Fintech to the Rescue: Navigating Climate Change

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Abstract

What role can Fintech play in climate change adaptation in developing countries? Combining the credit bureau data on formal loans in India with weather shock data, we demonstrate that Fintechs step in as credit providers in the aftermath of climate events. Their response is both rapid and economically meaningful. Fintechs especially help the vulnerable: they issue credit to borrowers who have a low to medium credit score or are new to formal credit. Default rates of Fintech lenders' loan portfolios do not show any economically meaningful increase. Thus, while Fintech lenders play a critical role in climate change adaptation, climate risk does not shift toward the balance sheets of Fintech lenders. We examine what allows Fintechs to show a stronger response than other lenders and find that a lower regulatory burden or shock-insensitive funding is unlikely to drive the result. Instead, we document that advanced technology and alternative data enable Fintechs to promptly react to climate disruptions and identify underserved but credit-worthy segments not reached by traditional banks. Broadly, our findings indicate that technology and alternative data-based lending are effective at managing fluctuations in credit demand due to climate disruptions, particularly benefiting individuals who are financially marginalized or excluded.

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1 Introduction

Developing nations confront significant hurdles in adapting to climate change. They are more vulnerable than their developed counterparts and lack the resources needed for an effective response (Nordhaus, 2019). Moreover, the existing resources may not be efficiently distributed to households and businesses in need due to incomplete financial markets. A significant stride toward more complete financial markets has been the emergence of technology-driven lending, known as Fintech (Morse, 2015; Thakor, 2020; Branzoli and Supino, 2020). Fintechs may be better at responding to climate shocks for three reasons. First, they face lower regulatory barriers than traditional banks, enabling them to engage in riskier lending practices in regions prone to climate-related disruptions. Second, they are less likely to experience a decrease in funding than traditional banks, which might observe a deposit outflow under shocks. Third, the integration of technology enhances their capacity to adapt to such challenges swiftly.[1] Alternatively, as climate change intensifies and prolongs climate shocks, profit-maximizing Fintechs might respond by reducing credit disbursal. Despite significant academic and policy discussions on the role of Fintechs in mitigating climate-related disruptions, empirical evidence remains limited.

This paper attempts to fillt his gap by investigating the role (if any) that Fintechs can play in climate adaptation. For our analysis, we utilize granular credit bureau data from India, which reports every formal loan issued nationwide by lender type. We combine the credit bureau data with granular monthly ZIP code level weather data. Specifcially we utilize the geo-spatial data on Standardized Precipitation and Evapotranspiration Index (SPEI) index observed at 0.5×0.5 degree to construct local climate shocks.[2] This allows us to investigate how Fintech lending responds to climate shocks, what types of loans are issued, and whether climate risk reflects on the loan portfolios of Fintech providers. Additionally, we investigate what features of Fintech enable it to respond differently than traditional lenders.

We employ a granular difference-in-difference strategy that includes year-month $\times$ ZIP $\times$ product fixed effects. Therefore, the coefficient of interest is the interaction term of the local climate shock and Fintech, capturing the effect of the weather shock on the outcome variable for Fintechs relative to other providers within the same ZIP code, the same year-month, and the same product category. We also include year-month $\times$ lender $\times$ product fixed effects to

[1] Buchak et al. (2018) combine empirical evidence with a structural model of the US mortgage market to demonstrate the importance of lower regulatory burdens and the technological advantages of Fintechs. Fuster et al. (2019) provide micro-evidence from the same market, showing that Fintechs process applications faster without increasing default rates, supporting the hypothesis of Fintechs' technological advantage.

[2] We use the terms local climate shocks and weather shocks interchangeably.

control for all time-varying shocks at the lender-product level. The inclusion of this fixed effect is important as Fintech lending can be a substitute when other lender types are hit by a negative shock and reduce credit (Tang, 2019; De Roure, Pelizzon and Thakor, 2022).

Our key identification assumption is that the interaction of the climate event with Fintech is plausibly exogenous. While a long-standing literature establishes the exogeneity of weather shocks as employed in this study (Dell, Jones and Olken, 2014), we need to address two potential threats to identification. First, Fintechs might react more strongly because they specialize in products that experience a large increase in credit demand after weather shocks. The inclusion of year-month × ZIP × product fixed effects effectively addresses this concern by controlling for product-specific demand shocks that may be collinear with weather shocks. A second potential concern may be that Fintechs might react more strongly because they focus on areas that experience a large increase in credit demand after a weather shock. We address this issue by including the ZIP × lender × product fixed effect that 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. Ultimately, we require the parallel trends assumption to hold. This ensures that the estimate is not influenced by pre-existing trends between Fintechs and other lenders. While this assumption is untestable, we will document parallel pre-trends in an event study analysis.

Our first result shows that Fintech providers issue more credit in response to climate shocks than traditional banks. The response is economically meaningful and statistically significant. Specifically, we document that Fintechs issue 1.49% more credit after climate shocks than other providers 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 201 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 7% of monthly expenditure in urban areas and 12% of monthly expenditure in rural areas.[3] Additionally, this relative increase in Fintech credit per borrower amounts to 5% of the average monthly income of a casual worker.

Next, we investigate the dynamic response of credit issuance over time and examine the pre-trends. There are two key takeaways from this analysis. First, the results indicate that the pre-trends are unlikely to drive our results suggesting that the parallel trends assumption

[3]For the bottom 5th percentile of monthly expenditure, the relative increase in Fintech credit per borrower corresponds to 18% in urban areas and 27% in rural areas. For the top 5th percentile, the effects are 3% of monthly expenditure in urban areas and 5% of monthly expenditure in rural areas.

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 this analysis indicates that the response of Fintech is both immediate and persistent.

On the extensive margin, we document that the number of loans by Fintechs, relative to other providers, on the ZIP-year-month-product level increases by 0.71%. In aggregate, this extensive margin effect translates to an effect of 3.68 thousand extra loans in a month and 261 thousand additional loans over our study period. We also document that the extensive margin result is unlikely to be driven by pre-trends, further indicating that the parallel trends assumption is likely to hold.

Our second result documents that the relative increase in credit issuance by Fintechs following a climate shock is driven by certain product types. Specifically, consumption loans increase by 1.07%, business loans by 5.08%, and microfinance loans by 7.86%. This result suggests that climate shocks increase the demand for credit to cover consumption and working capital needs, which Fintechs supply more readily. Meanwhile, we do not find a statistically significant effect for agricultural and gold loans. This may be explained by the fact that these loans are mostly collateralized, while Fintechs, primarily online lenders, do not typically engage in secured lending that requires a physical office presence.

Our third result documents that Fintechs primarily increase credit to borrowers with a low- and medium-credit score or who are new-to-credit.[4] Meanwhile, lending to high-credit-score segments does not increase. Using inquiries as a proxy for demand, we show that the heterogeneity in loan issuance by Fintechs across credit score types is not driven by greater demand by low- and medium-credit score individuals. Rather, the results indicate a supply-side mechanism, i.e., Fintechs supply disproportionally more credit to low- and medium-score borrowers following a climate shock.

A key takeaway from the second and third results is that Fintechs seem to serve vulnerable populations following a climate shock. For instance, the strongest impact is observed among MFI loans, which are specifically targeted at low-income individuals, especially women, in rural areas. These borrowers usually have an annual household income of less than 300,000 rupees (approximately 4,380 USD). Additionally, the increased credit issuance by Fintechs to new-to-credit and low- and medium-credit score borrowers supports the idea that Fintechs cater to marginalized populations after a climate shock. This finding is crucial from a policy perspective due to two reasons. First, low-income and financially excluded households

[4]New-to-credit borrowers are those with either no credit history, i.e., no prior borrowing in the formal lending markets or borrowers with unreliable credit history, i.e., borrowers with less than six months of credit history.

are most vulnerable to climate shocks (Nordhaus, 2019). Our results indicate that Fintechs can help increase the resilience of these groups to such shocks. Second, 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). Our results indicate that Fintechs increase credit to the unserved and underserved population following climate shocks, including them in the formal credit system. The inclusion of the unserved and underserved is crucial as it allows them to become permanent participants in the formal credit system (Balyuk, 2023).

Another implication of the documented heterogeneity in credit disbursal across credit score types is that Fintechs' loan portfolio shifts toward more risky credit. The fourth result in the paper documents if the ex-ante riskiness of the loan portfolio of Fintechs following a climate shock results in an ex-post risky balance sheet. Specifically, we examine Fintech's one- and three-year default rates and compare the default rates for loans issued following a climate shock and those during normal times. We do not observe economically meaningful increases in ex-post default. The result suggests that while Fintech seems 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 negligible. In other words, climate risk does not create ex-post risky balance sheets for Fintech lenders.

