Shadow Banks on the Rise: Evidence Across Market Segments

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Abstract

This paper studies how drivers of shadow bank growth differ across loan market segments, using novel credit bureau data on the universe of formal retail loans in India. Proxying credit demand shocks with weather variation, we show that Fintechs respond more strongly than other non-Fintech shadow banks and traditional banks, on average and in uncollateralized markets such as consumer loans. Conversely, non-Fintech shadow banks are more responsive in collateralized markets such as agricultural loans. Both types show stronger responses for borrowers with low credit scores or no credit history. We argue that the dominant comparative advantage of Fintechs in uncollateralized markets is technology. First, Fintechs' reaction is stronger in regions with more data sharing, as a staggered roll-out of a digital transaction platform demonstrates. Second, proprietary data of a Fintech lender shows that acceptance after demand shocks increases with higher alternative data scores. In contrast, the comparative advantage of non-Fintech shadow banks in secured markets is likely a combination of lax regulation and local presence to seize collateral. Thus, our findings suggest that the dominant factors driving shadow bank growth differ across market segments, thereby complementing the literature that has examined comparative advantages of shadow banks in the mortgage market.

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1 Introduction

Financial intermediation has undergone significant transformation over the past decade, marked by the rise of shadow banks – non-deposit-taking institutions. A crucial question that has emerged following the dramatic rise of shadow banks is what advantages these lenders hold over traditional banks. The literature suggests two main factors: technology that is specific to Fintech shadow banks and lax regulation that affects all shadow 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 greater consumer welfare and an expansion of credit availability, along with 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 et al., 2018). While the post-financial crisis mortgage market offers valuable insights, these may not be fully applicable to other market segments for several reasons. First, the mortgage market is more heavily regulated than many other segments, which may lead to an overemphasis on the importance of regulatory advantages in explaining shadow bank growth. Second, mortgages are collateralized loans, often with loan-to-value ratios greater than one. This reduces the lender's risk, which in turn may diminish the relative importance of technological advancements in assessing borrower risk. Third, mortgage loans involve long-term financial commitments, where the benefits of technological advancements – such as convenience and speed – may be less critical to borrowers. Moreover, examining the role of different mechanisms in explaining the growth of shadow banks across market segments is crucial for complete policy analysis as it may depend on the industrial organization of the credit markets as discussed in Buchak et al. (2024).

In this paper, we leverage a novel and unique dataset on the universe of formal retail loans in India to show that the dominant factor driving shadow bank growth varies by market segment. In other words, insights from the mortgage market are not directly applicable to other loan types. This credit bureau data has four key advantages. First, we observe all lender types and can distinguish between Fintech shadow banks and non-Fintech shadow banks. This is critical to distinguish between lax regulation (a feature of all shadow banks) and technology (a feature unique to Fintech shadow banks). The distinction between Fintech and non-tech shadow banks is possible in mortgage data (Buchak et al., 2018) but has not yet been explored

in non-mortgage data.[1]

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.[2] This allows us to demonstrate that the dominant factor driving shadow bank growth varies by loan type. Third, we observe a wide breadth of credit score types. This 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 U.S. unsecured consumer lending data, 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 842 million loans, the universe of formal retail loans in India from 2016 to 2021. This is larger by a factor of ten compared to mortgage data (Fuster et al., 2019) and larger by a factor of 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).

Equipped with this data, we observe the reaction of different lender types to a credit demand shock. Studying the response to a demand shock instead of descriptive statistics in equilibrium allows us to control for external factors that could be driving shadow bank growth. To identify demand shocks, we leverage the granularity of the credit bureau data, which is on the level of year-month $\times$ ZIP $\times$ lender $\times$ product. We combine this with granular weather data on the level of year-month $\times$ ZIP. Specifically, we utilize the geo-spatial data on 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 weather shocks as employed in this study (Dell, Jones and Olken, 2014).

We employ a granular difference-in-difference strategy. The coefficient of interest is the interaction term of the local weather shock with a lender type indicator. Specifically, we capture the effect of the weather shock on the outcome variable for the fintech and non-fintech shadow banks relative to other traditional banks. The design allows us to incorporate three key sets of fixed effects, effectively controlling for external factors that could be driving shadow bank growth. First, we control for year-month $\times$ ZIP $\times$ product fixed effects. This controls for time-varying, local product trends, such as an increase in consumer loans that shadow banks specialize on. Second, we include year-month $\times$ lender $\times$ product fixed effects. This allows us to account for the fact that shadow banks can be a substitute when other lenders are reducing credit following a credit supply shock as discussed in Tang (2019) and De Roure, Pelizzon and

[1] 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.

[2] It's 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 hawkers and street vendors.

Thakor (2022). Moreover, this fixed effect also controls for the industrial organization of the credit markets and its interaction with aggregate shocks that may affect lending outcomes as documented in Buchak et al. (2024). Third, we include ZIP × lender × product fixed effects. This addresses the concern that shadow banks might grow because they focus on areas that experience an increase in credit demand. To summarize, our granular difference-in-difference strategy allows us to control for many external factors that could shape shadow bank growth. We document parallel pre-trends in an event study analysis. This leaves interactions between a lender type and a demand shock as possible explanations, including a technological or regulatory advantage when responding to demand shocks.

We begin by demonstrating that Fintechs show a substantially stronger supply elasticity to demand shocks than other lenders on average. 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 a notable increase in credit issuance by non-Fintech shadow banks. After weather shocks, these institutions extend 0.31% more credit compared to other lenders within the same year-month, ZIP code, and product category. Although non-Fintech shadow banks exceed traditional banks in credit disbursal, their response is less pronounced than that of Fintech shadow banks. This difference is both economically and statistically significant. Given that both types of shadow banks are subject to similar regulations, yet Fintechs have a technological advantage, this suggests that technology may play a more significant role than lenient regulation on average.

Next, we leverage the breadth of our data across product types. We find that the primary drivers of shadow bank growth differ by market segment. In collateralized loan segments, non-Fintech shadow banks exhibit a stronger response (1.53%) than Fintech firms or traditional banks, particularly in agriculture (1.42%), gold (3.25%), and vehicle loans (0.33%). Conversely, in uncollateralized loan segments, Fintech firms demonstrate a stronger response (1.92%) than non-Fintech shadow banks or traditional banks, especially in business loans (4.49%), consump-

tion loans (1.08%), and microfinance institution (MFI) loans (8.37%). These findings suggest that non-Fintech shadow banks have a comparative advantage in collateralized markets for absorbing demand shocks, while Fintech firms hold a comparative advantage in uncollateralized markets. Overall, this indicates a clear market segmentation in how shadow banks respond to demand shocks.

We contend that the dominance of non-Fintech shadow banks in collateralized markets is likely related to their local presence, which is crucial for seizing collateral in case of default. Unlike Fintechs, non-Fintechs maintain a physical presence, a factor overlooked in previous studies (Buchak et al., 2018). The stronger response of non-Fintechs in collateralized lending suggests that their physical presence may be driving the effect in this market segment.

We further examine the impact of lax regulation in driving the rise of non-Fintech shadow banks. If lax regulation, along with local presence, is key to their growth, we would expect non-Fintech to be more responsive to demand shocks among lower-quality credit borrowers or those with high information asymmetry. To test this, we analyze the effect across different credit score categories within the collateralized market. Our findings show that non-Fintech respond more strongly than Fintech and traditional banks to prime borrowers (0.82%), near-prime borrowers (1.08%), and subprime borrowers (0.59%). The most pronounced effect is among new-to-credit borrowers (1.62%), who face the highest information asymmetry. In contrast, we do not see significant shifts in borrower credit quality within the uncollateralized market segment for non-Fintech. These results suggest that the combination of lax regulation and local presence may explain non-Fintechs' comparative advantage in absorbing demand shocks, especially in the collateralized market segment for new-to-credit and relatively low credit score customer segment.

We now examine the factors driving the growth of Fintechs, particularly their capacity to absorb excess demand following a climate shock. As previously noted, the majority of the increase in credit disbursal by Fintechs after demand shocks occurs within the uncollateralized lending segment. This may be due to Fintechs' lack of a physical presence, which limits their ability to seize collateral in the event of default. In other words, Fintechs operate under a different business model that does not depend on physical locations. We further analyze the effect across different credit score categories and find that Fintechs respond more strongly than non-Fintechs and traditional banks to prime borrowers (0.75%), near-prime borrowers (1.11%), and subprime borrowers (1.74%), with the effect increasing consistently across these categories. The most significant impact is observed among new-to-credit borrowers (2.67%), who face the highest levels of information asymmetry. This increasing trend in credit scores is driven entirely by the uncollateralized lending market. In the collateralized loan segment, Fintechs only respond to demand shocks among super-prime borrowers, aligning with the idea

that seizing collateral in case of default is difficult without a physical presence, and super-prime borrowers are least likely to default.

The ability of Fintechs to absorb excess demand among borrowers with low credit quality or high information asymmetry could be due to either – (1) their capacity to take on additional risk because of lax regulation, similar to non-Fintech shadow banks or (2) their technological advantage in identifying the best customers within this segment. If the latter is the key factor, we would not expect to see a significant increase in the ex-post default rates of loans disbursed during periods of excess demand. Our findings support this, as there is no economically significant effect on one-year or three-year default rates for Fintech-issued loans during these periods. Specifically, we do not observe a meaningful increase in default rates for Fintechs, either in aggregate or within the uncollateralized lending market. This suggests that although Fintechs appear to take on higher ex-ante risk, the ex-post economic riskiness of their portfolios remains small. Therefore, the technological prowess of Fintech may be the primary explanation for their ability to absorb excess demand during climate shocks.

In the second part of the paper, we turn towards providing more direct evidence that technology plays a key role in the growth of Fintech. We utilize two approaches for this. First, we exploit the staggered geographical rollout of the digital payment system in India, which allowed Fintechs access to bank transaction data. 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 and other lending outcomes.

We begin our analysis by examining the heterogeneity in the effect by geographic variation in the adoption of a key cashless transaction technology – Unified Payment Interface (UPI). UPI is an instant payment system that facilitates cashless transactions between two bank accounts. 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 et al. (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 a clear, increasing trend in the interaction coefficient between Fintech and 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 Fintech 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 non-Fintech lenders. These findings suggest that the technological advantage of Fintechs may be a key factor driving their growth.

A potential concern with this analysis is that the UPI index might be correlated with other unobserved factors that are positively related to digital adoption, potentially confounding the observed effect of Fintech loan issuance. 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. If the observed increasing pattern in the UPI index effect were due to unobserved factors rather than data sharing within the open banking framework, we would expect to see a similar pattern in areas with high Yono adoption. However, 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.

We then analyze data from one of India's largest Fintech companies, 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 climate shock at the application level. The results indicate that the score derived from alternative data is positively correlated with loan acceptance following a climate 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. These findings suggest that technology, specifically the use of alternative data, plays a critical role in enabling Fintech companies to

extend credit after shocks, especially to new-to-credit borrowers.

Lastly, we present an extensive set of robustness tests. Our first two tests examine the specification of our regression. First, we show that the baseline effect holds even in absolute terms. Second, our results are hold through with a Poisson transformation. Third, our results are robust to analyzing more severe events than in our baseline specification. We further test robustness by using weather shock measures over extended periods, such as three months. To address any concerns about the construction of our weather shock dummy, we show that the results hold when using the original continuous measure of water balance. Overall, these tests provide confidence in the robustness of our results. A placebo test with a random shock variable shows that our estimates fall to the far right of the simulated distribution of coefficients. We also rule out the impact of differences in funding sources and climate-related shocks as driving factors behind our results.

The key contribution of this paper is its exploration of how the dominant factors 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 local physical presence and lax regulation. Second, the growth of Fintech shadow banks in the uncollateralized market may be attributed to their lack of physical presence and technological expertise. To the best of our knowledge, we provide the first distinction between regulation and technology in market segments other than the mortgage market. One of the key papers in this field is Buchak et al. (2018), who distinguish between technology and regulation in the U.S. mortgage market after the financial crisis. Outside of the mortgage market, distinguishing between these two factors has been so far impossible due to data limitations.[3] In contrast, our data uniquely equips us to distinguish between technology and regulation for the first time outside of the U.S. mortgage market. Examining the effect across market segments is crucial, as noted by Buchak et al. (2024), who argue that a complete policy analysis must incorporate the industrial organization of the credit markets. Our results resonate with their thesis indicating that the relative strength of technology and regulation amongst types of shadow banks is dependent on the market segment, making such an analysis important from a policy perspective. Therefore, this paper contributes to the shadow bank literature that has focused specifically either on their technological or regulatory advantage, over and above how traditional banks operate.[4]

Second, this paper speaks to the literature on financial intermediation and climate. Prior

[3]For example, studies in the shadow banking literature either have data of a single lender, such as the P2P lending platform LendingClub, as in Tang (2019). 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).

[4]See Berger (2003), Frame, Wall and White (2018), Fuster et al. (2019), Irani et al. (2021), Ghosh, Vallee and Zeng (2022), Gopal and Schnabl (2022), Chernenko, Erel and Prilmeier (2022), and Erel and Inozemtsev (2024), among others. We direct readers to Philippon (2016), Vives (2019), Thakor (2020), Allen, Gu and Jagtiani (2021), and Berg, Fuster and Puri (2022) for a detailed review.

work has focused on the mortgage market generally finding an increase in credit following natural disasters (Morse, 2011; Berg and Schrader, 2012; Cortés, 2014; Chavaz, 2016; Cortés and Strahan, 2017; Kundu, Park and Vats, 2021; Collier et al., 2024). 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 climate shocks. We are more closely related to two recent papers investigating the relationship between Fintech and climate. Allen, Shan and Shen (2023) use HMDA data to show an increase in Fintech loan issuance after severe natural disasters. Similarly, Qi, Li and Sun (2021) use data from one peer-to-peer lender in the United States to show an increase in Fintech loan issuance after earthquakes. We add to this literature by documenting the role of different mechanisms across market segments and customer quality types in shaping the response of shadow banks to climate shocks. Additionally, our study explores the role of Fintech during climate shocks in a highly relevant context of emerging economies which are more vulnerable to climate change and are adopting technology at a fast pace. To the best of our knowledge, we are the first to shed light on the role of technology-oriented Fintechs in mitigating the effects of climate change.

