0.0033)	(0.0033)	(0.0033)	(0.0034)
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.02	0.09	0.02	0.00
Month-year × ZIP × Product FE	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓
ZIPs	9,335	10,580	10,196	7,156
Years	4	4	4	4
R-squared	0.85	0.87	0.88	0.88
Wald p-val Fintech (Q1=Q4)	.	.	.	0.49
Wald p-val Nontech (Q1=Q4)	.	.	.	0.06
Observations	2,147,200	2,149,276	2,148,945	2,153,180

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, separated by ZIP code level total Yono transaction value, scaled by a ZIP's population. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\ln(\text{Amount})_{ym,z,l,p}$ is the natural logarithm of the loan amount. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one if the lender is a Fintech and zero otherwise. Nontech_l is a dummy equal to one if the lender is a non-Fintech shadow bank and zero otherwise. $\text{Shock}_{ym,z}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock as defined in Section 2. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

Table D.4: **Role of Technology: Evidence from Application Level Data (Dep Var: Days to Disbursal)**

	# Days to Disbursal		
	All (1)	New-to-Credit (2)	Not New-to-Credit (3)
Alternative Data × Shock	-0.1266***	-0.5521***	-0.1389***
	(0.0489)	(0.1984)	(0.0524)
Alternative Data	-0.4177***	-0.5061***	-0.4543***
	(0.0332)	(0.1358)	(0.0367)
Year-month × ZIP × Merchant Type FE	✓	✓	✓
Onboarding Channel FE	✓	✓	✓
Swipe Machine FE	✓	✓	✓
Membership in Investment App FE	✓	✓	✓
ZIPs	5,749	2,395	5,334
Years	2	2	2
R-squared	0.24	0.32	0.27
Observations	315,478	38,406	251,263

Notes: This table presents the loan disbursement time in days by Fintech ABC after a shock. Equation 5 describes the regression. The data is on the application level. Days to Disbursal, is how many days taken to disburse loan by Fintech ABC. Alternative Data refers to a proprietary score created by Fintech ABC, 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. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table D.5: **Role of Technology: Evidence from Application Level Data (Dep Var: Loan Default)**

	Default Rate		
	All	New-to-Credit	Not New-to-Credit
	(1)	(2)	(3)
Alternative Data × Shock	-0.0028	-0.0005	-0.0069***
	(0.0021)	(0.0049)	(0.0023)
Alternative Data	0.0258***	0.0348***	0.0458***
	(0.0014)	(0.0037)	(0.0015)
Year-month × ZIP × Merchant Type FE	✓	✓	✓
Onboarding Channel FE	✓	✓	✓
Swipe Machine FE	✓	✓	✓
Membership in Investment App FE	✓	✓	✓
ZIPs	5,749	2,395	5,334
Years	16	13	16
R-squared	0.31	0.42	0.36
Observations	315,472	38,406	251,256

Notes: This table presents the loan default rate by Fintech ABC after a shock. Equation 5 describes the regression. The data is on the application level. Alternative Data refers to a proprietary score created by Fintech ABC, 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. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table D.6: **Role of Technology: Evidence from Application Level Data (Dep Var: Interest Rate)**

	Interest Rate		
	All	New-to-Credit	Not New-to-Credit
	(1)	(2)	(3)
Alternative Data × Shock	0.0040***	0.0009	0.0022
	(0.0015)	(0.0024)	(0.0014)
Alternative Data	-0.0766***	-0.1633***	-0.0940***
	(0.0010)	(0.0017)	(0.0010)
Year-month × ZIP × Merchant Type FE	✓	✓	✓
Onboarding Channel FE	✓	✓	✓
Swipe Machine FE	✓	✓	✓
Membership in Investment App FE	✓	✓	✓
ZIPs	5,749	2,395	5,334
Years	16	13	16
R-squared	0.32	0.79	0.40
Observations	315,489	38,406	251,273

Notes: This table presents the loan interest rate by Fintech ABC after a shock. Equation 5 describes the regression. The data is on the application level. Alternative Data refers to a proprietary score created by Fintech ABC, 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. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.