Next, we examine the underlying mechanism that allows Fintechs to respond stronger to climate shocks. We investigate three potential channels: lower regulatory burden faced by Fintechs, a less shock-sensitive funding base, and their relative technological advantage (Buchak et al., 2018; Fuster et al., 2019; Allen, Shan and Shen, 2023). The lower regulatory burden hypothesis would suggest that Fintechs are better equipped to take additional risk following climate shocks as they face lower regulatory constraints relative to traditional lenders. The funding hypothesis proposes that Fintechs experience less decrease in funding than traditional lenders, which might observe a deposit outflow as households and businesses need capital. The relative technological advantage hypothesis suggests that Fintechs are more capable of meeting heightened demand after a climate shock due to their technological capabilities. For instance, they can leverage advanced data mining techniques, including alternative and more timely data, to assess repayment capacity beyond traditional credit score metrics. This is crucial because climate shocks frequently lead to income disruptions. Credit score metrics relying on older, longer-term histories might be less effective in predicting future repayment behavior after such significant income shocks. Conversely, using more current alternative data, such as digital transaction records, could be more adept at evaluating immediate repayment capacity

following a climate shock.

We begin by examining the lower regulatory burden hypothesis. We reject this hypothesis on two grounds. First, the lower regulatory burden hypothesis suggests that reduced regulations lead to increased risk-taking, thereby raising the ex-ante riskiness of the portfolio. This hypothesis would also predict higher ex-post default rates as the portfolio shifts towards riskier borrowers. While we observe that Fintech lending increases for low-credit score and new-to-credit borrowers, we do not see a significant rise in ex-post defaults. This indicates that although the borrowers appear risky based on their credit scores, climate risk does not result in ex-post risky balance sheets for Fintech lenders.

Second, we compare outcomes among Fintechs and other shadow banks to those of traditional banks when confronted with climate shocks. The rationale behind this comparison is that if the reduced regulatory burden prompts Fintechs to increase lending to inherently riskier segments after climate shocks, we would anticipate similar behavior from other shadow banks, as they also operate under less regulatory scrutiny compared to traditional banks, and a regulatory burden similar to Fintechs. However, our findings show that shadow banks react similarly to traditional banks, suggesting that a lower regulatory burden alone is unlikely to fully explain how Fintechs respond to climate events. On the same grounds, we conclude that less shock-sensitive funding sources are unlikely to explain our results, as Fintechs have funding sources similar to those of other shadow banks.

Next, we investigate the relative technological advantage hypothesis. This hypothesis postulates that although Fintechs may elevate the ex-ante riskiness of their portfolio, indicated by credit scores, this does not necessarily lead to higher ex-post default rates. Our findings align with this prediction. We document that despite Fintechs extending more credit to low-credit score and new-to-credit borrowers, we do not observe an economically meaningful increase in ex-post default rates.

We provide a more direct test for this hypothesis by examining the heterogeneity in the effect based on geographic differences in the adoption of the Unified Payments Interface (UPI), which serves as the primary infrastructure for digital transactions in India. The rationale behind this test is that Fintechs leverage digital financial transaction records, which are accessible within an open banking framework. For example, when a borrower seeks a Fintech loan, she can grant access to her banking data to the lender. The lender can then analyze the latest transaction history alongside machine learning or AI models to ascertain the applicant's recent income, expenditure, and other data, thereby improving the assessment of her repayment capability.

We construct a UPI index à la Alok et al. (2024) that measures geographic variation in the early 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. 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 choose to rely on the UPI index instead of UPI transaction data since it is less prone to endogeneity issues, such as unobservable factors that drive credit demand and UPI transactions (Alok et al., 2024).

We document a monotonically increasing trend in the coefficient of the interaction of Fintech and Shock as we move from the first quartile to the fourth quartile of the UPI index distribution. The effect in the first quartile of the UPI index is 0.66% and rises to 2.33% in the fourth quartile of the UPI index. Overall, the result increases in magnitude as we move from the first to the fourth quartile of the UPI distribution, with the difference being both economically and statistically significant. This suggests that the technological advantage of Fintechs may be driving our main effect.

One concern with this analysis is that the UPI index may correlate with other unobserved factors positively related to digital adoption, which could confound the observed effect of Fintech loan issuance. To address this, we conduct a placebo test examining the heterogeneity of the effect based on geographic variation in Yono adoption. Yono is the digital banking platform of the State Bank of India, the country's largest bank. Since Yono also facilitates digital transactions, it could be expected to correlate with similar unobserved factors as the UPI index. However, unlike the UPI, Yono's transaction history is private and not included in the open banking framework, meaning it cannot be shared with other lenders. If the increasing pattern in the UPI index effect were due to unobserved factors rather than data sharing within the open banking framework, we would expect a similar pattern in areas with high Yono adoption. However, we do not observe an increasing trend in the effect across the quartiles of Yono adoption; instead, the effect remains flat. This indicates that the increase in coefficients across UPI adoption quartiles is not driven by unobserved factors but truly reflects the impact of data provision to Fintechs.

Next, we examine data from one of the largest Fintech companies in India, which focuses on lending to small businesses. This company creates a standardized score for each applicant based on their digital transactions, which we refer to as alternative data. Our goal is to

understand how the availability of this alternative data influences loan acceptance decisions after a climate shock at the application level. Our findings show that the score constructed from alternative data is positively correlated with loan acceptance following a climate shock, especially for new-to-credit borrowers. Moreover, applicants with higher alternative data scores, particularly new-to-credit applicants, tend to receive loans more quickly. These results suggest that technology, specifically the use of alternative data, plays a crucial role in enabling Fintech companies to provide 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. The primary specification analyzes the effect of Fintech relative to other providers, and we also show that this effect holds in absolute terms. Additionally, our results are robust when using a Poisson transformation. The second set of robustness tests focuses on the weather shock variable. The effect remains robust when we split our shock into wet events (e.g., floods) and dry events (e.g., droughts). It is also robust when 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. Finally, we conduct a placebo test by replacing our weather shock variable with a dummy that is randomly set to zero or one, based on the actual probability of the climate shock. Repeating this regression several times, we find that our baseline estimate does not fall within the range of placebo estimates, which are centered around zero. Collectively, these tests provide confidence in the robustness of our results.

The literature on Fintech and climate is still thin. Focusing on the collateralized mortgage market, Allen, Shan and Shen (2023) use HMDA data to show an increase in Fintech loan issuance in the United States after severe natural disasters that can destroy properties, such as strong storms. The authors find that loan-to-income ratios of borrowers increase post-disaster, while default rates remain stable. 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.[5] We complement this literature by providing first evidence on the universe of uncollateralized loans, offering a distinctive definition of the vulnerable based on new-to-credit, and showing the importance of technology as the key driver of Fintech loan issuance. 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

[5] Barros et al. (2023) show that natural disasters in Brazil increase the adoption of digital payment technology.

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.

This paper ties into a richer literature that investigates the response of traditional banks to natural disasters. Studies that have focused on the mortgage market generally find an increase in credit. Cortés and Strahan (2017) demonstrate that collateralized lending increases as households need to rebuild destroyed homes after disasters.[6] Similarly, Billings, Gallagher and Ricketts (2022) demonstrate an increase in bankruptcies for credit-constrained homeowners after a flood in the United States. Other studies have focused on agricultural credit, using bank balance sheet data. They confirm that weather shocks can increase agricultural credit issuance, but primarily in the short-run (Albert, Bustos and Ponticelli, 2021) and in regions with high ex-ante bank presence (Rajan and Ramcharan, 2023). Focusing on smaller credit providers, Lane (2024) extends microfinance credit in a randomized controlled trial to farmers in Bangladesh, showing that they are less severely affected after a flood. We contribute to this literature by investigating the role innovative Fintechs play, particularly in loan markets understudied by this literature, such as uncollateralized loans.

More broadly, our study speaks to a growing literature on Fintechs and other shadow banks. This literature has documented the rise of Fintechs and discussed potential drivers. In particular, our results that Fintechs leverage their technological advantage and utilize alternative data present micro-evidence of the conjecture presented in Gopal and Schnabl (2022) that the rise of non-bank lenders could be driven by their ability to overcome informational frictions. This hypothesis ties into a long-standing body of literature that highlights the role of information frictions in credit markets, traditionally focusing on banks as information producers.[7] Our result that especially marginal borrowers benefit ties into a discussion on whether Fintechs reduce disparities in credit access (Erel and Liebersohn, 2022). We add to this literature by documenting the underlying mechanism by which Fintechs can aid in reducing these disparities. This finding is also significant for policymakers, especially in emerging economies vulnerable to climate risks, as they consider data privacy regulations and the development of open banking frameworks.

[6]Other papers that have used natural disasters as exogenous variation in credit conditions include Morse (2011), Berg and Schrader (2012), Chavaz (2016), and Cortés (2014).

[7]See Bernanke (1983) ,James (1987), Hoshi, Kashyap and Scharfstein (1990), Petersen and Rajan (1994), Petersen and Rajan (1995), Berger and Udell (1995), Berger et al. (1998), Petersen and Rajan (2002), Berger et al. (2005), Degryse and Ongena (2005), Chava and Purnanandam (2011), Bolton et al. (2016), DeYoung et al. (2015), Berger, Bouwman and Kim (2017), Khwaja and Mian (2008), Paravisini (2008), Gormley (2010), Rampini and Viswanathan (2010), Amiti and Weinstein (2011), Chava and Purnanandam (2011), Schnabl (2012), Jiménez et al. (2014), Chodorow-Reich (2014),Duygan-Bump, Levkov and Montoriol-Garriga (2015), Paravisini et al. (2015), Paravisini, Rappoport and Schnabl (2023), Drechsler, Savov and Schnabl (2017), Amiti and Weinstein (2018), Gilje (2019), Wang et al. (2022), Boot (2000), Ongena and Smith (2000), and Berger (2014).