Our work also contributes to the emerging literature on cashless transaction technology, which has primarily explored its direct benefits on income, consumption, production, and adoption determinants (Jack and Suri, 2014; Muralidharan, Niehaus and Sukhtankar, 2016; Chodorow-Reich et al., 2020; Higgins, 2022; Crouzet, Gupta and Mezzanotti, 2023; Dubey and Purnanandam, 2024). We extend this literature by examining how cashless payments impact credit market outcomes. First, we document how cashless payments reduce information asymmetry, enabling Fintechs to extend credit after climate shocks. This finding aligns with the theoretical predictions of Brunnermeier, Payne et al. (2022) and is based on comprehensive data from the entire formal credit market in India, unlike previous studies that focus on a single Fintech (Ghosh, Vallee and Zeng, 2022). Second, we document how such a system can enhance financial inclusion by catering to the underserved population or new-to-credit borrowers during times of excess demand. To highlight the importance of these borrower segments: 50% of credit-eligible population in India is credit unserved or new-to-credit, and 20% is credit underserved due to low credit scores, accounting for a total of 572 million individuals (CIBIL Report, 2022). Third, our analysis documents the potential benefits of integrating cashless payments with an open banking framework. Fourth, our analysis centers on UPI, one of the largest global payment systems currently under scrutiny by central banks worldwide. Our findings are relevant for policymakers considering the introduction or regulation of similar systems. Our findings complement the contemporaneous work of Alok et al. (2024), which

documents Fintech credit expansion following UPI adoption. We differ from them in a key aspect: we trace the impact of new fintech credit in response to demand shocks. This temporal variation generated by random demand shocks enhances our ability to identify the effect.

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), as well as 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*a*). Furthermore, shadow banks are split into Fintechs and Nontechs. Fintechs are a special type of shadow banks that use digital technologies such as mobile applications to deliver financial services (RBI, 2021*b*). In contrast, Nontechs are any other shadow banks that do not use digital technologies to deliver 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.[5] 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 retail loans in India.

The data is recorded at a granular level of year-month × ZIP × lender × product. At this level, the data is further divided into credit score categories. We obtain this data from January 2016 until December 2021. We observe three outcomes: the number of loan accounts issued, total loan amount issued, and the number of defaulted loans that were issued in this

[5]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.

year-month × ZIP × lender × product. A loan is defined as defaulted once it reaches the 90 days past due (DPD), within both one or three years 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 or three years 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). The distinction between Fintechs and Nontechs is critical to identify the comparative advantage of shadow banks relative to traditional banks. It allows us to distinguish between lax regulation – a feature shared by both Fintechs and Nontechs – and technology – a feature unique to Fintech. This distinction between Fintechs and Nontechs is observable in the mortgage data (Buchak et al., 2018) but has not yet been explored in non-mortgage data. Di Maggio and Yao (2021) use data from the U.S. TransUnion credit bureau on personal loans, but only identify Fintechs, not non-Fintech shadow banks. Thus, observing all lender types provides us with a unique setting to distinguish between regulation and technology outside the mortgage market.

Second, we observe all product types, ranging from collateralized loans such as agriculture, gold, and vehicle to unsecured loans such as business, consumption, and MFI.[6] 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 do observe mortgage loans in the data. However, they are captured as the only product of the lender type of housing finance companies; thus they are eliminated in our regressions with product fixed effects and we do not include them in our analysis. 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.[7] New-to-credit borrowers do not yet have a credit score; thus, lenders experience the highest information asymmetry for these borrowers. Our breadth of borrowers is wider than what researchers observe in the mortgage market, which often excludes individuals who have a very low or no credit score. 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 842 million loans, the universe of formal retail loans in India from 2016 to 2021. This is larger by a factor of ten compared to mortgage data (Fuster et al., 2019) and larger by a factor of hundred compared to data on non-mortgage

[6] 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.

[7] 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).

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 et al. (2014). In contrast to the loan issuance and default data, this information is available on the annual level - year × ZIP × lender × 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 et al. (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 et al., 2023). The construction of the SPEI is outlined in detail by Vicente-Serrano, Beguería and López-Moreno (2010). We provide here 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. 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.[8] 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, 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

[8]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.

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.[9] 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.[10] 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, 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 et al., 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 et al. (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

[9] 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 A1). 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.

[10] We show our results are robust to employing alternative definitions of the local shock variable, such as using different cutoffs, different lengths over which the water balances are measured, or directly using the continuous measure. See Section 5.6.

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.[11] 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 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.

[11] 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 et al. (2020) for more details on the demonetization episode. The adoption dates of UPI by banks is public information and can be accessed here.

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

To explore how social connectedness at the ZIP-code level affects the role of Fintechs, we use data on the Social Connectedness Index (SCI) from Facebook. SCI measures the strength of connectedness between two locations, represented by Facebook friendship ties. This index has been used to predict trade flows, mutual fund investments, geographic spread of Covid-19, and others (Kuchler et al., 2021; Kuchler, Russel and Stroebel, 2022; Bailey et al., 2021). The SCI is formally computed as follows:

$$\text{Social Connectedness Index}_{i,j} = \frac{\text{FB_Connections}_{i,j}}{\text{FB_Users}_i \times \text{FB_Users}_j} \tag{2}$$

Here, FB_Users_i and FB_Users_j are the number of Facebook users in locations i and j, respectively, and $\text{FB_Connections}_{i,j}$ is the total number of Facebook friendship connections between individuals in the two locations.

The index is at the district × location pair level. We transform it to the district level by taking the average of the index for a given district for across and within districts in India. We then use this district-level data to match with our weather shock data at the PIN code level by overlaying polygon areas.

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 A1 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 76,000 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) (Figure 2). 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 accounts and 4% in terms of amount. Fintechs have been experiencing the largest growth by far among all lenders. Between 2016 and 2021, Fintech 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 accounts instead of amounts, consumption loans make up 98% of Fintechs' loan portfolio (see Table A1).

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 A3, 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, ranging from around 5-8% after one year to 11-13% after three years. Other traditional bank types have slightly lower default rates between 3-4% after one year to 8-10% after three years. We do not observe information on interest rates in our data. Finally, Nontechs and Fintechs have a wide geographical spread comparable to that of other lenders as depicted in Figure A4.

3.2 Granular Summary Statistics

Going more granular, Table A2 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 and three default rates, 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 938,310 rupees (≈13,699 USD). This corresponds to a loan size of 156,385 (≈2,283 USD). The average one and three year default rates are 4.25% and 10.94%, respectively. The median number of inquiries is two. The ratio of the number of inquiries to the number of loans given by around one third, which is less than one. As noted earlier, this mismatch is because loans can be issued without an inquiry. Appendix Table A3 presents these statistics by lender type. A Nontech cell has a median number of ten loans with a total loan amount of 1,061 thousand rupees (≈15,500 USD). A Fintech cell has a median number of five loans, corresponding to a total loan amount of 104 thousand rupees (≈1,518 USD). Table A4 presents the key statistics by product type. Appendix Table A5 depicts them by lender type and credit score type, and Table A6 shows them by lender type and product type.[12]

3.3 Weather Shocks and Credit Demand

To obtain exogenous increases in credit demand, we focus on weather shocks, which have long been recognized as drivers of income and expense fluctuations of workers across occupations.

[12] These tables indicate that Fintechs tend to inquire at a much higher rate than public or private sector banks. Especially agriculture and gold loans are less likely to be inquired.

Most prominently, weather shocks affect farmers and agricultural workers, a group that comprised one in five Indians in 2011 (MOAFW, 2020). Our data reflects this, showing an uptick in credit applications for agricultural purposes (Table A10). Beyond that, weather shocks affect the broader economy. Studies have shown that extreme weather reduces labor supply, e.g., due to excessive heat or damaged infrastructure (Dell, Jones and Olken, 2009; Graff Zivin and Neidell, 2014). It also encourages consumers to stay at home, which has implications for the revenue of 111 million workers in non-agricultural micro, small, and medium enterprises (Liu, Shamdasani and Taraz, 2023; MMSME, 2023).

While incomes decrease, expenses increase, resulting in liquidity needs for rising food prices, health issues, home repairs, or migration (Economic Times, 2023; BBC, 2020, 2022; Indian Express, 2023). Consistent with this broad impact of weather shocks, we observe an increase in a wide range of product types that allow borrowers to obtain liquidity such as consumption loans, business loans, microfinance loans, and gold loans (Table A10).[13]

4 Empirical Strategy

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

[13]The increase in vehicle loan demand likely reflects the need to travel further for work as local opportunities diminish.

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.

Our key identification assumption is that the interaction of the climate event ($Shock_{z,ym}$) with Fintech and Nontech is 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).

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 on products that experience a large increase in credit demand after weather shocks. For instance, a climate 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 climate 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.[14] One can interpret this fixed effect ($FE_{ym,z,p}$) as directly controlling for time-varying aggregate investment opportunity set available to lenders in an area à la Drechsler, Savov and Schnabl (2017).[15]

A second potential concern one needs to address is that Fintechs or Nontechs might react more strongly because they focus on areas that experience a large increase in credit demand after a weather shock. For example, a climate shock might induce extra demand in more rural areas, which Fintechs can reach more easily than traditional lenders. 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. In other words, this fixed effect effectively controls for the comparative advantage of a lender in an area. Additionally, the year-month × ZIP × product fixed effect ($FE_{ym,z,p}$) ensures that we are identifying the estimate using variation from an area where Fintechs, Nontechs, and traditional lenders operate.

Finally, the inclusion of our fixed effects addresses a comprehensive set of other variation. The year-month × ZIP × product fixed effect ($FE_{ym,z,p}$) incorporates a year-month × ZIP fixed effect and thus controls for all time-varying heterogeneity at the ZIP level such as local economic conditions, shocks to investment opportunities, and local vulnerability and resilience to climate shocks. The inclusion of the year-month × lender × product fixed effect ($FE_{ym,l,p}$) accounts for all time-varying shocks at the lender-product level. These shocks may include regulatory changes

[14] Cortés and Strahan (2017) document expansion in credit demand following disaster shocks in the US.
[15] Vats (2020) and Kundu, Park and Vats (2021), among others also rely on a similar identification assumption.

affecting different lender types, economic shocks such as overall deposit fluctuations that vary by lender type, changes in aggregate demand for various product types, and capital supply shocks specific to certain lender types, among others. Thus, our fixed effects control for a wide set of key potential alternative stories. 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.

5 Results – Effect on Credit Issuance

We begin by investigating whether Fintech shadow banks or Nontech shadow banks issue more credit after weather shocks, relative to traditional banks. Table 1 presents our first main result, on which we will build going forward. The estimates of interest are the coefficients on the interaction of Fintech and Shock as well as Nontech and Shock. Column 1 presents the results without any fixed effects. 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 these two factors. Specifically, these elements collectively account for 14% of the observed variation in loan amounts.

Moving from columns 1 to 4, we add fixed effects. In our strictest specification, we incorporate year-month × ZIP × product fixed effects, year-month × lender × product fixed effects, and ZIP × lender × product fixed effects. The coefficient of interest associated with the interaction term of Fintech and shock is positive and statistically significant across all specifications. The positive estimate demonstrates that Fintechs increase their lending relative to traditional banks following a climate shock. Specifically, we find that Fintechs issue 1.57% more credit after climate shocks than traditional lenders in the same year-month, the same ZIP code, and the same product category. This corresponds in the aggregate to an effect of 3 million USD in a given month, or 211 million USD during our study period.[16] The coefficient on Fintech is statistically different from that of Nontech, which shows a smaller response of 0.31%.[17] Thus, Fintechs increase their lending after weather shocks substantially more than both Nontechs and traditional banks.

[16] In the following calculations, we apply the average exchange rate in the middle of the sample, 2019, which is 0.0146. The average loan amount of Fintechs is 10 thousand USD in a given ZIP code, year-month, and product. An effect of 1.57% compared to this mean corresponds to 162 USD. Applying the coefficient to the average loan amount issued across products in a given year-month and ZIP code (16 thousand USD) gives an effect of 250 USD. The average loan amount across products and ZIP codes in a given year-month is 190 million USD, providing an effect of 3 million USD. Finally, over our entire sample, Fintechs issue 13 billion USD, which corresponds to an effect of 211 million USD.

[17] The average loan amount of Nontech is 60 thousand USD in a given ZIP code, year-month, and product. An effect of 0.31% compared to this mean corresponds to 187 USD. Applying the coefficient to the average loan amount issued across products in a given year-month and ZIP code (231 thousand USD) gives an effect of 717 USD. The average loan amount across products and ZIP codes in a given year-month is 4.30 billion USD, providing an effect of 13 million USD. Finally, over our entire sample, Nontechs issue 305 billion USD, which corresponds to an effect of 946 million USD.

5.1 Extensive Margin

Next, we examine the effect at the extensive margin. Table 2 presents the results using the number of new loans at the ZIP-year-month-product level as the dependent variable. Overall, we find that our results hold at the extensive margin level.

Specifically, we find that the number of loans at the ZIP-year-month-product level increases by 0.20 or 0.68%, in our preferred specification reported in column 4 (the effect evaluated at the mean of 29 loans for Fintechs in a given year-month × ZIP × product, see Table A3). In aggregate, this translates to an effect of 3.6 thousand extra loans in a month and 255 thousand additional loans over our study period.[18]

5.1.1 Effect on Credit Inquiries

In alignment with an increase in loan issuance, there is a corresponding increase in the number of loan inquiries made by Fintech shadow banks.. Since the inquiry data is at the annual level, we redefine our weather shock as 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. Table A8 presents the results. In our strictest specification, we find that Fintechs have 0.71 (=8.50/12) extra inquiries after the shock relative to traditional providers. This corresponds to an increase of 2.6% (at a monthly mean of 27.26 inquiries). The ratio of accepted loans to inquired loans is 27.56% (=0.20/0.71). The reader should note that this does not necessarily reflect the acceptance rate because borrowers may apply for loans with multiple lenders (which would lead to more inquiries), and not all loans are inquired about (which would lead to fewer inquiries). The coefficients on the extensive margin for Nontech are – on average – small and insignificant, both for credit issuance and inquiries. This further suggests that on average, across product categories, Fintechs respond substantially stronger than Nontechs and traditional lenders.

5.2 Economic Magnitude of Baseline Effect

The average monthly Fintech loan amount in a ZIP code-lender-product cell (the unit of observation in Table 1) is 705k rupees (≈10,000 USD) and average number of loans is 28.76, which equals 24,520 rupees (≈358 USD) per loan. The point estimates in Column 4 of Table 1 shows a 1.57% increase in Fintech credit after a weather shock, which translates to a 385 rupee (≈6 USD) increase in credit per borrower. These effects are economically meaningful for the Indian population. We benchmark these numbers against the average monthly expenditure using

[18] The average number of loans of Fintechs is 28 in a given ZIP code, year-month, and product. An effect of 0.68% compared to this mean corresponds to 0.2 new loans. Applying the coefficient to the average number of loans issued across products in a given year-month and ZIP code (44 accounts) gives an effect of 0.30 new loans. The average number of loans across products and ZIP codes in a given year-month is 530 thousand, providing an effect of 3.6 thousand loans. Finally, over our entire sample, Fintechs issue 38 million loans, which corresponds to an effect of 255 thousand loans.

the Household Consumption Expenditure Survey Data (Table A7).[19] For the bottom 5th percentile of monthly expenditure, the increase in Fintech credit per borrower corresponds to 19% and 28% of average monthly expenditure for urban and rural households, respectively. For households between the 40th and 50th percentile, the increase in Fintech credit per borrower corresponds to 8% for urban and 12% for rural households. For the top 5th percentile, the effects correspond to 2% for urban and 4% for rural households. In Section 5.4.1, we show that marginal and new-to-credit borrowers benefit the most from the increase in Fintech credit, and hence benchmarking estimates closer to the bottom percentile of monthly expenditure are likely to be more appropriate in our setting.