Our paper contributes to the growing literature on the role of technology in finance (see Philippon (2016) for an overview). A key result of the paper is that while Fintechs serve ex-ante risky population after climate shocks, climate risk does not show up on their balance sheet as increased default. We argue that their use of alternative data enables better acceptance decisions. This finding is closest in spirit to Fuster et al. (2019). Our contribution over this paper is to document the role Fintechs play in mitigating the effects of climate change by smoothing credit demand fluctuations following climate shocks. Moreover, we demonstrate that the technological advantage of Fintechs extends beyond faster credit disbursement. Lastly, our work ties into a new strand of literature that documents the importance of alternative data (Wilson, Summers and Hope, 2000; Khandani, Kim and Lo, 2010; Iyer et al., 2016; Frost et al., 2019; Gambacorta et al., 2019; Berg et al., 2020; Di Maggio, Ratnadiwakara and Carmichael, 2022; Ghosh, Vallee and Zeng, 2022; Dubey and Purnanandam, 2023; Alok et al., 2024; Babina et al., 2024). We contribute to this literature by documenting how Fintechs exploit alternative data to absorb excess demand after climate shocks.

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 baseline results documenting the relative increase in credit issuance by Fintechs after climate shocks. Section 6 documents the underlying mechanisms. Section 7 concludes.

2 Data

2.1 Credit Bureau Data

Our credit data comes from TransUnion CIBIL, which is India's oldest credit bureau.[8] The dataset covers the universe of all retail loans reported to CIBIL. 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 entirety of retail loans in India.

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

The monthly credit bureau data is provided to us at the ZIP code level from January 2016 until December 2021. Specifically, we track the total count of loans and the total loan amount approved each month within a ZIP code, categorized by lender type, and product type. That means that our data is on the level of year-month × ZIP × lender × product. On this level, we additionally observe a split of loan accounts and loan amount by credit score categories.

CIBIL reports six lender types, including Fintech – it is defined as a special type of lender that uses digital technologies such as mobile applications to deliver financial services (RBI, 2021). The other five lender types are non-banking financial companies (NBFCs), public sector banks, private sector banks, foreign banks, and other financial institutions. The seven product types are agriculture, business, consumption, gold, microfinance, vehicle, and other products. Microfinance loans are defined by CIBIL as loans of a comparatively smaller amount without collateral. They often have 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. Finally, credit score categories encompass super-prime, prime-plus, prime, near-prime, sub-prime, and new-to-credit borrowers.[9] New-to-credit borrowers do not yet have a credit score; thus, lenders experience the highest information asymmetry for these borrowers.

Besides loan issuance, we observe two more outcomes: the number of defaulted loans and loan inquiries. The number of defaulted loans are loans that are at least 90 days past due (DPD) within both one or three years of being issued. According to Reserve Bank of India (RBI) guidelines, a loan is officially considered in default once it reaches the 90 DPD threshold. For each category of year-month × ZIP × lender × product we observe the number of defaulted loans, where the year-month indicates the issuance time of the loan. 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.

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

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

not a perfect measure. To summarize, the CIBIL data is both comprehensive and available on a very granular level, which will be crucial for our empirical strategy.

2.2 Local Weather Shocks

Our construction of local weather shocks is based on the Standardized Precipitation and Evapotranspiration Index (SPEI), which we obtain from a database maintained by 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 measure to help readers understand the measure more readily. 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.[10] 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 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.[11] We use the ZIP code-level SPEI to construct our local weather shock variable. Our local weather shock

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

[11] 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.

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.[12] 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.

2.3 Mechanism Data

2.3.1 UPI Index

In addition to the credit bureau dataset and the local weather shocks dataset, we employ several other datasets to better identify the underlying mechanism. To explore the degree to which technology plays a role in Fintechs' relative advantage, 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 that applies for a loan at a Fintech can request her bank to share financial details like income and transaction from the bank to the lender. Thus, previous 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 follow Alok et al. (2024) to construct an UPI index that predicts UPI presence. The authors' empirical strategy is based on two observations. First, a bank account is necessary to use the full functionality of UPI. Second, previous literature has documented strong network externalities in digital payment adoption (Higgins, 2022; Crouzet, Gupta and Mezzanotti, 2023). The UPI index for a ZIP code z is defined as the share of total deposits of early adopter banks over total deposits of all banks. By construction, it thus ranges from zero to one and is a cross-sectional measure. The empirical strategy exploits

[12] We show our results are robust to employing alternative definitions of the local shock variable, such as using different cutoffs, separately estimating the effect of dry and wet shocks, or directly using the continuous measure, and among others. See Section 5.4. Figure A2a and A2b show examples of the dry and wet shock variables based on the SPEI measure in December 2020, to provide an example.

the staggered adoption of UPI by banks. Early adopters refer to banks that adopted UPI in November 2016, following Dubey and Purnanandam (2024).[13] Information on banks that were live on UPI as of November 2016 is provided by the Government of India.[14] 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:

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

2.3.2 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.

[13] 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.

[14] Available from the website http://cashlessindia.gov.in/upi_services.html.

3 Context and Summary Statistics

3.1 Weather Shocks and Credit Demand

Weather shocks have been on the rise globally. A long literature has discussed how these weather shocks can translate into *income shocks*. Most naturally, the reader might connect weather shocks with agricultural income shocks. Indeed, water balance is a critical input for agriculture. Farmers (119 million people in 2011) as well as agricultural wage workers (144 million people in 2011) are likely to experience change in incomes as agricultural yields are affected (Paxson, 1992; Guiteras, 2009; MOAFW, 2020).

However, literature has demonstrated that weather shocks translate also into income shocks for many other occupations. First, workers across occupations are likely to adjust their labor supply, for instance because it is too hot to go to work or critical transport infrastructure is damaged (Dell, Jones and Olken, 2009; Graff Zivin and Neidell, 2014). Second, as incomes decrease and customers are more likely to stay home, demand for goods and services slows down (Liu, Shamdasani and Taraz, 2023). This especially affects the 111 million workers in non-agricultural micro, small, and medium enterprises (MSMEs). With 1.76 workers on average, many of these MSMEs depend on day-to-day business revenues (MMSME, 2023). That weather shocks affect performance of non-agricultural firms has been confirmed by Aguilar-Gomez et al. (2024) and de Roux (2021).

Besides income shocks, weather shocks translate into *expense shocks*. Households might have liquidity needs to pay for rising food prices, and in extreme cases, health treatments as diseases spread, renovation of houses, or migration (Economic Times, 2023; BBC, 2020, 2022; Indian Express, 2023). Thus, there is strong evidence – both anecdotal and scientific – that weather shocks affect households across occupations, both through income shocks and expense shocks. These are likely to translate into credit needs. The open question is who will be able to serve this credit demand – and how?

3.2 Fintechs in the Indian Lending Landscape

Across the world, Fintechs have been on the rise. 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 million USD) (Figure 2). Table A1 presents summary statistics of the Indian lending landscape. As of 2021, Fintechs captured 8% of the market in terms of number of loans, and 2% in terms of loan amount. While these market shares

are substantially lower than that of traditional lenders such as public and private banks, key facts highlight Fintechs' important role in the lending landscape. First, Fintechs have been experiencing the largest growth by far. 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.

Second, especially the vulnerable population is likely to benefit from Fintechs' specialization on three dimensions: loan size, product type, and credit score type. The loan size of Fintechs is 20,800 rupees (≈304 USD) (see Table A3, median loan amount divided by median number of loans). This is around a tenth of the loan sizes of public and private banks, and a fifth of that of NBFCs. A small loan size allows borrowers to take up loans for immediate needs without having to pose collateral or risk financial distress, smoothing income or expense shocks. In alignment with this focus, Fintechs specialize on consumption loans. In 2021, they captured 16% of the market issuance of consumption loans in terms of accounts and 4% in terms of loan amounts. Finally, lower credit score borrowers such as near-prime and sub-prime present 35% of Fintechs' loan portfolio in terms of accounts and 29% in terms of loan amounts. New-to-credit borrowers present 14% of accounts and 8% of loan amounts. Additionally, Fintechs already have a wide geographical spread comparable to that of other lenders as depicted in Figure A3. Thus, Fintechs already present an important player in the Indian landscape, and their influence is on a sharp upward trend.

3.3 Granular Summary Statistics

Going more granular, Table A2 presents the summary statistics on our level of variation, the 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. We observe that a Fintech cell has a median number

of five loans, corresponding to a total loan amount of 103,995 rupees (≈1,550 USD), and a loan size of 20,800 rupees or 304 USD. The average one and three year default rates are 7.87% and 11.11% respectively. The median number of inquiries is 4.50. Table A4 present 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.[15]

4 Empirical Strategy

We exploit a differences-in-differences (DID) estimation strategy to examine the effect of local weather shocks on Fintechs' loan portfolio. Specifically, we examine the lending response of Fintechs relative to other lender types following a weather shock using the specification outlined in Equation 2:

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

$y_{ym,z,l,p}$ 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. The coefficient of interest is β, which captures the effect of the weather shock on the outcome variable for Fintechs relative to other providers. If $\beta > 0$, this suggests that the shock has a larger positive effect on the outcome for Fintechs compared to other providers. We include granular fixed effects: year-month × ZIP × product fixed effect ($\text{FE}_{ym,z,p}$), ZIP × lender × product fixed effect ($\text{FE}_{z,l,p}$), and year-month × lender × product fixed effect ($\text{FE}_{ym,l,p}$). 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 ($\text{Shock}_{z,ym}$) with Fintech 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

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

could bias β. First, Fintechs might react more strongly 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, on which Fintechs are specialized. 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 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.[16] 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).[17]

A second potential concern one needs to address is that Fintechs 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 both Fintech and other 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 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 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

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

pre-existing trends between Fintechs and other lenders. While this assumption is untestable, we will document parallel pre-trends in an event study analysis.

5 Results

5.1 Credit Issuance

We begin by investigating whether Fintechs issue more credit after weather shocks, relative to other providers. Table 1 presents our main result, on which we will build going forward. The estimate of interest is the coefficient on the interaction of Fintech and Shock. Moving from Column 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 is positive and statistically significant across all specifications. The positive estimate demonstrates that Fintechs increase their lending relative to other lender types following a climate shock. Specifically, we find that Fintechs issue 1.49% more credit after climate shocks than other providers 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 201 million USD during our study period[18]. Table 8 shows that Fintechs' response is substantially stronger than that of all other lender types. We extend Equation 2 with interactions for other lenders, for instance, NBFC × Shock, with public banks as the omitted category. The coefficient for Fintechs is statistically different from all other lender types with a p-value of 0.00. Thus, Fintechs increase their lending after weather shocks, and substantially more so than other credit providers.

5.1.1 Extensive Margin

The result on Fintech credit issuance holds on the extensive margin as Table 2 demonstrates. In our preferred specification, the number of loans on the ZIP-year-month-product level increases by 0.20 or 0.71% (the effect evaluated at the mean of 29 loans for Fintechs in a given year-month × ZIP × product). In aggregate, this translates to an effect of 3.68 thousand

[18] 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 705 thousand rupees or 10 thousand USD in a given ZIP code, year-month, and product. An effect of 1.49% compared to this mean corresponds to 11 thousand rupees or 153 USD. Applying the coefficient to the average loan amount issued across products in a given year-month and ZIP code (1 million rupees or 16 thousand USD) gives an effect of 16 thousand rupees or 237 USD. The average loan amount across products and ZIP codes in a given year-month is 13 billion rupees or 190 million USD, providing an effect of 193 million rupees or 3 million USD. Finally, over our entire sample, Fintechs issue 922 billion rupees or 13 billion USD, which corresponds to an effect of 14 billion rupees or 201 million USD.

extra loans in a month and 261 thousand additional loans over our study period[19]. In alignment with a higher number of loans issued, we observe an increase in the number of loans Fintechs inquire about. Since the inquiry data is on the annual level, we redefine a 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 describes the results. In our strictest specification, we identify that Fintechs have 0.65 (=7.86/12) extra inquiries after the shock relative to other providers. This corresponds to an increase of 2.4% (at a monthly mean of 27.26 inquiries). In aggregate, this translates into an effect of 12 thousand additional inquiries per month and 856 thousand inquiries during our study period.[20] The ratio of accepted loans to inquired loans is 30.77% (=0.20/0.65). 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).

5.1.2 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 INR 705,198 rupees and average number of loans is 28.76, which equals INR 24,517 per loan. The point estimates in Column 4 of Table 1 shows a 1.49% increase in Fintech credit after a weather shock, which translates to a INR 365 increase in credit per borrower. These effects are economically meaningful. We benchmark these numbers against the average monthly expenditure using the Household Consumption Expenditure Survey Data (Table A7).[21] For the bottom 5^{th} percentile of monthly expenditure, the increase in Fintech credit per borrower corresponds to 18% and 27% of average monthly expenditure for urban and rural households, respectively. For households between the 40^{th} and 50^{th} percentile, the increase in Fintech credit per borrower corresponds to 7% for urban and 12% for rural households. For the top 5^{th} percentile, the effects correspond to 3% for urban and 5% for rural

[19] The average number of loans of Fintechs is 28 in a given ZIP code, year-month, and product. An effect of 0.71% 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 0.31 new loans. The average number of loans across products and ZIP codes in a given year-month is 530 thousand, providing an effect of 3.68 thousand loans. Finally, over our entire sample, Fintechs issue 38 million loans, which corresponds to an effect of 261 thousand loans.

[20] The average number of inquiries for Fintechs is 27 in a given ZIP code, year-month, and product. An effect of 2.40% compared to this mean corresponds to 0.65 extra inquiries. Applying the coefficient to the average number of inquiries across products in a given year-month and ZIP code (42 accounts) gives an effect of 1.01 additional inquiries. The average number of inquiries across products and ZIP codes in a given year-month is 502 thousand, providing an effect of 12 thousand inquiries. Finally, over our entire sample, Fintechs inquire 35 million times, which corresponds to an effect of 856 thousand inquiries.

[21] Available from the Ministry of Statistics and Program Implementation, Government of India website https://www.mospi.gov.in/.

households. In Section 5.2.2, 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 above to benchmark our estimates. Nonetheless, for completeness, we also benchmark our results against average income and average savings. Assuming an average annual income of INR 234,551 (Bharti et al., 2024), these effects correspond to 2% [=365/(234,551/12)] of monthly income. The average annual income for the bottom 50% is INR 71,163, implying that the Fintech credit increase corresponds to 6% [=365/(71,163/12)] of average monthly income. Numbers from the Periodic Labour Force Surveys (PLFS)[22] yield similar estimates. Using the 2019 average salary of INR 19,568, the Fintech credit increase is 2%[=365/19,568] of monthly income. However, given the stronger impact on marginal borrowers in Section 5.2.2, a more appropriate benchmark may be the average salary for casual workers. The increase in Fintech credit is 5% [=365/7,591] of the average monthly salary of a casual worker. The effect is also meaningful when benchmarked against the average savings of INR 15,625[23] The estimate corresponds to 2% of savings for the bottom quartile and 0.36% of savings for the top quartile of households.

5.1.3 Dynamic Response

Next, we investigate the dynamic response of credit issuance over time. This corresponds to Equation 2 but additionally includes specific dummies for pre- and post-periods. Figure 3 depicts the dynamic effects of the loan amount. Additionally, Figure 4 draws a similar picture for the extensive margin of loan accounts. There are two key takeaways from the dynamic estimation of Equation 2. 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.

[22] https://www.mospi.gov.in/Periodic-Labour-Surveys
[23] Data as of 2019 from All India Debt and Investment Survey (AIDIS).

5.2 Heterogeneity

5.2.1 Heterogeneity by Product Type

We begin by investigating the heterogeneity in the baseline effect across product types. The rationale for this test is that Fintechs typically specialize in small, unsecured loans. Therefore, if Fintechs are increasing credit disbursement after climate shocks, we should see greater effects in these types of loans. To this end, we estimate our baseline Equation 2 for each product type separately. Table 3 presents the results. Column 1 reports the baseline specification. Columns 2-8 report baseline results estimated separately for each product type. Specifically, Columns 2-8 report results for agricultural loans, business loans, consumption loans, gold loans, microfinance (MFI) loans, vehicle loans, and other loans, respectively.

The results indicate that the relative increase in credit issuance by Fintechs following a climate shock is driven by consumption loans, business loans, and microfinance loans. Specifically, consumption loans increase by 1.07%, business loans by 5.08%, and microfinance loans by 7.86%. Overall, these result supports the idea that climate shocks may lead to income or expense shocks, which in turn increase the demand for credit. Households and businesses, especially micro-enterprises, may need more credit to finance their consumption and working capital needs due to the adverse effects of these shocks.

Meanwhile, we do not find a statistically significant effect for agricultural loans and gold loans. The absence of statistically significant results for agriculture and gold loans may be due to the fact that these types of loans are mostly collateralized. Fintechs, primarily online lenders operating through apps, do not typically engage in such secured lending, which often requires a physical office presence. Moreover, agricultural loans are considered priority sector loans that are usually catered by commercial banks such as public sector banks (Banerjee, Cole and Duflo, 2004, 2005).

5.2.2 Heterogeneity by Credit Score Types

Next, we investigate the heterogeneity in the effect by credit score categories. This exercise is motivated by the observation that Fintechs are believed to be serving individuals who are considered infra-marginal borrowers. Therefore, we should expect to find greater effects among individuals with low credit scores or new-to-credit borrowers.