Given the cyclicality in incomes, we prefer the average monthly expenditures to benchmark our estimates. Nonetheless, for completeness, we also benchmark our results against average income and average savings. Assuming an average annual income of 234,551 rupees (Bharti et al., 2024), these effects correspond to 2% [=385/(234,551/12)] of monthly income. The average annual income for the bottom 50% is 71,163 rupees, implying that the Fintech credit increase corresponds to 6% [=385/(71,163/12)] of average monthly income. Numbers from the Periodic Labour Force Surveys (PLFS) yield similar estimates.[20] Using the 2019 average salary of 19,568 rupees, the Fintech credit increase is 2%[=385/19,568] of monthly income. However, given the stronger impact on marginal borrowers – documented in Section 5.4.1 –, a more appropriate benchmark may be the average salary for casual workers. The increase in Fintech credit is 5% [=385/7,591] of the average monthly salary of a casual worker. The effect is also meaningful when benchmarked against the average monthly savings of 15,625 rupees (2%).[21]

5.3 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 3 presents the dynamic effects of the loan amount. There are two key takeaways from the dynamic estimation of Equation 3. First, the results indicate that the pre-trends are unlikely to drive our results. Specifically, the absence of pre-trends indicates that 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 five months. Overall the results indicate that the response of Fintech is both immediate and persistent. In contrast, the Figures show a substantially smaller response for Nontech, relative to Fintechs.

[19] Available from the Ministry of Statistics and Program Implementation, Government of India website https://www.mospi.gov.in/.
[20] https://www.mospi.gov.in/Periodic-Labour-Surveys
[21] Data as of 2019 from All India Debt and Investment Survey (AIDIS).

5.4 Heterogeneity by Collateralization

We begin by investigating the heterogeneity in the baseline effect across collateralization. Conducting a heterogeneity analysis by collateralization is crucial for identifying the key drivers of shadow bank growth across loan segments, particularly in evaluating the relative importance of technology and regulation. In collateralized markets, a stronger response to demand shocks may result from a combination of lax regulation and the need for a local presence to seize collateral in cases of default. In uncollateralized markets, however, superior performance likely reflects the greater importance of technological innovation. This segmentation by collateralization is essential for a more precise understanding of market dynamics and the forces driving growth. By doing so, we offer a clearer perspective on how technology and regulation interact across different lending environments, a necessary step for informed policy-making in financial intermediation.

Table 3 presents the results investigating the heterogeneity in the baseline effect across collateralization. Column 2 focuses on the sub-sample of collateralized loans – agriculture, gold, and vehicle loans. Column 3 on the other hand demonstrates results for the sub-sample of uncollateralized loans – business, consumption, and MFI loans. We observe that in collateralized loan segments, Nontechs show a stronger response (1.53%) than Fintechs or traditional banks. In contrast, in uncollateralized loan segments, Fintechs show a stronger response (1.92%) than Nontechs or traditional banks. This is the first evidence that Nontechs appear to have comparative advantages in collateralized markets, compared to traditional banks and Fintechs.

Note that the overall effect across both loan segments in Column 1 is the weighted average of collateralized and uncollateralized loan segments. The Fintech portfolio is heavily tilted towards uncollateralized loans (e.g., 97% of loan amount in 2021, see Table A1), while the Nontech portfolio has a strong focus on collateralized lending (64%) but still a substantial share in uncollateralized lending (36%). Consequently, the overall effect for Fintechs (1.57%) is relatively close to the effect of uncollateralized loans (1.92%), while the overall estimate of the Nontech (0.31%) gets pulled towards zero due to the null effect in the uncollateralized market segment.

Additionally, we estimate our baseline regression for each product type separately. Table 4 presents the results. We find that very consistently, Nontechs show a stronger response than Fintechs and traditional banks for collateralized loan products: agriculture (1.42%), gold (3.25%), and vehicle loans (0.33%). Nontech coefficients are statistically different from traditional banks in all cases, and from Fintechs for gold and vehicle loans. In the uncollateralized loan segment, Fintechs show a stronger response across business loans (4.49%), consumption loans (1.08%), and MFI loans (8.37%). All differences to traditional banks and Nontechs are

statistically significant at the one percent level.

Overall, these findings suggest that non-Fintech shadow banks have a comparative advantage in collateralized markets for absorbing demand shocks, while Fintech firms hold a comparative advantage in uncollateralized markets. This indicates a clear market segmentation in how shadow banks respond to demand shocks. Moreover, these results also suggest that that lax regulation likely plays a more significant role in enabling Nontech lenders to absorb demand shocks in collateralized loan segments. In contrast, technology appears to be a crucial factor driving the responsiveness of fintechs in uncollateralized loan markets.

5.4.1 Heterogeneity by Credit Score Type

Next, we examine the heterogeneity in the effect by credit score categories. The objective of this exercise is to understand the borrower segments that shadow banks serve. This analysis aims to clarify whether shadow banks compete with or complement traditional banks. The answer is crucial for two reasons. First, it could offer insights into the drivers of shadow bank growth. Shadow banks, operating under lighter regulations than traditional banks, may be more willing to take on riskier borrowers that traditional banks are unable to serve. Second, if shadow banks complement traditional banks, they could improve financial inclusion by extending credit to underserved borrowers. However, if they compete directly with banks, the credit expansion they provide may largely benefit borrowers already eligible for traditional bank loans. Therefore, understanding the borrower segments served by shadow banks is key to assessing the reasons for their growth and their broader welfare implications.

We estimate our baseline Equation 3 for each credit score category separately. Table 5 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 strongest effect is observable for new-to-credit borrowers (2.67%), who have the highest information asymmetry. New-to-credit borrowers are also the only ones for which Nontechs show a positive effect, even though substantially smaller than Fintechs (1.15%). In contrast, we do not find an increase for high-score credit types such as super-prime and prime-plus borrowers, neither for Fintechs nor for Nontechs.

Table 6 and 7 present the split by credit score types for collateralized and uncollateralized product types, respectively. For collateralized loans, Fintechs only issue credit to super-prime borrowers, consistent with the fact that seizing collateral in case of default is very challenging without a physical presence. The overall effect in collateralized markets of Nontechs (1.53%) comes primarily from credit issuance to those in the prime, near-prime, sub-prime, and new-to-credit segments. In the uncollateralized market, we again observe the overall effect of Fintechs (1.92%) coming from prime, near-prime, sub-prime, and new-to-credit borrowers.

The reaction of Nontechs is mostly negligible, with the strongest effect in the new-to-credit borrower segment.

One potential explanation for the monotonically increasing pattern for Fintechs across the credit score distribution is that borrowers with lower credit scores are hit harder by the shock and experience stronger credit demand. Specifically, this increased credit demand by low credit score borrowers is targeted at Fintechs. We investigate this hypothesis by examining the relationship between inquiries and the incidence of local climate shocks by credit score type. Appendix Table A11 presents the results. While we observe the strongest effect on inquiries among new-to-credit borrowers, the effect across the credit score distribution does not seem to support this demand-side hypothesis.[22] Particularly, moving from prime to sub-prime borrowers shows a *decreasing* trend in effect and an increasing trend when moving from super-prime to prime. Thus, the inquiry effect (or demand patterns) among scored borrowers do not seem to explain the heterogeneity in loan issuance observed in Table 5 and 7.

The observed heterogeneity in the greater credit issuance by Fintech across credit score types indicates a supply-side mechanism, i.e., Fintechs supply disproportionally more credit to low-score borrowers, and this behavior cannot be explained by greater applications to Fintechs. This might be because weather shocks induce demand that is relatively less likely to be tied to issues of adverse selection and moral hazard.

5.5 Default Rates

We next analyze default rates on new loans issued by shadow banks following climate shocks. The objective of this exercise is two-fold. First, given that Fintech and Nontech lenders primarily cater to borrower segments with high information asymmetry, examining default rates allows us to assess whether the surge in credit issuance after the shock leads to higher defaults. Second, this analysis helps determine whether the increased lending stems from lax regulatory standards, resulting in ex-post risk, or if shadow banks possess a comparative advantage in identifying and managing borrowers with higher information asymmetry.

Table 8 presents the results. The main outcome variable is the fraction of loans that default after one year and three years, respectively. We do not find economically meaningful effect on one-year or three-year default rates of Fintechs or Nontechs relative to traditional lender types. For collateralized loans, the default rate increases by a maximum of 0.62 percentage points, and for uncollateralized by a maximum of 0.10 percentage points. These results indicate that while Fintechs and Nontechs seem to take on ex-ante higher risk as measured by credit scores, the ex-post difference in the economic riskiness of their portfolio is economically small. Furthermore, the results suggest that increased funding is unlikely to be the main driver of excessive risk-

[22] New-to-credit borrowers are likely first-time borrowers who do not substitute away from other lenders.

taking by shadow banks. If that were the case, we would expect to see a substanital rise in default rates, which is not observed.

5.6 Robustness

This section conducts a series of robustness tests to validate the main effect of loan issuance. First, our specification in Equation 3 investigates the effect of Fintechs and Nontechs relative to traditional banks. A potential concern is that both traditional and shadow banks may reduce lending after climate shocks, with traditional banks cutting back even more. This could occur for various reasons, such as depositors withdrawing funds from traditional banks post-shock, leading to reduced funding if alternative sources are not available (Kundu, Park and Vats, 2021). To address this, we separately regress the loan amounts of Fintechs, Nontechs, and traditional banks on the weather shock variable. Appendix Table A14 presents the results. The results indicate that Fintechs and Nontechs increase lending following deposit shocks, while the impact on most traditional banks is minimal and positive for public sector banks. This suggests that our findings are not driven by shadow banks reducing lending less than traditional banks or by a funding decline at traditional banks.

Second, our main specification focuses on year-month $\times$ ZIP $\times$ lender $\times$ product categories with any credit issuance. In an alternative approach, we include categories that transition from zero to positive credit by running a Poisson regression. Appendix Table A15 demonstrates that the results remain robust under this specification. The coefficient for Fintech increases to 4.00%, while the coefficient for Nontech stays relatively small at 0.59%.[23]

Third, we discuss a set of robustness tests related to our weather shock variable. Appendix Table A16 demonstrates robustness to different shock severity. Specifically, our results are robust to if we define a weather dummy as one if a given year-month falls below the 10th percentile or above the 90th percentile of a ZIP's historical distribution, instead of the 20-80 split as in the baseline. Appendix Table A17 shows that our results remain robust to using longer periods such as three or six months to define the shock variable. Appendix Table A19 demonstrates that our results remain robust even when excluding observations from the peak of the COVID-19 period in 2020 and 2021. Lastly, Appendix Table A18 shows that our results are robust to directly using the continuous measure of weather shock, i.e., the underlying standardized water balance measure itself, the SPEI. Overall, these tests suggest that our baseline result is qualitatively insensitive to the definition of the weather shock variable,

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

[23] Note that we do not employ Poisson as our main specification due to the high computational intensity with the large size of our data.

mirror the 20th and 80th percentile definition of the weather shock. We repeat this exercise 100 times. Figure A7 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 placebo test provides further confidence in our results.

6 Mechanisms

The objective of this section is to examine why Fintechs show stronger reactions in uncollateralized markets and Nontechs exhibit stronger responses in collateralized markets. We begin with the Fintechs' advantage – their use of technology in digital lending. First, we present two approaches that provide direct evidence of technology's pivotal role in Fintechs' stronger response. Next, we address why alternative explanations, such as laxer regulations or different funding sources, are unlikely to account for the results. Finally, we explore possible reasons for the growth of Nontechs in collateralized markets.

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, as measured by the 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 9 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 6a and 6b 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 10. 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 11 and Figure 7 show how our baseline effect varies with 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 Additionally, Tables 12 and 13 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 the collateralized or uncollateralized lending. In terms of magnitude of the effect for Fintechs, – in the first quartile, the effect is 0.97% and statistically significant at the ten percent level. In the fourth quartile, the coefficient is 2.43% and highly statistically significant (Table 13). A Wald test confirms that the coefficients in the first and fourth quartiles are significantly different, with a p-value of 0.05. This evidence suggests that Fintechs' technological advantage is a key driver of the key findings.

While Table 9 provides suggestive evidence that unobservables are unlikely to drive our results, the evidence is not conclusive. We address this concern further 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 Figure A6 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.

6.2 Technology: Fintech Micro Data

As a second test, we examine proprietary Fintech micro-data. We target to identify whether borrowers with better alternative data have a higher likelihood of getting their application accepted after a weather shock. Alternative data is the standardized score assigned by the lender to the applicant, based on digital transactions conducted by the merchant. Table 14 presents the results, for the entire sample of applicants as well as the split by new-to-credit and not new-to-credit applicants. 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%). The coefficient is statistically significant. Splitting the sample demonstrates that the effect is 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.

We can also explore how alternative data shapes other dimensions of borrowing. Among those who borrow, we observe the days to disbursal (Table A20). We find that 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 smaller reduction of 0.14 days (-1.60% at a mean of 8.69 days). In terms of interest rate, we do not find an effect for those new-to-credit or those not new-to-credit (Table A21). Finally, we do not observe a significant change in default for new-to-credit borrowers. However, those not new-to-credit experience a statistically significant decrease of -0.0069 (-2.4% at a mean default rate of 29%) (Table A22). Thus, better alternative data appears to increase the likelihood of acceptance after a shock and allow for faster disbursal, especially for new-to-credit borrowers. In contrast, interest rates and defaults do not seem to adjust for new-to-credit borrowers.

6.3 Regulation and Funding Sources

Next, we investigate whether Fintechs have an advantage relative to other lenders due to fewer regulatory restrictions or less shock-sensitive funding sources. Here, we argue that Fintechs and Nontechs have similar regulatory guidelines as well as funding sources. Since Fintechs react stronger than Nontechs, and Nontechs react very similarly to traditional banks, this then suggests that technology is the key advantage. Both Fintechs and Nontechs are shadow banks

or in the language of the RBI – non-banking financial companies (NBFCs).[24] In terms of funding sources, both Fintech and Nontech shadow banks rely on funding sources other than demand deposits. While some shadow banks theoretically can take deposits, their number is very low (49 compared to 9,467 in 2022). Overall, public deposits constitute only two percent of the total liabilities of the shadow bank sector (CAFRAL, 2023). Thus, Fintech and Nontech shadow banks rely on alternative forms of financing such as bank loans, private equity, or venture capital. This carefully suggests, in combination with the more direct evidence, that technology is the primary key comparative advantage, allowing Fintechs to react stronger on average and in the uncollateralized market.