To this end, we estimate our baseline Equation 2 for each credit score category separately. Table 4 presents the results. Column 1 reports the baseline specification. Columns 2-8 report

baseline results estimated separately for each credit score category. Specifically, Columns 2-7 report results for super-prime, prime-plus, prime, near-prime, sub-prime borrowers (in descending order of creditworthiness). Column 8 presents the result for new-to-credit borrowers, who do not yet have a credit score. The largest effect comes from new-to-credit borrowers, with an effect size of 2.30%. While we find no effects for super-prime or prime-plus borrowers, prime borrowers see an increase with 0.87%, followed by near-prime borrowers with 1.04% and sub-prime borrowers with 1.80%. Thus, Fintech issuance is responding stronger for new-to-credit borrowers, and there is a monotonically increasing pattern from high credit scores to low credit score borrowers. The result documented in Table 4 is robust to examining the effect across other bank types (Table A9).

One potential explanation for the monotonically increasing pattern 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. Table A10 reports 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.[24] 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. This result is robust to examining the inquiry effect across other bank types (Table A11). Thus, the inquiry effect (or demand patterns) among scored borrowers do not seem to explain the heterogeneity in loan issuance observed in Table 4.

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.

5.3 Default Rates

Since Fintechs primarily serve the vulnerable, the question arises whether the issuance of credit in response to the shock translates into increased default rates. Here, the main outcome variable is the fraction of loans that default after one year and three years, respectively. Table

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

5 presents the results. We do not find any statistically or economically meaningful effect on one-year default rates of Fintechs relative to other lender types. However, we do note that the 3-year default rate is 0.09 percentage points higher for Fintechs relative to other lender types. While this effect is statistically significant it is economically small relative to the average 3-year default rate of 11%. This result indicates that while Fintech seems to take on ex-ante higher risk as measured by their credit scores, the ex-post difference in the economic riskiness of their portfolio is economically small.

5.4 Robustness

We show an extensive set of robustness tests on the main effect of loan issuance. First, our specification in Equation 2 investigates the effect of Fintechs relative to other providers. If other providers see a strong decrease, it is possible that Fintech loan amounts also decrease, just to a lesser degree. To show that Fintech loan amounts also increase in absolute, we regress the loan amount of Fintechs on the weather shock variable (Table A13, Equation 5). The effect remains stable (1.27%) and statistically significant, even with the strongest possible set of fixed effects, which is year-month × product and ZIP × product. We employ Equation 2 as our main specification instead of Equation 5 because it allows us to study the relative effect of Fintechs and to incorporate the strictest set of fixed effects. Second, our main specification focuses on year-month × ZIP × lender × product categories that have any credit issuance. In an alternative specification, we can incorporate categories that move from zero to any credit. To include these zeros, we run a Poisson regression. Table A14 shows that the result is robust to this specification, and increases to 3.83%, which corresponds in the aggregate to 7 million USD in a given month, or 515 million USD over our study period. Note that we do not employ Poisson as our main specification due to the high computational intensity with the large size of our data.

Next, we discuss a set of robustness tests related to our weather shock variable. Table A15 demonstrates robustness to shock splits (by wet and dry shocks) and shock severity. In our main analysis, we define a weather dummy as one if the SPEI in a given year-month falls below the 20th percentile or above the 80th percentile of a ZIP's historical distribution. If we split the weather shock by wet events (above the 80th percentile, in extreme cases floods) and dry events (below the 20th percentile, in extreme cases droughts), we observe that the effect remains statistically significant for both. However, it is stronger for droughts (2.42%) than for floods (0.56%), suggesting that in dry times more credit is issued. Additionally, we look

at more severe shocks by adjusting the percentile. Here, 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 in Column 4 to 6. We find that the total effect is slightly larger for these more extreme cases (1.57%), and again stronger for droughts (3.05%) than for floods (0.68%). All effects are statistically significant. Thus, our analysis is robust to different shock splits and severities, and the effect is stronger for droughts compared to floods and more severe events.

In Table A16, we exploit the fact that the SPEI can not only be defined over a given month but also over longer periods such as three or six months. For a three-month SPEI, water balances are for instance summed over January to March, and then compared to January to March of the historical water balance values in the given location. If we define our weather shock dummies based on longer-term SPEI values, we find that the effect remains positive, statistically significant, and in the range of our main results. As a next step, to address any remaining concerns on might raise about the construction of the weather shock dummies, we run a robustness test with the underlying standardized water balance measure itself, the SPEI. Since the measure ranges from negative values (dry) to positive values (wet) and we are interested in deviations from a normal water balance, we take the absolute value of the SPEI. This variable replaces in Table A17 our weather shock dummy. The coefficients remain positive, statistically significant, and in the range of our main results.

Finally, we run a placebo test. We replace our weather shock dummy with a dummy variable that is randomly set to one for 40% of the year-month observations in a ZIP code, to mirror the 20th and 80th percentile definition of the weather shock. We repeat this exercise 50 times. Figure A5 plots the kernel density of the resulting coefficients. As expected, the distribution of the coefficients is centered around zero, varying between -0.006 and 0.003. Thus, our main coefficient in Table 1 Column 4 (0.0149) – indicated in blue in the figure – does not fall within the range of the placebo estimates. Thus, the placebo test provides further confidence in our results.

6 Mechanism

We next target to understand what characteristic allows Fintechs to issue more loans in times of shocks, especially to the vulnerable. The literature has put forward three potential explanations. First, a distinguishing feature of Fintechs is that they use technology in their loan issuance process. Second, Fintechs might utilize the fact that they are less regulated than traditional lenders. India has had a long history of regulating traditional lenders, for instance,

priority lending standards for certain sectors such as agriculture or bank branch regulations. Third, Fintechs might have a less shock-sensitive funding base. In India, Fintechs are primarily funded by Venture Capital (VC) and Private Equity (PE). Thus, Fintechs' lending sources are arguably less likely to be sensitive to weather shocks than that of traditional lenders, who experience a withdrawal of deposits in bad times (Kundu, Park and Vats, 2021). We provide evidence for the technology mechanism, before demonstrating that laxer regulations or less shock-sensitive funding are unlikely to drive our result.

6.1 Technology: UPI Index

To investigate whether Fintechs' technological advantage allows them to serve credit after a shock, we first utilize the UPI index data. The main idea is that UPI records digital financial transactions, which can be used in an open banking framework. For instance, if a borrower applies for a Fintech loan, she can share her banking data with the lender. Thus, in ZIP codes with a higher UPI index – so a higher proxy for UPI presence – we should see stronger effects. Table 6 and Figure 5 present the findings. As expected, we see a monotonically increasing trend in the coefficient of interaction between Fintech and Shock as we move from the first quartile to the fourth quartile of the UPI index distribution. In the first quartile, the effect is 0.66% and statistically insignificant. In the fourth quartile, the coefficient is 2.33% and highly statistically significant. Critically, a Wald test shows that we can reject the null that the coefficients in quartile one and quartile four are equal. The p-value of the test is 0.02. This strongly suggests that the technological advantage of Fintechs drives our main effect.

One concern might be that the UPI index correlates with other unobservables that are positively related to Fintech loan issuance. For a placebo test, we utilize data from Yono, the digital banking platform of the public State Bank of India, the largest Indian bank. In particular, we examine the total monthly ZIP-code Yono transaction value, scaled by a ZIP code's population. Since Yono is also a digital transaction platform, one might expect it to correlate with similar unobservables as the UPI index. Critically, however, the transaction history on Yono cannot be shared with other lenders. If unobservables were responsible for the increasing pattern, we would also see it for Yono transaction value. As expected, the pattern is relatively flat (Figure 5). This suggests that the increase in coefficients across UPI exposure quartiles is not driven by unobservables, but instead truly captures the data provision to Fintechs.

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 7 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 A18). 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 A19). 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 A20). 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 Fintech have an advantage relative to other lenders due to less regulatory restrictions or less shock-sensitive funding sources. Here, we utilize the fact that Fintech is *a type of NBFC* that additionally has an element of technology in the loan issuance process. Fintechs and other NBFCs are separately reported in our data. This means that Fintechs and NBFCs should only differ on the technology dimension, but not in terms of

strictness of regulatory restrictions and funding sources. Under this assumption, we observe in Table 8 that Fintechs react substantially stronger than NBFCs after a shock, relative to the omitted category of public banks. In our most strict specification, Fintechs increase their credit issuance by 1.29% after a shock, while NBFCs see a negligible effect (<0.01%). This pattern holds under different fixed effect specifications. Finally, we can reject equality of the coefficients for Fintech and NBFCs, with a p-value of 0.00. This provides suggestive evidence that other mechanisms, including regulation and funding sources, are not driving Fintech's stronger reaction after shocks.