6.4 Nontech Effect in Collateralized Markets

What explains the stronger reactions of Nontechs in collateralized markets? We observe that Nontechs react the strongest, followed by traditional lenders, and finally Fintechs. First, we consider the fact that Nontechs react stronger than traditional banks. There are two key comparative advantages of Nontechs. First, they have a laxer regulation than traditional banks. Second, they have a different funding base than traditional banks; they do not rely on deposits. We argue that the funding base is unlikely to explain the difference in reaction between Nontechs and traditional banks, leaving regulation as a possible explanation. Two potential stories emerge from the funding base hypothesis. First, Nontechs might react stronger than traditional banks because traditional banks rely on deposits, and savers withdraw deposits in times of distress such as climate shocks. This could lead to a decrease in funding and consequently lending of traditional banks. However, in absolute we do not see a decrease for traditional banks A14, contradicting this hypothesis. Second, Nontechs might react stronger than traditional banks because their own funding reacts positively to shocks. While this is theoretically possible, we would expect an increase in default rates if excess funding was the key explanatory force behind increased lending. Therefore, we posit that lax regulation may be a better candidate to explain their advantage relative to traditional banks, not the funding base.

Next, we investigate the pattern that Nontechs react more strongly than Fintechs in the collateralized lending segment. As outlined, Nontechs and Fintechs are very similar. Besides technology, a key distinguishing feature is that Nontechs have a local office presence. This could be critical to seize collateral in case of default. Without it, Fintechs have little chance to recover their losses, and indeed we see very little engagement of Fintechs in collateralized

[24] The regulation only starts distinguishing between Fintech NBFCs and non-Fintech NBFCs in September 2022 ("Digital Lending Guidelines"), falling outside of our study period. These guidelines aim to address concerns related to the rapid growth of digital lending platforms and the associated risks, such as data privacy, transparency, and consumer protection.

loan markets. Thus, the stronger response of Nontechs compared to Fintechs is most likely explained through local presence.

7 Conclusion

In conclusion, our study leverages novel and comprehensive credit bureau data on retail loans in India to disentangle the drivers of shadow bank growth 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.

Specifically, fintech shadow banks exhibit a stronger response to demand shocks in uncollateralized markets, such as consumer loans, due to their technological advantage, which is particularly pronounced in regions with higher levels of digital data sharing. This technological edge allows fintechs to extend credit even to borrowers with low credit scores or no credit history, without a corresponding increase in default rates.

On the other hand, Nonfintech shadow banks demonstrate a stronger response in collateralized markets, where their ability to seize collateral due o their local presence play a crucial role, combined with laxer regulatory scrutiny they are under than traditional banks. This segmentation in the market responses highlights the distinct comparative advantages that different types of shadow banks hold, driven by their respective business models and operational strategies.

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 interact to shape the growth of these institutions across different segments of the credit market.

References

Agarwal, Sumit, Mohit Desai, Pulak Ghosh, and Nishant Vats. 2024. "Bridging the Information Gap: Sowing the Seeds of Productivity with High-Speed 4G Internet." *Available at SSRN 4805486*.

Albert, Christoph, Paula Bustos, and Jacopo Ponticelli. 2021. "The effects of climate change on labor and capital reallocation." National Bureau of Economic Research.

Allen, Franklin, Xian Gu, and Julapa Jagtiani. 2021. "A survey of fintech research and policy discussion." *Review of Corporate Finance*, 1: 259–339.

Allen, Linda, Yu Shan, and Yao Shen. 2023. "Do fintech mortgage lenders fill the credit gap? evidence from natural disasters." *Journal of Financial and Quantitative Analysis*, 58(8): 3342–3383.

Alok, Shashwat, Pulak Ghosh, Nirupama Kulkarni, and Manju Puri. 2024. "Does Open Banking Expand Credit Access?" *Work in progress*.

Bailey, Michael, Abhinav Gupta, Sebastian Hillenbrand, Theresa Kuchler, Robert Richmond, and Johannes Stroebel. 2021. "International trade and social connectedness." *Journal of International Economics*, 129: 103418.

BBC. 2020. "Bihar: Destroyed lives and submerged homes in flood-hit India." May 24, 2024.

BBC. 2022. "Assam: India floods destroy millions of homes and dreams." May 24, 2024.

Beguería, Santiago, Sergio M. Vicente Serrano, Fergus Reig-Gracia, and Borja Latorre Garcés. 2023. "SPEIbase v.2.9." Dataset.

Berger, Allen N. 2003. "The economic effects of technological progress: Evidence from the banking industry." *Journal of Money, credit and Banking*, 141–176.

Berg, Gunhild, and Jan Schrader. 2012. "Access to credit, natural disasters, and relationship lending." *Journal of financial intermediation*, 21(4): 549–568.

Berg, Tobias, Andreas Fuster, and Manju Puri. 2022. "Fintech lending." *Annual Review of Financial Economics*, 14(1): 187–207.

Bharti, Nitin Kumar, Lucas Chancel, Thomas Piketty, and Anmol Somanchi. 2024. "Income and Wealth Inequality in India, 1922-2023: The Rise of the Billionaire Raj." *World Inequality Lab Working Paper*.

Brunnermeier, Markus, Jonathan Payne, et al. 2022. "Platforms, tokens, and interoperability." *Unpublished Working Paper*.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2018. "Fintech, regulatory arbitrage, and the rise of shadow banks." *Journal of financial economics*, 130(3): 453–483.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2024. "Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy." *Journal of Political Economy*, 132(2): 616–693.

Business Wire. 2023. "World's Major Economies Playing Catch-Up as Widespread Adoption Drives Global Real-Time Payments Growth – ACI Worldwide Report." May 24, 2024.

CAFRAL. 2023. "India Finance Report 2023." August 23, 2024.

Chavaz, Matthieu. 2016. "Dis-integrating credit markets: diversification, securitization, and lending in a recovery."

Chernenko, Sergey, Isil Erel, and Robert Prilmeier. 2022. "Why do firms borrow directly from nonbanks?" *The Review of Financial Studies*, 35(11): 4902–4947.

Chintala, Sudhakar Reddy, Chandra Jha, P. Diwakar, and Vinay Dadhwal. 2015. "Nationwide classification of forest types of India using remote sensing and GIS." *Environmental Monitoring and Assessment*, 187.

Chodorow-Reich, Gabriel, Gita Gopinath, Prachi Mishra, and Abhinav Narayanan. 2020. "Cash and the economy: Evidence from India's demonetization." *The Quarterly Journal of Economics*, 135(1): 57–103.

CIBIL Report. 2022. "More than 160 Million Indians are Credit Underserved." April 25, 2022.

Collier, Benjamin L, Daniel A Hartley, Benjamin J Keys, and Jing Xian Ng. 2024. "Credit when you need it." National Bureau of Economic Research.

Corno, Lucia, Nicole Hildebrandt, and Alessandra Voena. 2020. "Age of marriage, weather shocks, and the direction of marriage payments." *Econometrica*, 88(3): 879–915.

Cortés, Kristle Romero. 2014. "Rebuilding after disaster strikes: How local lenders aid in the recovery."

Cortés, Kristle Romero, and Philip E Strahan. 2017. "Tracing out capital flows: How financially integrated banks respond to natural disasters." *Journal of Financial Economics*, 125(1): 182–199.

Crouzet, Nicolas, Apoorv Gupta, and Filippo Mezzanotti. 2023. "Shocks and technology adoption: Evidence from electronic payment systems." *Journal of Political Economy*, 131(11): 3003–3065.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2009. "Temperature and income: reconciling new cross-sectional and panel estimates." *American Economic Review*, 99(2): 198–204.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2014. "What do we learn from the weather? The new climate-economy literature." *Journal of Economic literature*, 52(3): 740–798.

De Roure, Calebe, Loriana Pelizzon, and Anjan Thakor. 2022. "P2P lenders versus banks: Cream skimming or bottom fishing?" *The Review of Corporate Finance Studies*, 11(2): 213–262.

De Roure, Calebe, Loriana Pelizzon, and Paolo Tasca. 2016. "How does P2P lending fit into the consumer credit market?"

Di Maggio, Marco, and Vincent Yao. 2021. "Fintech borrowers: Lax screening or cream-skimming?" *The Review of Financial Studies*, 34(10): 4565–4618.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The deposits channel of monetary policy." *The Quarterly Journal of Economics*, 132(4): 1819–1876.

Dubey, Tamanna Singh, and Amiyatosh Purnanandam. 2024. "Can Cashless Payments Spur Economic Growth?" *SSRN Working Paper*.

Dutta, Harsha, Pulak Ghosh, Arkodipta Sarkar, and Nishant Vats. 2021. "Political Power-Sharing, Firm Entry, and Economic Growth: Evidence from Multiple Elected Representatives." *Firm Entry, and Economic Growth: Evidence from Multiple Elected Representatives (November 21, 2021)*.

Economic Times. 2023. "Economic Times (Indian newspaper), Vegetable prices on boil on flood rain, household budgets suffer." May 24, 2024.

Erel, Isil, and Eduard Inozemtsev. 2024. "Evolution of debt financing toward less-regulated financial intermediaries in the united states." *Journal of Financial and Quantitative Analysis*, 1–38.

Frame, W Scott, Larry D Wall, and Lawrence J White. 2018. "Technological change and financial innovation in banking: Some implications for fintech."

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery. 2019. "The role of technology in mortgage lending." *The Review of Financial Studies*, 32(5): 1854–1899.

Ghosh, Pulak, Boris Vallee, and Yao Zeng. 2022. "FinTech lending and cashless payments."

Gopal, Manasa, and Philipp Schnabl. 2022. "The rise of finance companies and fintech lenders in small business lending." *The Review of Financial Studies*, 35(11): 4859–4901.

Graff Zivin, Joshua, and Matthew Neidell. 2014. "Temperature and the allocation of time: Implications for climate change." *Journal of Labor Economics*, 32(1): 1–26.

Higgins, Sean. 2022. "Financial technology adoption: Network externalities of cashless payments in mexico." *American Economic Review, Forthcoming*.

Indian Express. 2023. "Delhi floods aftermath: After the deluge, come disease and disorder." May 24, 2024.

Irani, Rustom M, Rajkamal Iyer, Ralf R Meisenzahl, and Jose-Luis Peydro. 2021. "The rise of shadow banking: Evidence from capital regulation." *The Review of Financial Studies*, 34(5): 2181–2235.

Jack, William, and Tavneet Suri. 2014. "Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution." *American Economic Review*, 104(1): 183–223.

Jayachandran, Seema. 2006. "Selling labor low: Wage responses to productivity shocks in developing countries." *Journal of political Economy*, 114(3): 538–575.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2014. "Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?" *Econometrica*, 82(2): 463–505.

Kuchler, Theresa, Dominic Russel, and Johannes Stroebel. 2022. "JUE Insight: The geographic spread of COVID-19 correlates with the structure of social networks as measured by Facebook." *Journal of Urban Economics*, 127: 103314. JUE Insights: COVID-19 and Cities.

Kuchler, Theresa, Yan Li, Lin Peng, Johannes Stroebel, and Dexin Zhou. 2021. "Social Proximity to Capital: Implications for Investors and Firms." *The Review of Financial Studies*, 35(6): 2743–2789.

Kundu, Shohini, Seongjin Park, and Nishant Vats. 2021. "The geography of bank deposits and the origins of aggregate fluctuations." *Available at SSRN 3883605*.

Lane, Gregory. 2024. "Adapting to climate risk with guaranteed credit: Evidence from Bangladesh." *Econometrica*, 92(2): 355–386.

Liu, Maggie, Yogita Shamdasani, and Vis Taraz. 2023. "Climate change and labor reallocation: Evidence from six decades of the Indian Census." *American Economic Journal: Economic Policy*, 15(2): 395–423.

Mishra, Prachi, Nagpurnanand Prabhala, and Raghuram G Rajan. 2022. "The relationship dilemma: Why do banks differ in the pace at which they adopt new technology?" *The Review of Financial Studies*, 35(7): 3418–3466.

MMSME. 2023. "Ministry of MSME Annual Report." May 24, 2024.

MOAFW. 2020. "Ministry of Agriculture and Farmers Welfare Press Release Agrarian Land." May 24, 2024.

Morse, Adair. 2011. "Payday lenders: Heroes or villains?" *Journal of Financial Economics*, 102(1): 28–44.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar. 2016. "Building state capacity: Evidence from biometric smartcards in India." *American Economic Review*, 106(10): 2895–2929.

Philippon, Thomas. 2016. "The fintech opportunity." National Bureau of Economic Research.

Qi, Shusen, Runliang Li, and Hang Sun. 2021. "A lender in need is a lender indeed: Role of fintech lending after natural disasters." *Available at SSRN 3888096*.

Rajan, Raghuram, and Rodney Ramcharan. 2023. "Finance and climate resilience: Evidence from the long 1950s us drought." National Bureau of Economic Research.

RBI. 2021*a*. "FAQ: All you wanted to know about NBFCs." January 10, 2017.

RBI. 2021*b*. "RBI Bulletin: Responsible Digital Innovation - T Rabi Sankar." May 23, 2024.

Shah, Manisha, and Bryce Millett Steinberg. 2017. "Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital." *Journal of Political Economy*, 125(2): 527–561.

Tang, Huan. 2019. "Peer-to-peer lenders versus banks: substitutes or complements?" *The Review of Financial Studies*, 32(5): 1900–1938.

Thakor, Anjan V. 2020. "Fintech and banking: What do we know?" *Journal of financial intermediation*, 41: 100833.

Vats, Nishant. 2020. "What Does Financial Heterogeneity Say About the Transmission of Monetary Policy?" *Available at SSRN 3559650*.

Vicente-Serrano, Sergio M, Santiago Beguería, and Juan I López-Moreno. 2010. "A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index." *Journal of climate*, 23(7): 1696–1718.

Vives, Xavier. 2019. "Digital disruption in banking." *Annual Review of Financial Economics*, 11(1): 243–272.

Figures

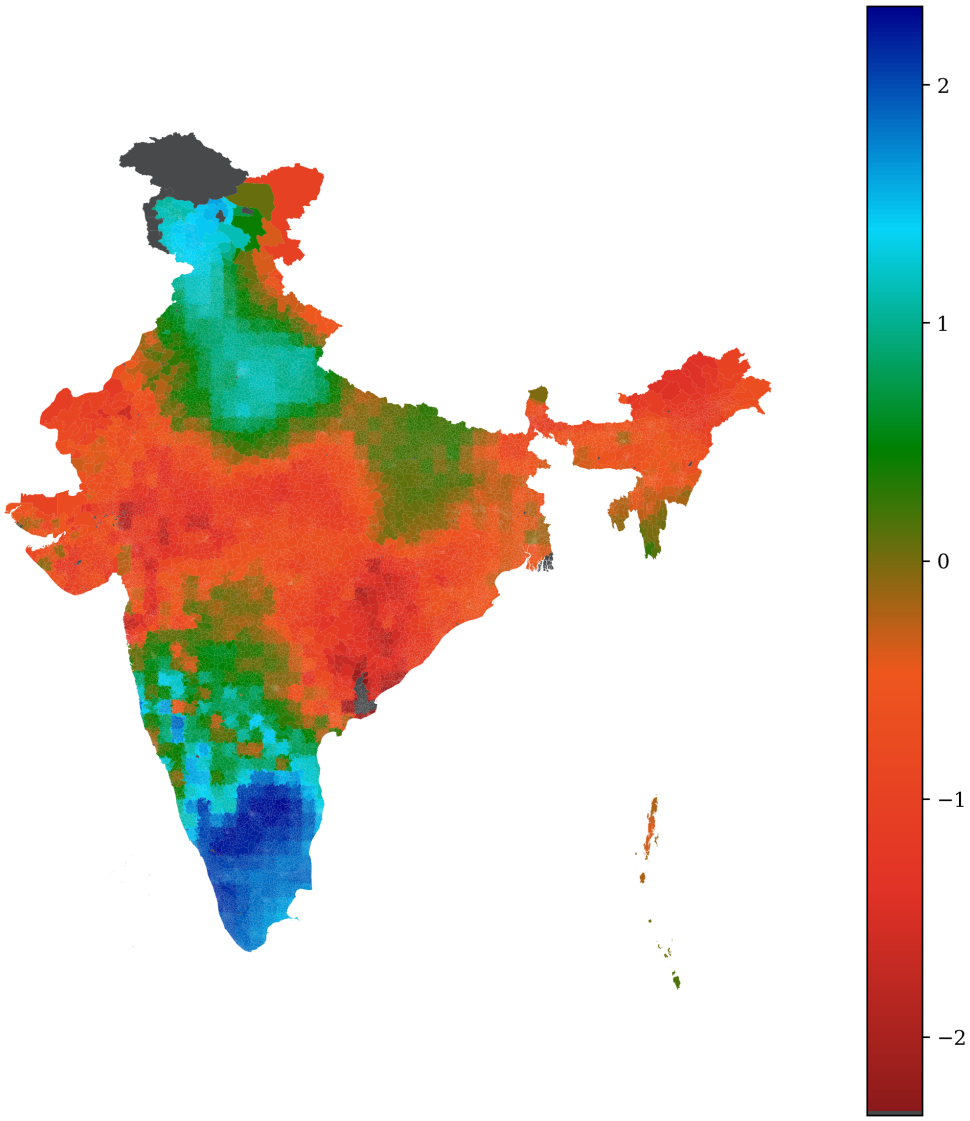


Figure 1: **Continuous Water Balance Variable (SPEI).** The figure presents the geographic ZIP-level distribution of the continuous water balance variable SPEI, for December 2020 as an example. The definition of the SPEI is outlined in Section 2. It has a mean of zero and standard deviation of one. The 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 A1). 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.

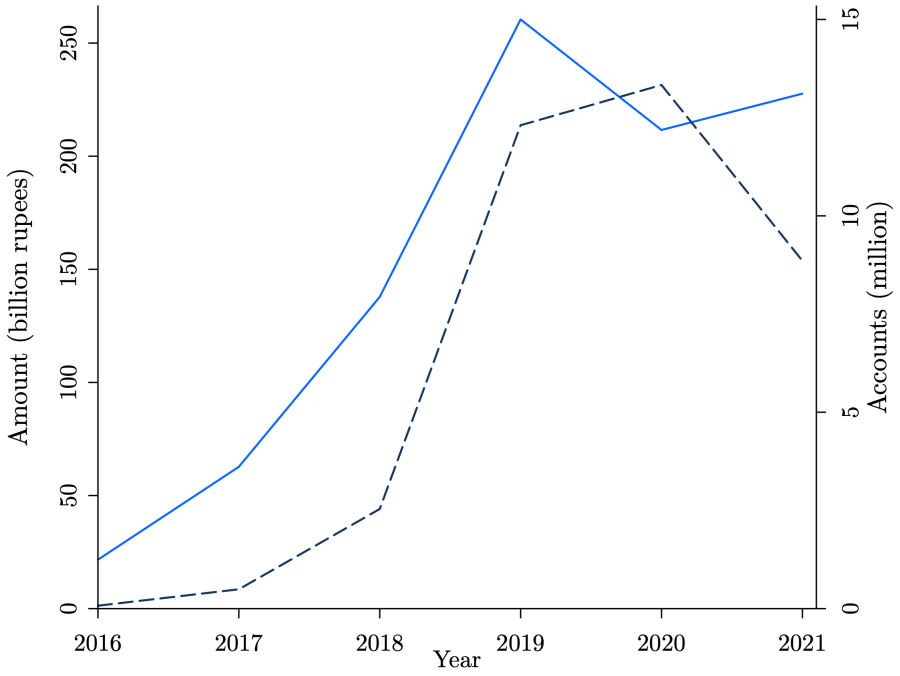


Figure 2: **Loan amount and number of accounts issued in a given year.** This figure shows the time series of Fintech growth between 2016 and 2021. The left-hand axis describes the aggregate loan amount in billion rupees (solid line). The right-hand axis denotes the aggregate loan accounts in millions (dashed line).

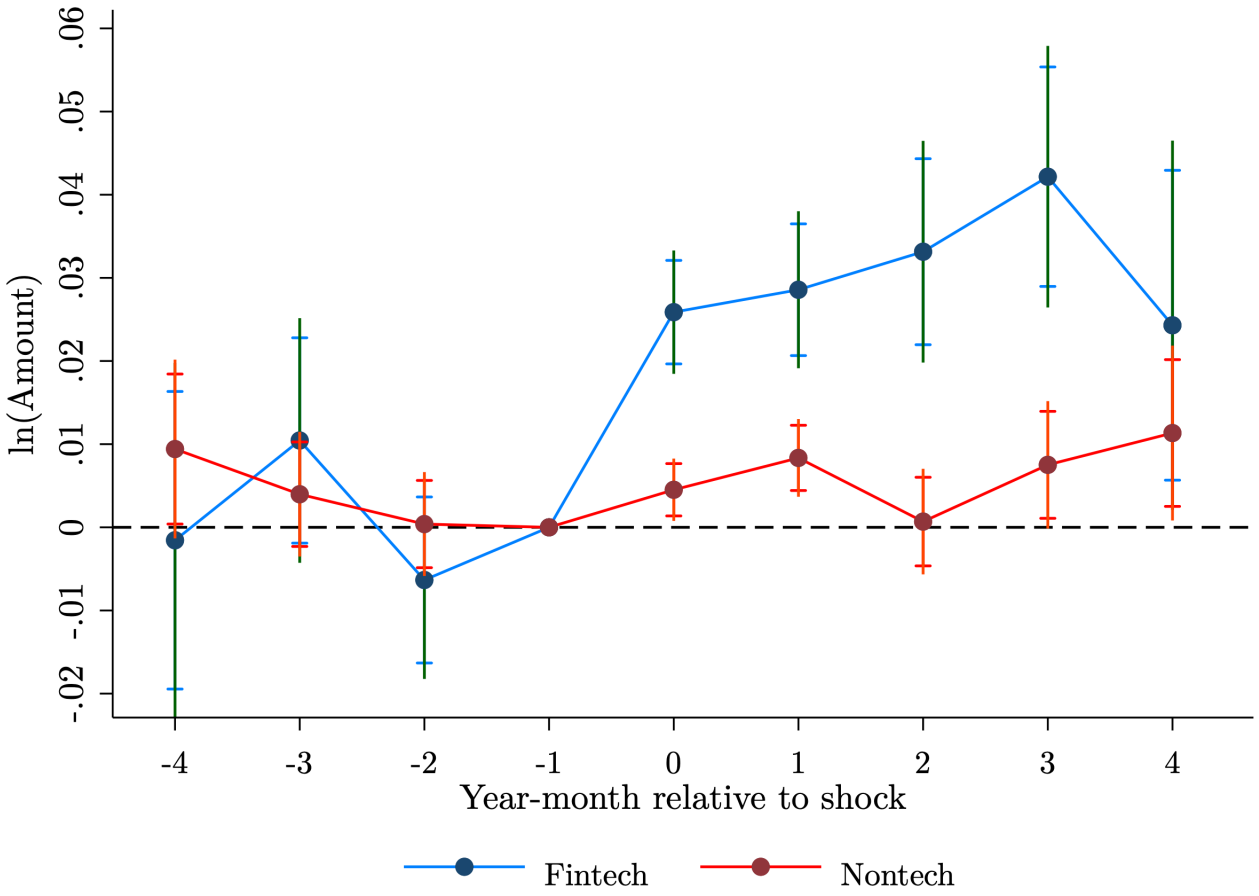


Figure 3: **Fintech and Nontech Credit Issuance, Amount**. This figure presents the dynamic effects of Fintech and Nontech credit issuance in response to a shock, compared to traditional lenders. Equation 4 describes the regression, where t is the year-month relative to the shock and the reference period 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.

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

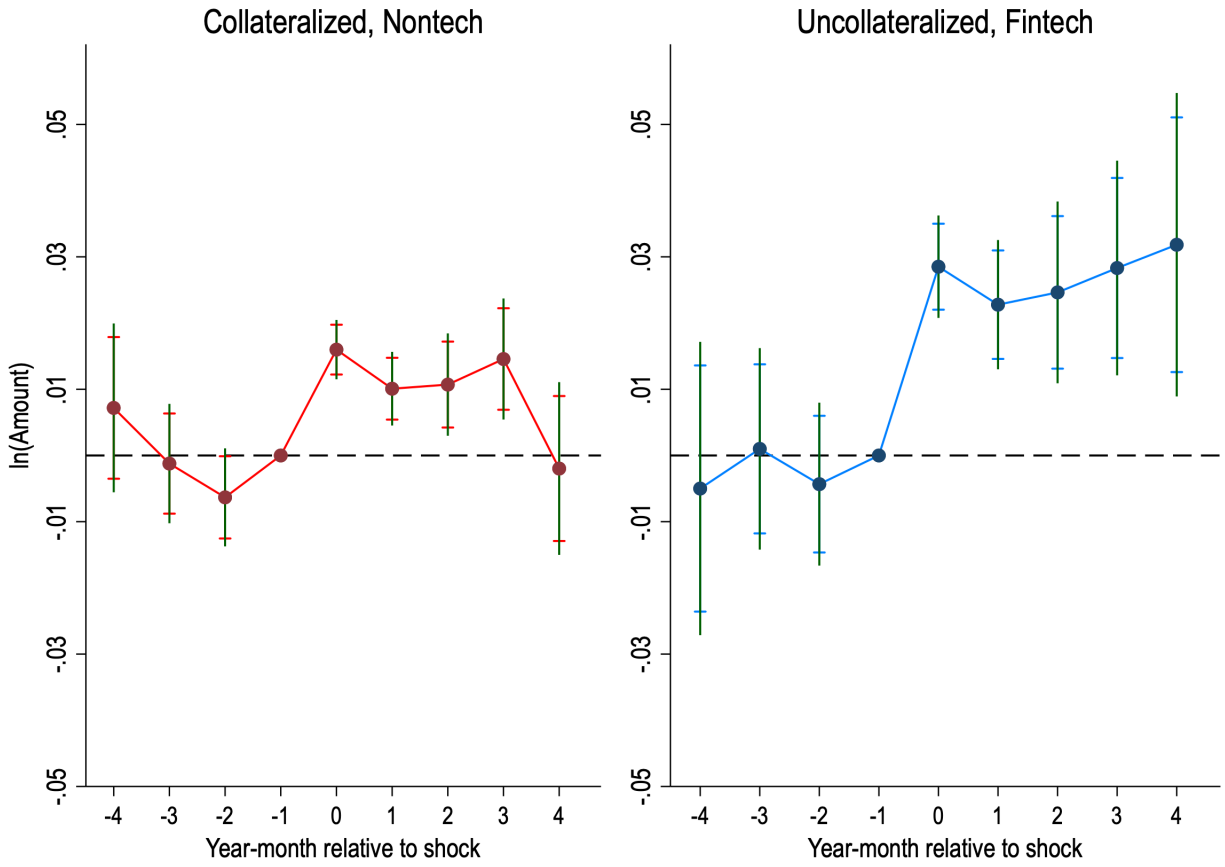


Figure 4: **Fintech and Nontech Credit Issuance, Amount, by Collateralization**. This figure presents the dynamic effects of Fintech and Nontech credit issuance in response to a shock, compared to traditional lenders, for collateralized loans (agricultural, gold, vehicle) and uncollateralized loans (business, 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. The figure shows 90% and 95% confidence intervals.