7 Conclusion

Our paper is the first to investigate the the role of Fintechs in climate adaptation. Specifically, we investigate this issue in an emerging economy context that are more vulnerable to climate change. Using granular data from India, we show that Fintechs respond more robustly to climate shocks compared to other providers, significantly increasing credit issuance without an accompanying rise in default rates. We attribute this effect to Fintechs' use of alternative data and technological advantages, enabling them to better assess and manage credit risk. Therefore, we document that while Fintechs play a key role in mitigating demand fluctuations following climate shocks, climate risk does not show up on thieir balance sheet as increased default.

Our analysis highlights several key findings – Fintechs primarily increase credit to consumption, business, and microfinance loans, especially targeting low- and medium-credit score borrowers and new-to-credit borrowers. This suggests that Fintechs play a crucial role in supporting vulnerable populations during climate shocks, enhancing their resilience by providing timely financial support.

Additionally, our investigation into the mechanisms behind Fintechs' increased lending capacity highlights the importance of their technological advantage. We document that regions with higher adoption of digital financial infrastructure, such as the Unified Payments Interface (UPI), see greater Fintech credit expansion after climate shocks. This finding supports the notion that technological advancements and access to alternative data are central to Fintechs' ability to mitigate the impacts of climate disruptions. Specifically, this technological edge enables Fintechs to effectively screen and identify the most creditworthy borrowers among those with low and medium credit scores, as well as new-to-credit borrowers. As a result,

they can avoid an increase in defaults while simultaneously extending credit to unserved and underserved populations following climate shocks.

Our study contributes to the broader literature on Fintech and climate adaptation by offering the first empirical evidence on the significant role of technology-driven lending in emerging economies. It highlights the potential of Fintechs to reduce disparities in credit access and enhance financial inclusion, particularly in the face of climate risks. Policymakers should consider these findings when developing regulations and frameworks to support the growth of Fintechs and their integration into the financial ecosystem, ensuring that vulnerable populations can benefit from their innovative solutions.

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Figures

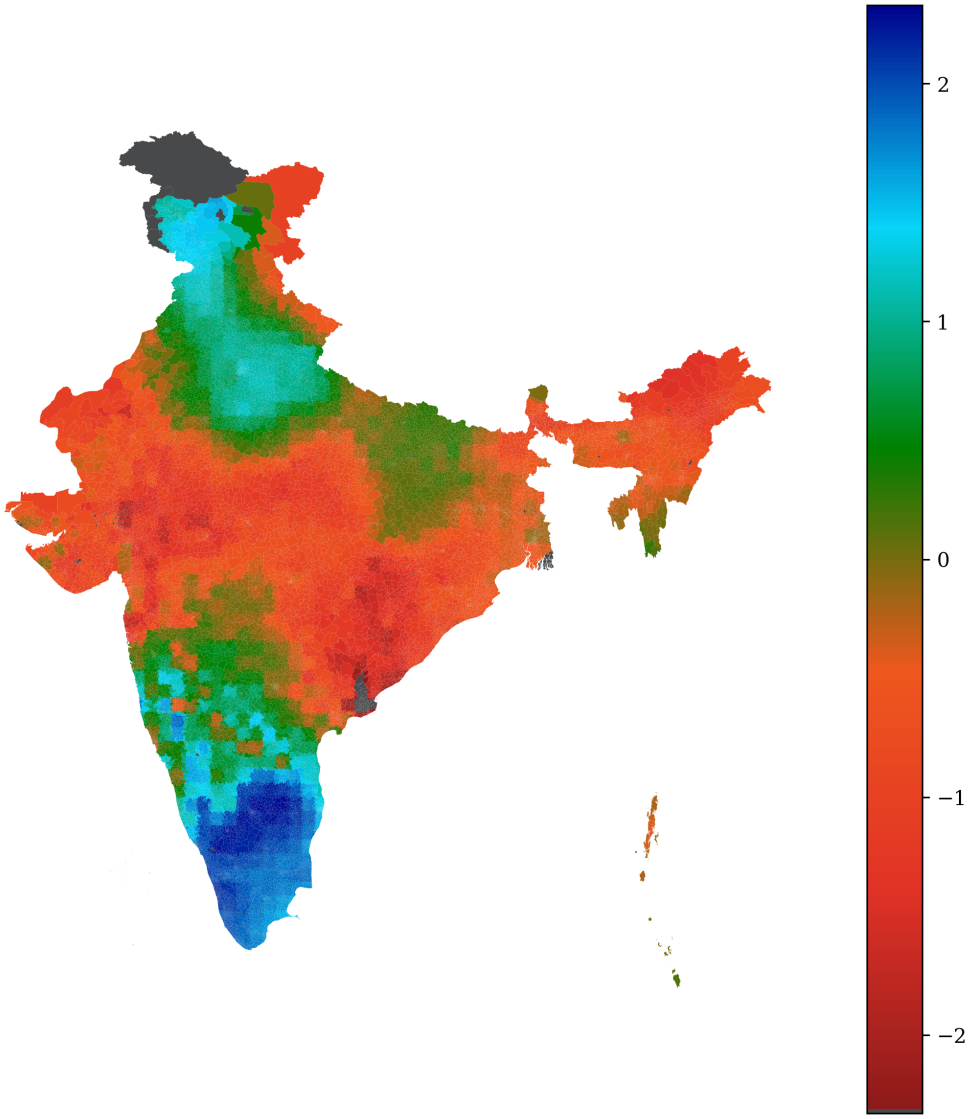


Figure 1: **Continuous Water Balance Variable (SPEI).** The figure presents the geographic ZIP-level distribution of the continuous water balance variable SPEI, for December 2020 as an example. The definition of the SPEI is outlined in Section 2. It has a mean of zero and standard deviation of one. The continuous SPEI forms the basis for our weather shock dummy. Note that the SPEI values are geographically clustered. This geographic clustering can be explained by time-invariant geographic determinants such as elevation (see Appendix Figure 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.

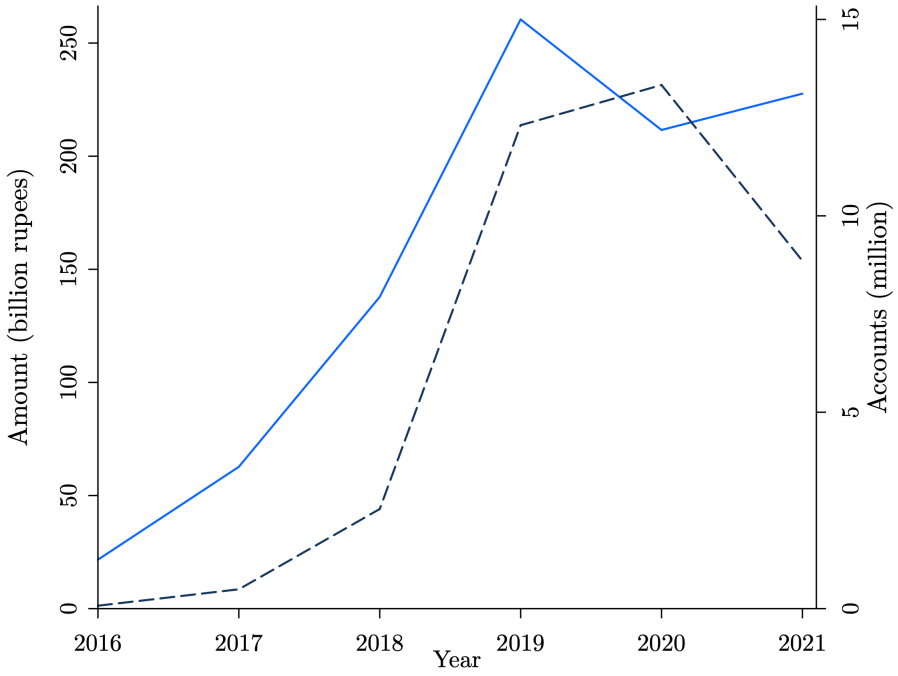


Figure 2: **Loan amount and number of accounts issued in a given year.** This figure shows the time series of Fintech growth between 2016 and 2021. The left-hand axis describes the aggregate loan amount in billion rupees (solid line). The right-hand axis denotes the aggregate loan accounts in millions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