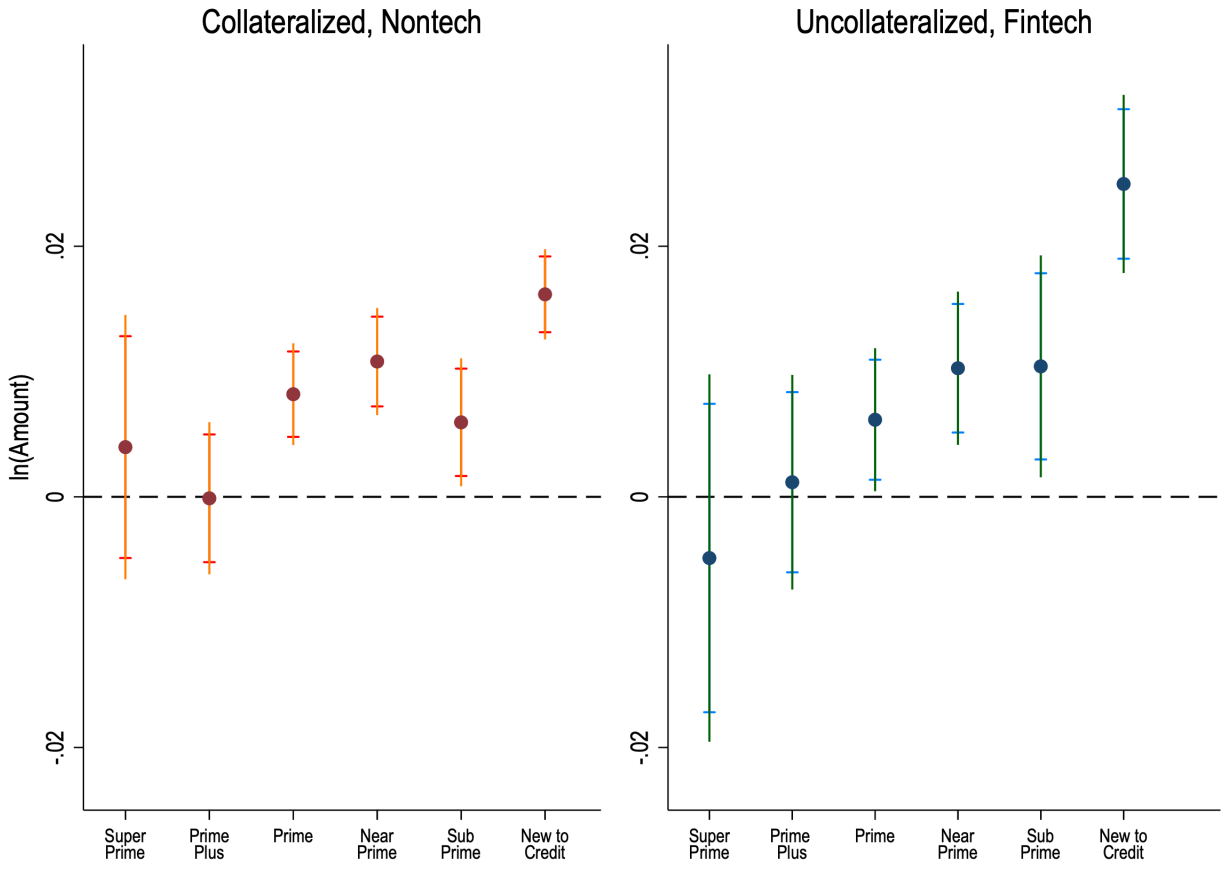
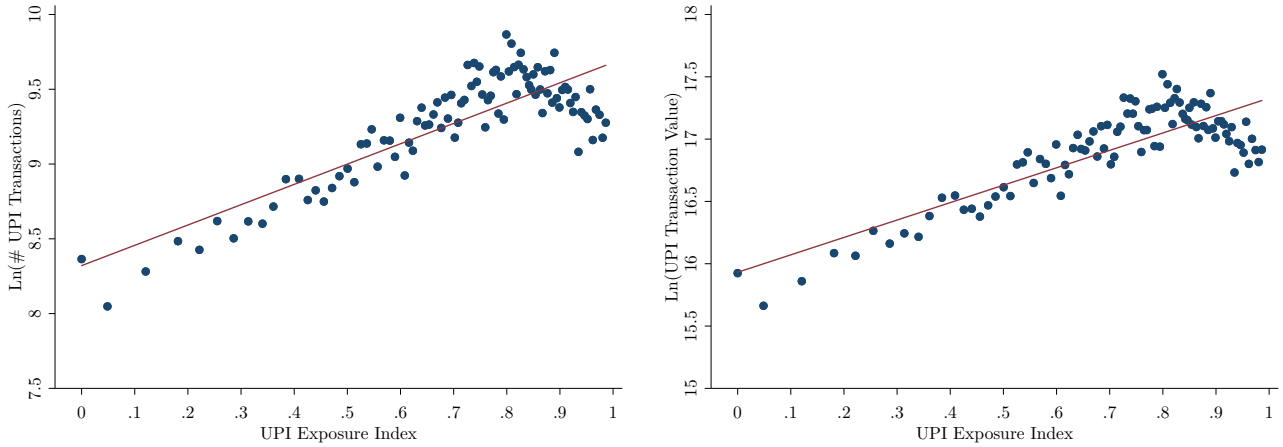


Figure 5: **Fintech and Nontech Credit Issuance, Amount, by Credit Score**. This figure presents the coefficients of Fintech and Nontech credit issuance in response to a shock, compared to traditional lenders by product type for collateralized loans (agricultural, gold, vehicle) and uncollateralized 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. The figure shows 90% and 95% confidence intervals.



(a) UPI Transaction Volume

(b) UPI Transaction Value

Figure 6: **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 6a plots the natural logarithm of UPI transaction volume or the number of UPI transactions. The Y-axis of Figure 6b plots the natural logarithm of UPI transaction value. All variables are winsorized at 1% level.

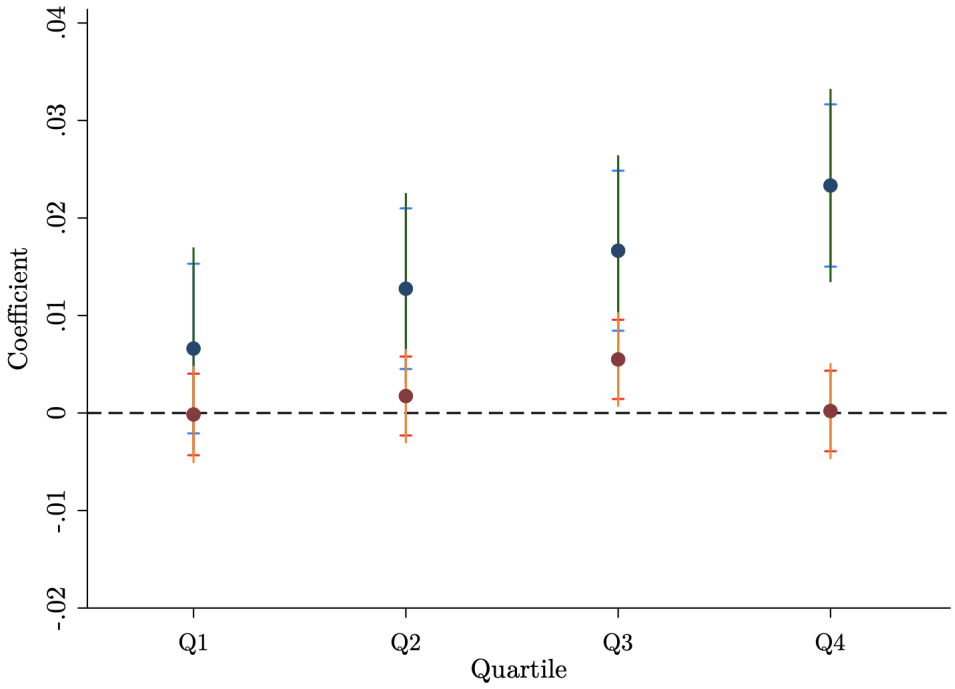


Figure 7: **Heterogeneity by UPI Index, Fintech and Nontech**. Blue circles represent Fintech, while maroon circles represent Nontech. This figure presents Fintech and Nontech credit issuance after a shock, compared to other lenders, separately by ZIP code level UPI index. The data is on the year-month-ZIP-lender-product 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. $\text{Shock}_{ym,z}$ 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 1: **Fintech and Nontech Credit Issuance**

	ln(Amount)			
	(1)	(2)	(3)	(4)
Fintech × Shock	0.0519***	0.0480***	0.0535***	0.0157***
	(0.0032)	(0.0029)	(0.0030)	(0.0023)
Nontech × Shock	-0.0101***	-0.0094***	-0.0095***	0.0031***
	(0.0015)	(0.0015)	(0.0015)	(0.0011)
Shock	0.0215***	0.0015**		
	(0.0018)	(0.0007)		
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	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
Years	6	6	6	6
R-squared	0.14	0.36	0.39	0.84
Observations	20,459,958	20,459,958	20,459,958	20,459,958

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 2: **Fintech and Nontech Credit Issuance – Extensive Margin**

	Accounts			
	(1)	(2)	(3)	(4)
Fintech × Shock	1.4105***	1.4536***	1.4490***	0.1953**
	(0.1017)	(0.0851)	(0.0841)	(0.0837)
Nontech × Shock	0.3851***	0.4400***	0.4414***	-0.0307
	(0.0709)	(0.0714)	(0.0721)	(0.0412)
Shock	0.9128***	-0.0683***		
	(0.0517)	(0.0241)		
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.01
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
Year	6	6	6	6
R-squared	0.02	0.17	0.18	0.91
Observations	20,459,958	20,459,958	20,459,958	20,459,958

Notes: This table presents Fintech and Nontech number of loans ("accounts") issued after the shock, compared to traditional lenders. Equation 3 describes the regression. The data is on the year-month-ZIP-lender-product level. $\text{Accounts}_{ym,z,l,p}$ 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. $\text{Shock}_{ym,z}$ 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: **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 4: **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 5: **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 6: **Heterogeneity by Credit Score Type, Collateralized**

	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)6 . 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 7: **Heterogeneity by Credit Score Type, Uncollateralized**

	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. $\ln(\text{Amount})_{ym,z,l,p}$ 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 8: **Default Rates**

	Default Rate					
	All		Collateralized		Uncollateralized	
	1 Year	3 Years	1 Year	3 Years	1 Year	3 Years
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech × Shock	0.0003	0.0009**	0.0018	0.0062**	0.0007*	0.0010**
	(0.0003)	(0.0004)	(0.0019)	(0.0030)	(0.0003)	(0.0004)
Nontech × Shock	0.0001	-0.0000	-0.0004**	-0.0006**	0.0009***	0.0009***
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.54	0.03	0.24	0.02	0.60	0.74
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIPs	19,060	19,060	19,006	19,006	19,052	19,052
Years	6	6	6	6	6	6
R-squared	0.45	0.51	0.45	0.54	0.44	0.48
Observations	20,459,958	20,459,958	9,262,879	9,262,879	8,045,001	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 rate of defaulted loans, between zero and one, issued in that given year-month, after 1 year and 3 years. 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 9: **UPI Index & Other Observable Characteristics at Zipcode 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 et al. (2021). Average nightlight data comes from Agarwal et al. (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 10: **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 11: **Mechanism – Technology (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 12: **Mechanism – Technology (UPI Exposure, Collateralized)**

	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 13: **Mechanism – Technology (UPI Exposure, Uncollateralized)**

	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	0.0097*	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	Traiditional	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 14: **Mechanism – Technology (Fintech ABC)**

	Application Accepted (0 or 1)		
	All	New-to-Credit	Not New-to-Credit
	(1)	(2)	(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.

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

Table 15: **Mechanism – Connectedness (Facebook SCI exposure)**

	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 credit issuance after the shock, compared to other 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. $\ln(\text{Amount})_{ym,z,l,p}$ 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

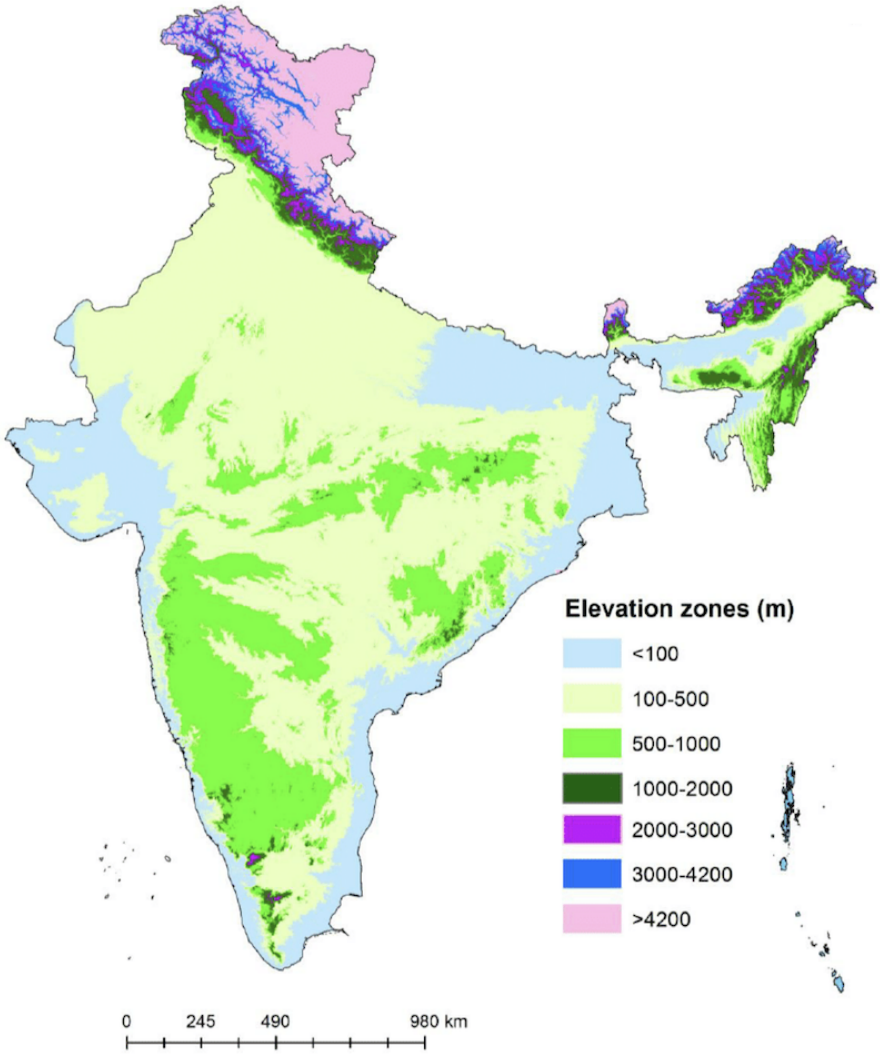


Figure A1: **Elevation.** The Figure presents the geographic distribution of the elevation profile of India, an important determinant of the weather, sourced from Chintala et al. (2015).