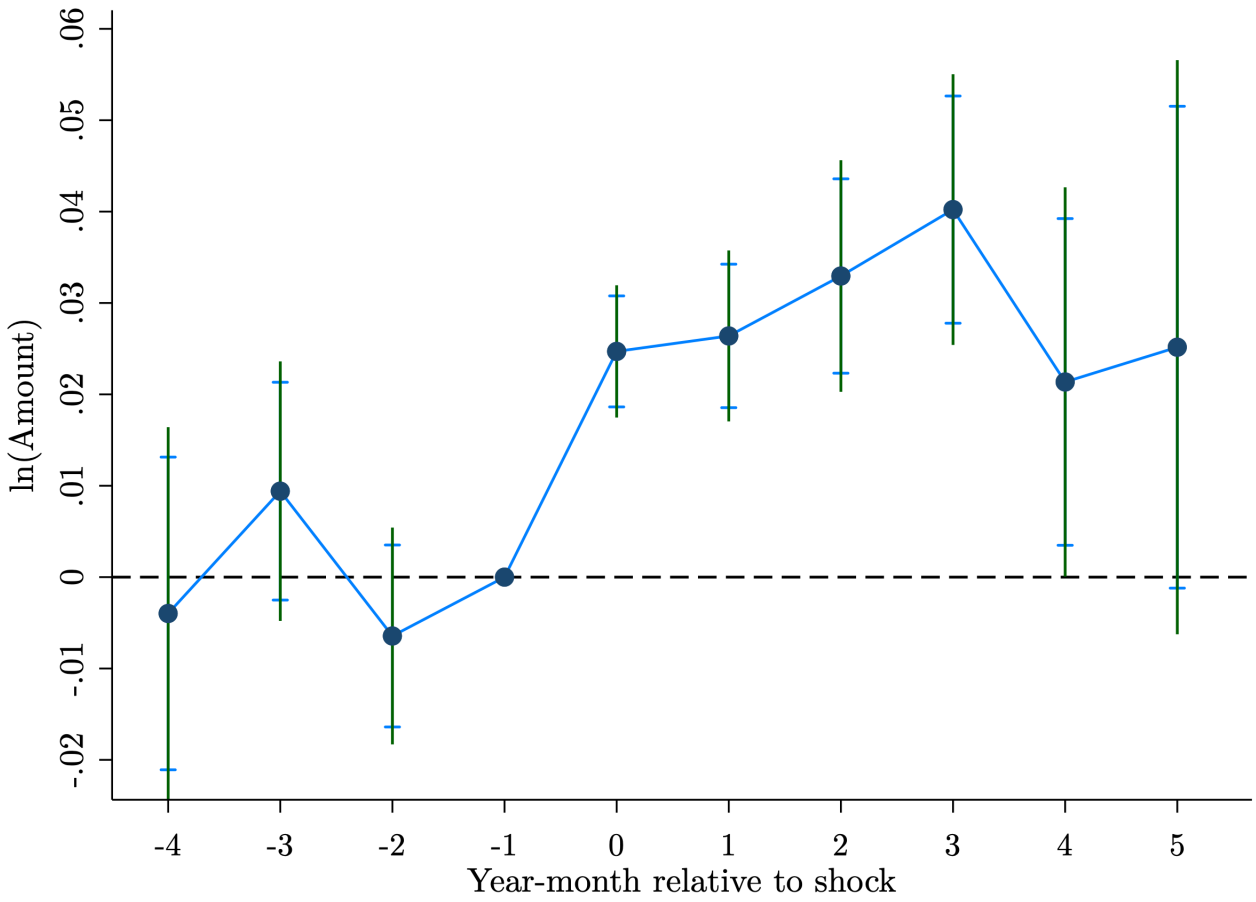


Figure 3: **Fintech Credit Issuance, Amount**. This figure presents the dynamic effects of Fintech credit issuance in response to a shock, compared to other lenders. Equation 3 describes the regression, where t is the year-month relative to the shock and the reference period is t=-1. The data is on the 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. $\text{Shock}_{ym,z}$ 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.

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

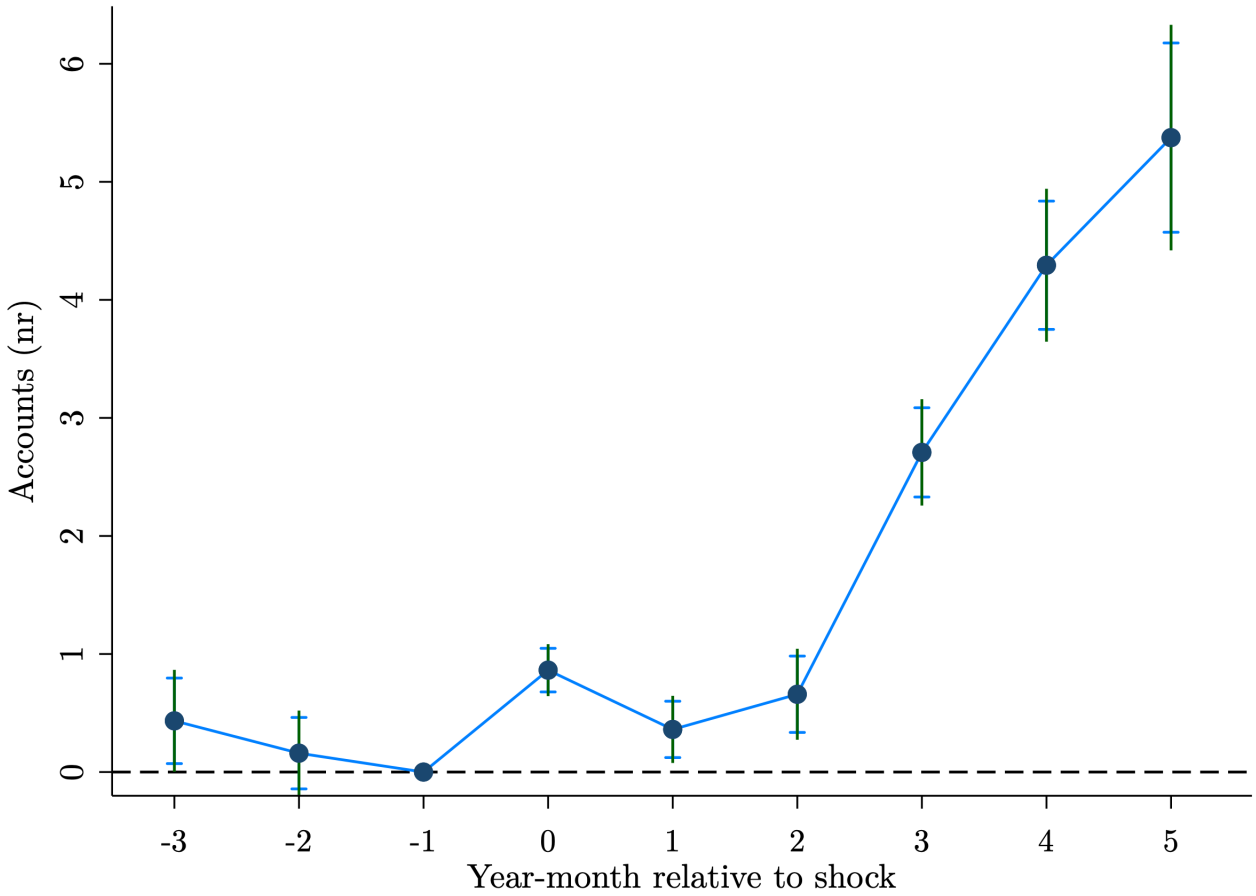


Figure 4: **Fintech Credit Issuance – Extensive Margin Effect, # of Accounts**. This figure presents the dynamic effects of Fintech loan account issuance in response to a shock, compared to other lenders. Equation 3 describes the regression, where t is the year-month relative to the shock and the reference period is t=-1. The data is on the year-month-ZIP-lender-product level. $\text{Accounts}_{ym,z,l,p}$ 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. $\text{Shock}_{ym,z}$ 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.