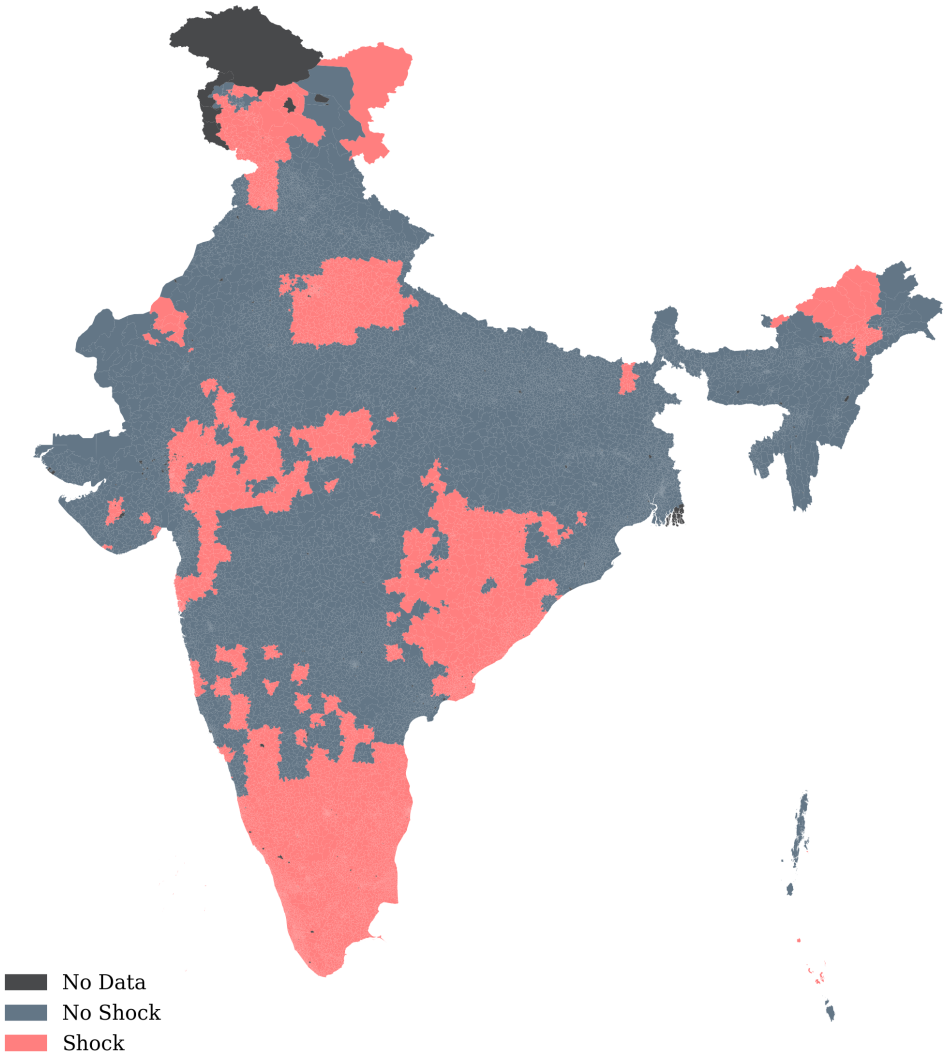
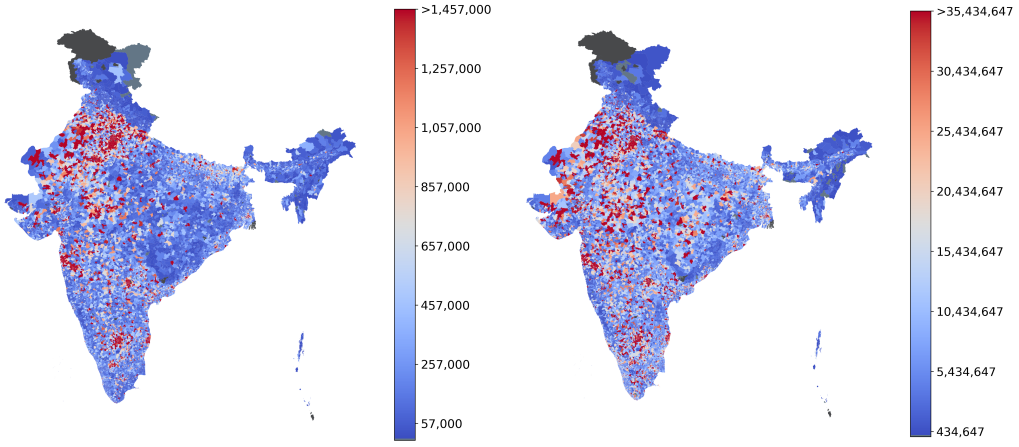


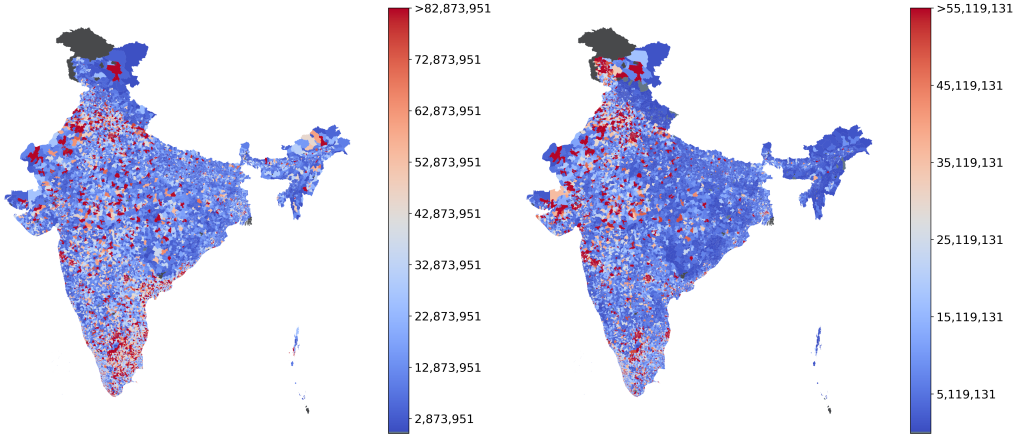
Figure A2: Weather Shock

Figure A3: **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 A1). 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.



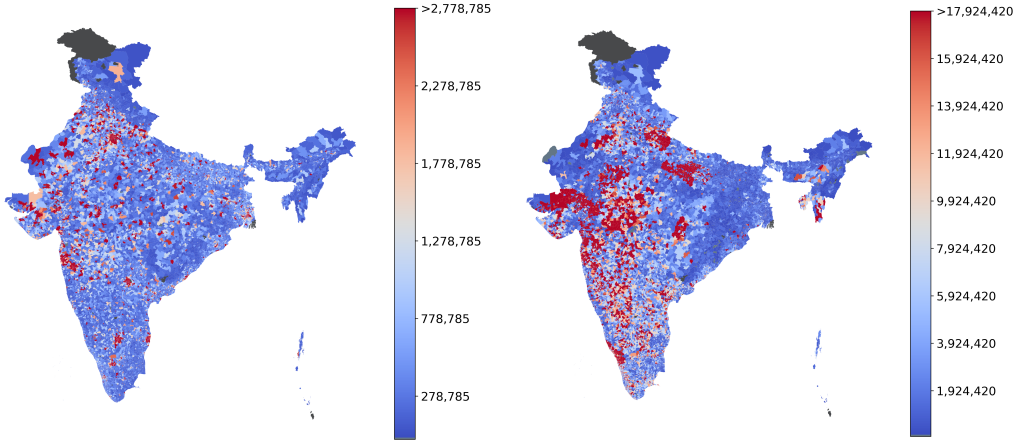
(a) Fintech

(b) Nontech



(c) Public

(d) Private



(e) Foreign

(f) Others

Figure A4: **Geographical Distribution of Lending.** 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.

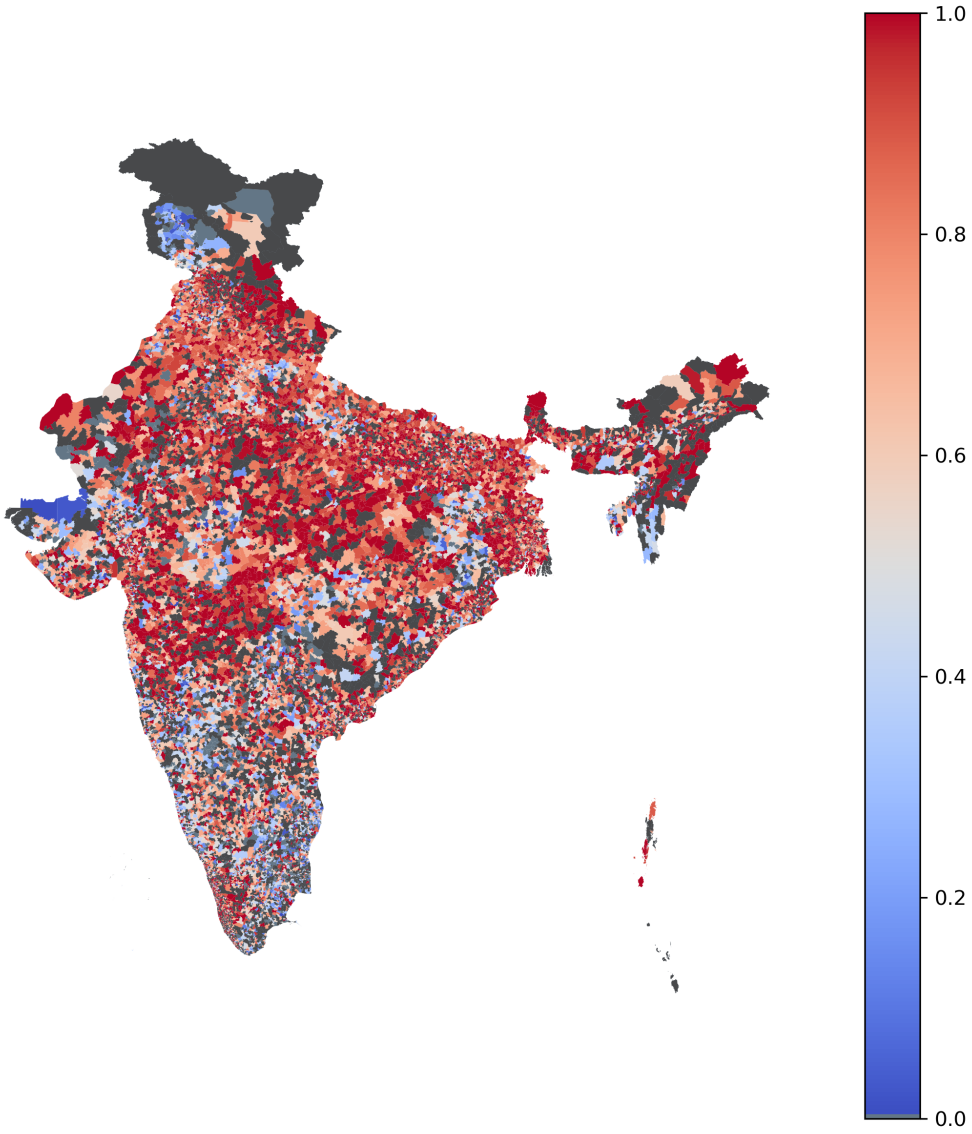


Figure A5: **UPI Index.** This figure reports the cross-sectional UPI index on the ZIP-level, constructed as described in Section 2. Light gray indicates zero, dark gray indicates missing.

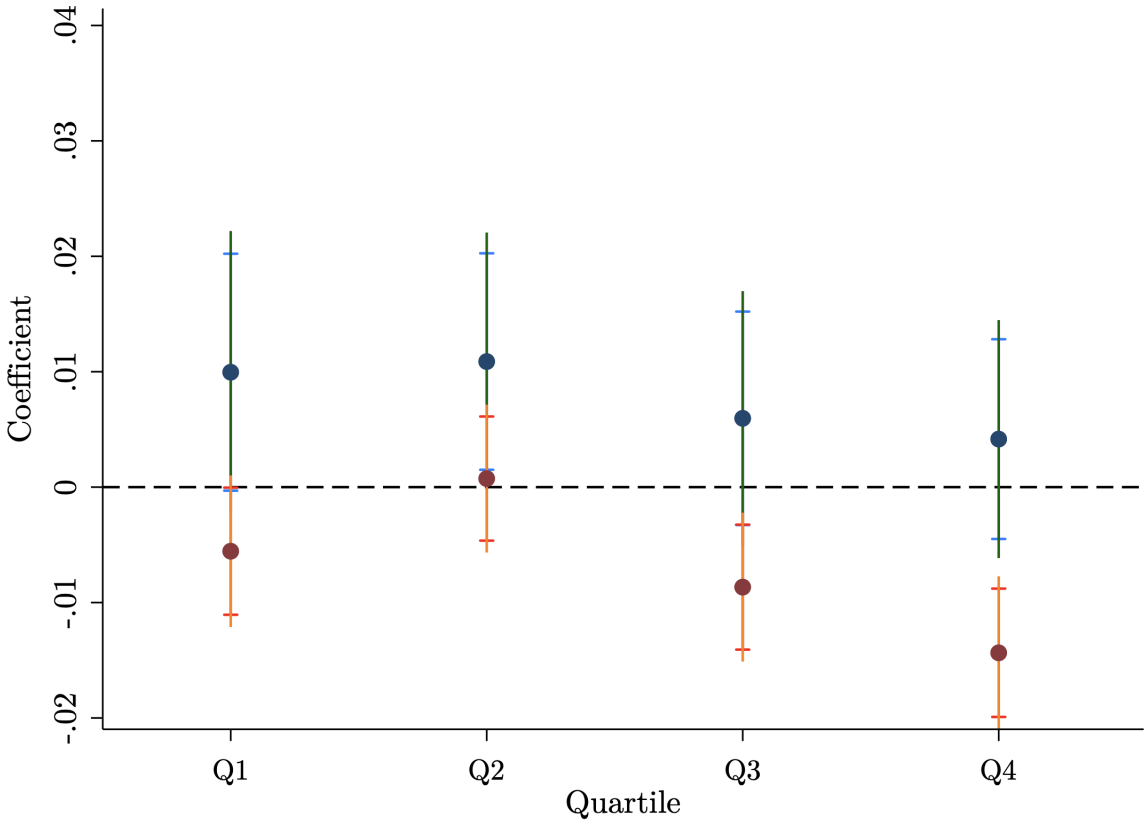
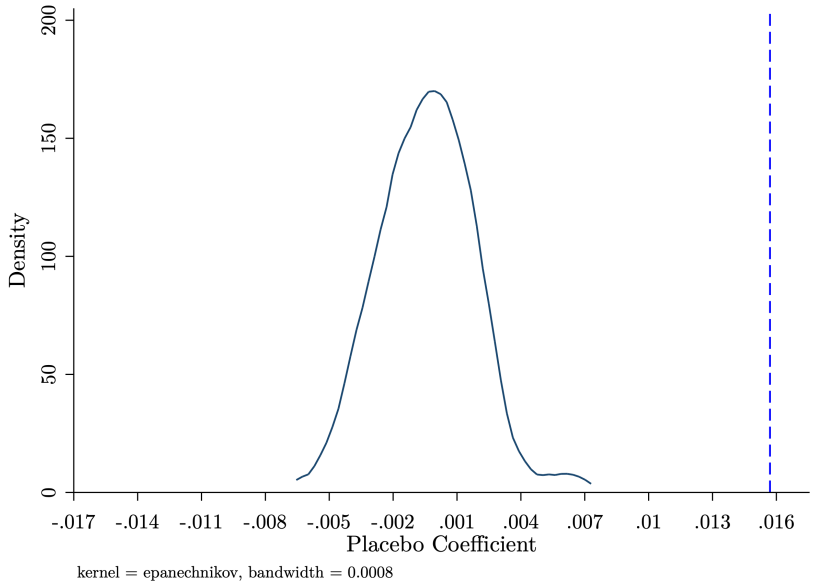
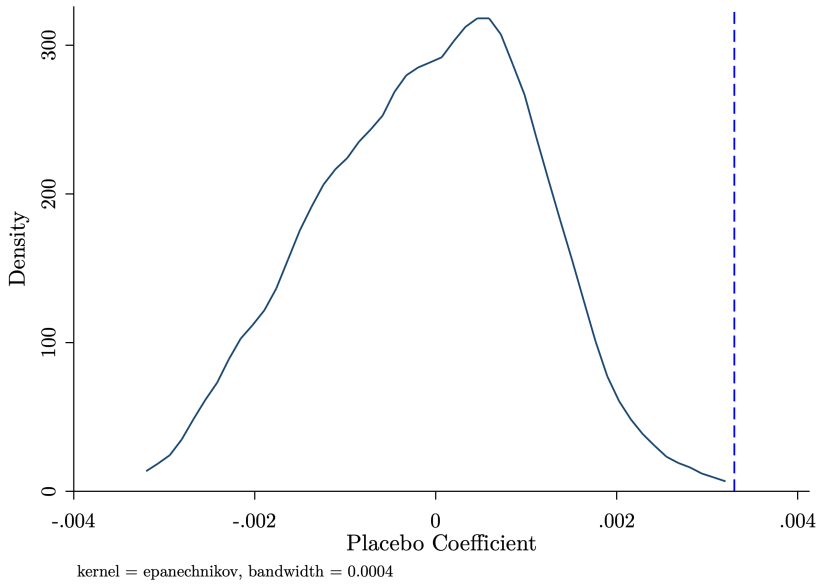


Figure A6: **Heterogeneity by Yono Transaction Value, Fintech and Nontech**. Blue circles represent Fintech, while maroon circles represent Nontech. This figure presents Fintech and Nontech credit issuance after a shock, compared to other lenders, separately by ZIP code level total Yono transaction value, scaled by a ZIP's population. 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. $\text{Shock}_{ym,z}$ 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.



(a) Fintech



(b) Nontech

Figure A7: **Placebo Test: Random Shock Dummies.** This figure presents the results of a placebo test. We run our regression Equation 3, corresponding to Column 4 in Table 1, 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 A1: **Indian Lending Landscape**

	Loan accounts (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%
	Amounts (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 accounts (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%
	Amounts (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 accounts (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%
	Amounts (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 accounts and amounts are winsorized at the 1st and 99th percentile.

Table A2: **Granular CIBIL Summary Statistics**

	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	20,459,958	0.0000	0.0000	0.1250	0.1094	0.2096
# 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 A3: **Granular CIBIL Summary Statistics by Lender**

Panel A: Public Sector Banks						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	4,612,254	0	0	0.0909	0.0832	0.1725
# 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
# Loans	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
36-month Default Rate	5,293,364	0	0	0.125	0.1013	0.1953
# Inquiries	5,293,364	0.58	3.58	14	18.81	45.66
Panel C: Foreign Banks						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	1,065,930	0	0	0.1014	0.088	0.1902
# Inquiries	1,065,930	0	0	0.17	1.05	7.35
Panel D: Nontech						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	5,055,554	0	0.0335	0.1905	0.13	0.2071
# Inquiries	5,055,554	0.08	3.92	27.83	32.4	66.14
Panel E: Fintech						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	1,307,221	0	0	0.125	0.1111	0.2144
# 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
# Loans	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
36-month Default Rate	3,125,635	0	0	0.1111	0.1352	0.2749
# 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 A4: **Granular CIBIL Summary Statistics by Product**

	# Obs	p25	p50	p75	Mean	SD
Panel A: Agriculture Loans						
# Loans	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
36-month Default Rate	3,269,797	0	0.0016	0.2	0.1453	0.2507
# Inquiries	3,269,797	0	0.67	3.83	4.99	14.48
Panel B: Gold Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	2,488,014	0	0	0.0311	0.0435	0.1211
# Inquiries	2,488,014	0	0	0.42	1.39	6.38
Panel C: Vehicle Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	3,505,068	0	0.0357	0.2282	0.1383	0.1997
# Inquiries	3,505,068	2.08	9.75	29.67	28.57	50.99
Panel D: Business Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	1,590,155	0	0	0.25	0.1675	0.2932
# Inquiries	1,590,155	0.33	1.58	5.5	6.94	19.03
Panel E: Consumption Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	6,069,098	0	0	0.1034	0.0874	0.1738
# Inquiries	6,069,098	0.42	6.5	27.75	34.06	67.75
Panel F: Microfinance Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	385,748	0	0	0.1263	0.1406	0.2816
# Inquiries	385,748	0	0.08	0.75	2.44	12.71
Panel G: Other						
	# Obs	p25	p50	p75	Mean	SD
# Loans	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
36-month Default Rate	3,152,078	0	0	0.1053	0.1012	0.2108
# 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 A5: **Granular CIBIL Summary Statistics by Lender and Credit Score**

Panel A: Public Sector Banks

	# Loans				Loan Amount				Default Rate 1 Yr				Default Rate 3 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.00	0.01	0.04	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	0.00	0.02	0.11	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	0.00	0.05	0.15	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	0.00	0.06	0.17	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	0.00	0.07	0.20	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	0.00	0.07	0.18	4,612,254	1.42	4.05	8.01

Panel B: Private Sector Banks

	# Loans				Loan Amount				Default Rate 1 Yr				Default Rate 3 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.01	0.04	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	0.00	0.03	0.12	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	0.00	0.06	0.17	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	0.00	0.07	0.20	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	0.00	0.06	0.20	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	0.00	0.08	0.20	5,293,364	0.92	5.27	12.21

Panel C: Foreign Banks

	# Loans				Loan Amount				Default Rate 1 Yr				Default Rate 3 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.01	0.06	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	0.04	0.15	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	0.07	0.19	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	0.05	0.19	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	0.03	0.14	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	0.04	0.15	1,065,930	0.00	0.05	0.49

Panel D: Nontech

	# Loans				Loan Amount				Default Rate 1 Yr				Default Rate 3 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.01	0.05	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	0.00	0.03	0.14	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	0.00	0.07	0.18	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	0.00	0.09	0.21	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	0.00	0.11	0.25	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	0.00	0.11	0.21	5,055,554	1.42	10.61	19.71

Panel E: Fintech

	# Loans				Loan Amount				Default Rate 1 Yr				Default Rate 3 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.00	0.04	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	0.00	0.02	0.11	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	0.00	0.06	0.17	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	0.00	0.08	0.19	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	0.00	0.07	0.21	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	0.00	0.07	0.19	1,307,221	1.33	7.91	16.29

Panel F: Other Financial Institutions

	# Loans				Loan Amount				Default Rate 1 Yr				Default Rate 3 Yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.00	0.04	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	0.02	0.13	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	0.06	0.21	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	0.06	0.22	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	0.07	0.23	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	0.08	0.24	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 A6: **Granular CIBIL Summary Statistics by Lender and Product**

Panel A: Public Sector Banks

	# Loans				Loan Amount				Default Rate 1 yr				Default Rate 3 yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.04	0.11	0.16	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	0.00	0.04	0.14	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	0.00	0.21	0.32	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	0.00	0.03	0.10	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	0.00	0.15	0.30	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	0.04	0.10	0.15	1,028,730	6.25	16.90	30.90

Panel B: Private Sector Banks

	# Loans				Loan Amount				Default Rate 1 yr				Default Rate 3 yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.00	0.15	0.27	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	0.00	0.04	0.11	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	0.04	0.13	0.19	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	0.00	0.11	0.25	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	0.05	0.09	0.13	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	0.00	0.10	0.21	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	0.00	0.11	0.24	682,216	2.25	11.91	33.80

Panel C: Foreign Banks

	# Loans				Loan Amount				Default Rate 1 yr				Default Rate 3 yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.12	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	0.09	0.26	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	0.09	0.19	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	0.00	0.02	0.12	22,480	0.08	1.91	11.73

Panel D: Nontech

	# Loans				Loan Amount				Default Rate 1 yr				Default Rate 3 yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.00	0.21	0.32	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	0.04	0.11	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	0.20	0.22	0.18	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	0.00	0.14	0.25	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	0.04	0.07	0.11	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	0.21	0.34	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	0.00	0.10	0.23	457,742	3.42	11.32	25.42

Panel E: Fintech

	# Loans				Loan Amount				Default Rate 1 yr				Default Rate 3 yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.07	0.24	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	0.14	0.32	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	0.16	0.31	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	0.00	0.18	0.31	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	0.05	0.09	0.15	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	0.00	0.02	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	0.11	0.27	150,959	0.00	0.58	3.53

Panel F: Other Financial Institutions

	# Loans				Loan Amount				Default Rate 1 yr				Default Rate 3 yr				# Inquiries			
	# Obs	Median	Mean	SD	# 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	0.00	0.13	0.26	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	0.15	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	0.00	0.14	0.30	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	0.00	0.24	0.36	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	0.00	0.24	0.36	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	0.23	0.37	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	0.00	0.10	0.22	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 A7: **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/.

Table A8: **Fintech Credit Demand**

	Applications			
	(1)	(2)	(3)	(4)
Fintech × Shock	63.5872***	66.6162***	64.3486***	8.5038***
	(1.1300)	(1.0678)	(1.0503)	(1.3125)
Nontech × Shock	35.7538***	34.3700***	34.7332***	0.6529
	(0.8908)	(0.8727)	(0.8790)	(0.7330)
Shock	23.7335***	-14.6126***		
	(0.9352)	(0.3564)		
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	0.00
Lender FE	✓	✓	✓	
Year FE		✓		
ZIP FE		✓		
Year × ZIP FE			✓	
Year × ZIP × Product FE				✓
Year × Lender × Product FE				✓
ZIP × Lender × Product FE				✓
ZIPs	19,080	19,080	19,080	19,080
Years	6	6	6	6
R-squared	0.04	0.25	0.26	0.94
Observations	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. 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 A9: **Fintech Credit Demand – Heterogeneity by Collateralization**

	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 A10: **Fintech Credit Demand – Heterogeneity by Product Type**

	Applications						
		Collateralized			Uncollateralized		
	All	Agric	Gold	Vehicle	Busi	Cons	MFI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fintech × Shock	8.5038***	-4.3645*	-44.8231	0.6435	7.2851***	9.5386***	42.8424***
	(1.3125)	(2.2741)	(45.3679)	(1.6224)	(0.7463)	(2.8996)	(5.2131)
Nontech × Shock	0.6529	15.7899***	4.6678***	6.3546***	-1.1718	-21.3644***	6.9190***
	(0.7330)	(1.1863)	(1.0689)	(1.0328)	(0.9021)	(2.9104)	(1.5536)
Omitted Category	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.28	0.00	0.00	0.00	0.00
Year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,080	18,512	8,409	19,062	18,913	19,077	16,476
Years	6	6	6	6	6	6	6
R-squared	0.94	0.87	0.96	0.98	0.92	0.92	0.74
Observations	3,002,434	336,592	74,471	440,135	501,262	572,726	205,095

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 A11: **Fintech Credit Demand – 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. $\text{Inquiries}_{y,z,l,p}$ 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 A12: **Fintech Credit Demand, Collateralized – 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 A13: **Fintech Credit Demand, Uncollateralized – 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	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 A14: **Robustness – Absolute Specification**

	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 6 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.

$$y_{ym,z,p} = \beta \cdot \text{Shock}_{ym,z} + \text{FE}_{ym,p} + \text{FE}_{z,p} + \epsilon_{ym,z,p} \tag{6}$$

Table A15: **Robustness – Poisson Transformation**

	Amount
	(1)
Fintech × Shock	0.0400***
	(0.0039)
Nontech × Shock	0.0059***
	(0.0013)
Omitted Category	Traditional
Fintech × Shock = Nontech × Shock	0.00
ZIP × Year-month × Product FE	✓
Years × Lender × Product FE	✓
ZIP × Lender × Product FE	✓
ZIPs	19,083
Year-months	6
R-squared	0.93
Observations	35,991,285

Notes: This table presents robustness for our results in Table 1, 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 A16: **Robustness – Different Shock Severity**

	ln(Amount)	
	> 80th or < 20th Pct	> 90th or < 10th Pct
	(1)	(4)
Fintech × Shock	0.0157***	0.0161***
	(0.0023)	(0.0028)
Nontech × Shock	0.0031***	0.0013
	(0.0011)	(0.0014)
Omitted Category	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00
ZIP × Year-month × Product FE	✓	✓
Year-month × Lender × Product FE	✓	✓
ZIP × Lender × Product FE	✓	✓
ZIPs	19,060	19,060
Years	6	6
R-squared	0.84	0.84
Observations	20,459,958	20,459,958

Notes: This table presents robustness for our results in Table 1 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 A17: **Robustness – Different Shock Lengths**

	ln(Amount)		
	1 Month	3 Months	6 Months
	(1)	(2)	(3)
Fintech × Shock	0.0157***	0.0064***	0.0086***
	(0.0023)	(0.0024)	(0.0026)
Nontech × Shock	0.0031***	-0.0071***	-0.0094***
	(0.0011)	(0.0011)	(0.0013)
Omitted Category	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00
ZIP × Year-month × Product FE	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,060	19,060
Years	6	6	6
R-squared	0.84	0.84	0.84
Observations	20,459,958	20,459,958	20,459,958

Notes: This table presents robustness for our results in Table 1 based on number of months the SPEI refers to (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 A18: **Robustness – Continuous Water Balance Measure**

	ln(Amount)			
	(1)	(2)	(3)	(4)
Fintech × Shock	0.1233***	0.0521***	0.0575***	0.0119***
	(0.0028)	(0.0024)	(0.0026)	(0.0019)
Nontech × Shock	0.0274***	-0.0150***	-0.0179***	-0.0007
	(0.0014)	(0.0013)	(0.0015)	(0.0010)
Omitted Category	Traditional	Traditional	Traditional	Traditional
Fintech × Shock = Nontech × Shock	0.00	0.00	0.00	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
Years	6	6	6	6
R-squared	0.14	0.36	0.39	0.83
Observations	20,459,958	20,459,958	20,459,958	20,459,958

Notes: This table presents robustness for our results in Table 1 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 A19: **Robustness – Excluding Covid Period**

	ln(Amount)			
	(1)	(2)	(3)	(4)
Fintech × Shock	0.0804***	0.0701***	0.0819***	0.0288***
	(0.0048)	(0.0042)	(0.0043)	(0.0033)
Nontech × Shock	-0.0034*	-0.0031*	-0.0025	0.0155***
	(0.0017)	(0.0017)	(0.0017)	(0.0013)
Shock	0.0230***	0.0035***		
	(0.0022)	(0.0009)		
Omitted Category	Traditional	Traditional	Traditional	Traditional
FinTech × Shock = Nontech × Shock	0.00	0.00	0.00	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	19,049	19,049	19,049	19,049
Years	4	4	4	4
R-squared	0.13	0.37	0.40	0.84
Observations	13,343,960	13,343,960	13,343,960	13,343,960

Notes: This table presents Fintech and Nontech credit issuance after the shock, compared to traditional lenders, excluding Covid period (excluding 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 A20: **Fintech ABC – Days to Disbursal**

	Days to Disbursal		
	All	New-to-Credit	Not New-to-Credit
	(1)	(2)	(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 A21: **Fintech ABC – 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.

Table A22: **Fintech ABC – 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.