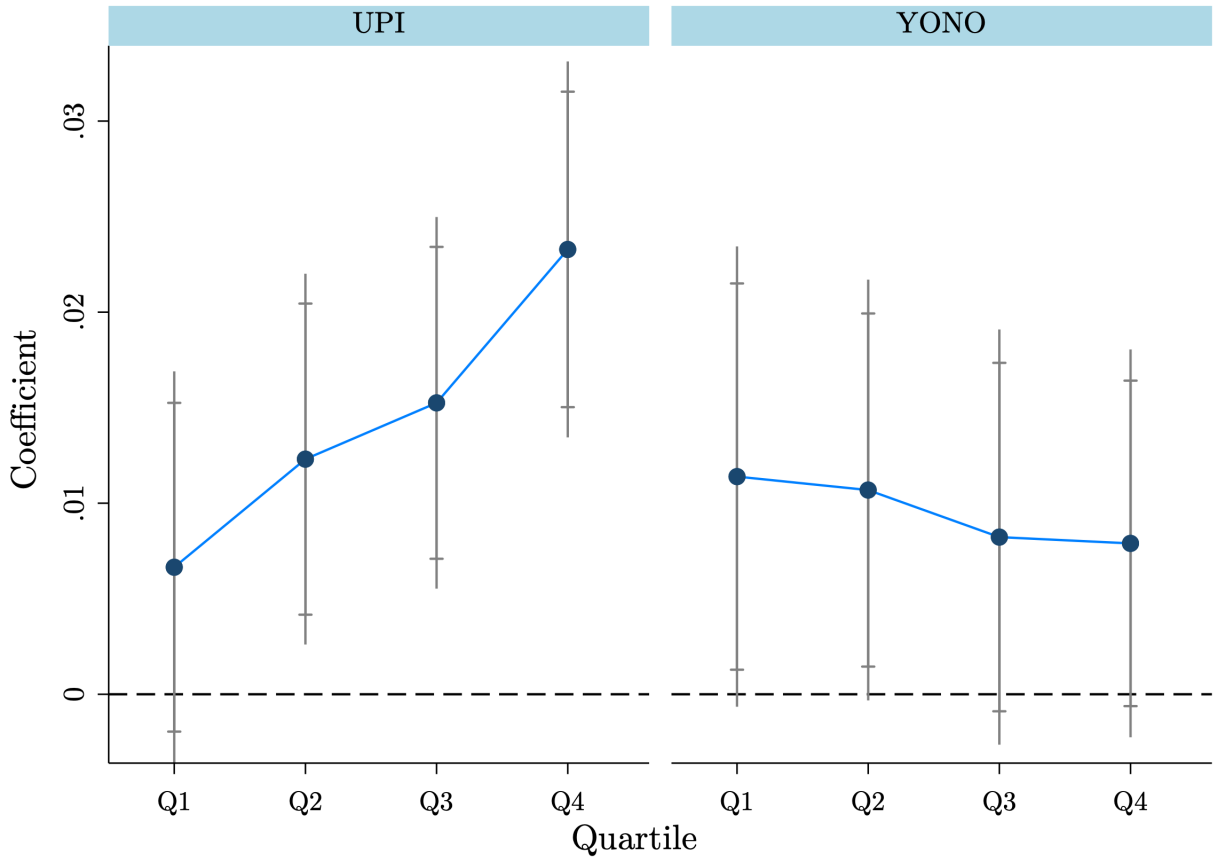


Figure 5: **Heterogeneity by UPI Index and Yono Transaction Value**. This figure presents Fintech credit issuance after a shock, compared to other lenders, separately by ZIP code level UPI index and ZIP code level total Yono transaction value; the latter is scaled by a ZIP's population. The data is on 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.

Tables

Table 1: **Fintech Credit Issuance**

Dep Var: LN(Amount)	(1)	(2)	(3)	(4)
FinTech × Shock	0.0560***	0.0547***	0.0607***	0.0149***
	(0.0032)	(0.0028)	(0.0029)	(0.0022)
FinTech	-2.2503***	-2.4852***	-2.4842***	
	(0.0061)	(0.0041)	(0.0041)	
Shock	0.0174***	-0.0014**		
	(0.0017)	(0.0006)		
Year-month FE		✓		
ZIP FE		✓		
Year-month × 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-months	71	71	71	71
R-squared	0.08	0.30	0.32	0.84
Observations	20,459,958	20,459,958	20,459,958	20,459,958

Notes: This table presents Fintech credit issuance after the shock, compared to other lenders. Equation 2 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. $\text{Shock}_{ym,z}$ 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 Credit Issuance – Extensive Margin**

Dep Var: # Loan Accounts	(1)	(2)	(3)	(4)
FinTech × Shock	1.3534***	1.4105***	1.4147***	0.2033**
	(0.0980)	(0.0824)	(0.0819)	(0.0819)
FinTech	-3.8722***	-12.7963***	-12.7589***	
	(0.1709)	(0.1751)	(0.1756)	
Shock	0.9699***	0.0480**		
	(0.0605)	(0.0187)		
Year-month FE		✓		
ZIP FE		✓		
Year-month × 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-months	71	71	71	71
R-squared	0.00	0.15	0.16	0.91
Observations	20,459,958	20,459,958	20,459,958	20,459,958

Notes: This table presents Fintech number of loans ("accounts") issued after the shock, compared to other lenders. Equation 2 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. $\text{Shock}_{ym,z}$ 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 Product Type**

Dep Var: LN(Amount)	All (1)	Agric (2)	Busi (3)	Cons (4)	Gold (5)	MFI (6)	Vehicle (7)	Other (8)
FinTech × Shock	0.0149***	-0.0427	0.0508***	0.0107***	-0.0399	0.0786***	-0.0261**	-0.0112
	(0.0022)	(0.0556)	(0.0076)	(0.0021)	(0.0278)	(0.0128)	(0.0108)	(0.0092)
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,060	18,711	16,549	19,052	18,078	11,716	18,962	18,794
Year-months	71	71	71	71	71	71	71	71
R-squared	0.84	0.82	0.72	0.86	0.88	0.84	0.84	0.77
Observations	20,459,958	3,269,797	1,590,155	6,069,098	2,488,014	385,748	3,505,068	3,152,078

Notes: This table presents how much more credit Fintechs issue in the period of a shock, compared to other lenders, by product. In sequence, the columns show all products, agricultural loans, business loans, consumption loans, microfinance loans, vehicle loans, gold loans, and other loans. Equation 2 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. $\text{Shock}_{ym,z}$ 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 Credit Score Type**

Dep Var: LN(Amount)	Total (1)	Super-Prime (2)	Prime-Plus (3)	Prime (4)	Near-Prime (5)	Sub-Prime (6)	New-to-Credit (7)
FinTech × Shock	0.0149***	-0.0052	-0.0008	0.0087***	0.0104***	0.0180***	0.0230***
	(0.0022)	(0.0073)	(0.0042)	(0.0028)	(0.0029)	(0.0041)	(0.0034)
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,060	15,468	18,821	19,007	18,940	18,601	18,968
Year-months	71	71	71	71	71	71	71
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 credit issuance after the shock, compared to other lenders, by credit score type. Equation 2 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. $\text{Shock}_{ym,z}$ 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: **Default Rates**

Dep Var: Default Rate (0 to 1)	1 Year (1)	3 Years (2)
FinTech × Shock	0.0003 (0.0003)	0.0009** (0.0004)
Year-month × ZIP × Product FE	✓	✓
Year-month × Lender × Product FE	✓	✓
ZIP × Lender × Product FE	✓	✓
ZIPs	19,060	19,060
Year-months	71	71
R-squared	0.45	0.51
Observations	20,459,958	20,459,958

Notes: This table presents the default rates for loans issued by Fintechs in the period of a shock, compared to default rates of other lenders. Equation 2 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. 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: **Mechanism – Technology (UPI Exposure)**

Dep Var: 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	0.0123**	0.0153***	0.0233***
	(0.0052)	(0.0049)	(0.0050)	(0.0050)
Month-year × ZIP × Product FE	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓
ZIPs	3,406	2,952	2,997	3,834
Year-months	71	71	71	71
R-squared	0.83	0.85	0.85	0.81
Q1 = Q4	.	.	.	0.02
Observations	3,974,444	3,973,448	3,974,116	3,973,383

Notes: This table presents Fintech credit issuance after the shock, compared to other lenders, separately by ZIP code level UPI index quartiles described in Section 2. Equation 2 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. $\text{Shock}_{ym,z}$ 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: **Mechanisms – Technology (Fintech ABC)**

Dep Var: Application Accepted (0 or 1)	All (1)	New-to-Credit (2)	Not New-to-Credit (3)
Alternative Data × Shock	0.0080***	0.0237***	0.0041*
	(0.0021)	(0.0052)	(0.0023)
Alternative Data	0.0621***	0.0564***	0.0789***
	(0.0017)	(0.0035)	(0.0019)
Year-month × ZIP × Merchant Type FE	✓	✓	✓
Onboarding Channel FE	✓	✓	✓
Swipe Machine FE	✓	✓	✓
Membership in Investment App FE	✓	✓	✓
ZIPs	8,138	4,934	7,687
Year-months	16	14	16
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 4 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.

$$y_{app} = \beta_0 \cdot \text{Shock}_{ym,z} \times \text{Alternative Data}_{app} + \beta_1 \text{Alternative Data}_{app} + \text{FE} + \epsilon_{app} \quad (4)$$

Table 8: **Mechanisms – Regulatory Burden and Financing Sources**

Dep Var: LN(Amount)	(1)	(2)	(3)	(4)
FinTech × Shock	0.0734***	0.0494***	0.0519***	0.0129***
	(0.0035)	(0.0028)	(0.0031)	(0.0024)
NBFC × Shock	0.0113***	-0.0079***	-0.0110***	0.0001
	(0.0022)	(0.0012)	(0.0018)	(0.0014)
Private × Shock	0.0311***	0.0127***	0.0097***	-0.0035**
	(0.0022)	(0.0012)	(0.0018)	(0.0014)
Foreign × Shock	0.0142***	-0.0135***	-0.0157***	-0.0026
	(0.0036)	(0.0025)	(0.0028)	(0.0023)
Other × Shock	0.0031	-0.0151***	-0.0185***	-0.0069***
	(0.0022)	(0.0022)	(0.0026)	(0.0018)
Omitted Category	Public	Public	Public	Public
FinTech × Shock = NBFC × Shock	0.00	0.00	0.00	0.00
FinTech × Shock = Private × Shock	0.00	0.00	0.00	0.00
FinTech × Shock = Foreign × Shock	0.00	0.00	0.00	0.00
FinTech × Shock = Other × Shock	0.00	0.00	0.00	0.00
Lender FE	✓	✓	✓	✓
Year-month FE		✓		
ZIP FE		✓		
Year-month × 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-months	71	71	71	71
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 lender credit issuance after the shock, compared to public banks. Equation 2 describes the regression, plus interactions for other lenders. Public banks are omitted. Tests of coefficient equality are reported. 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. $\text{Shock}_{ym,z}$ 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

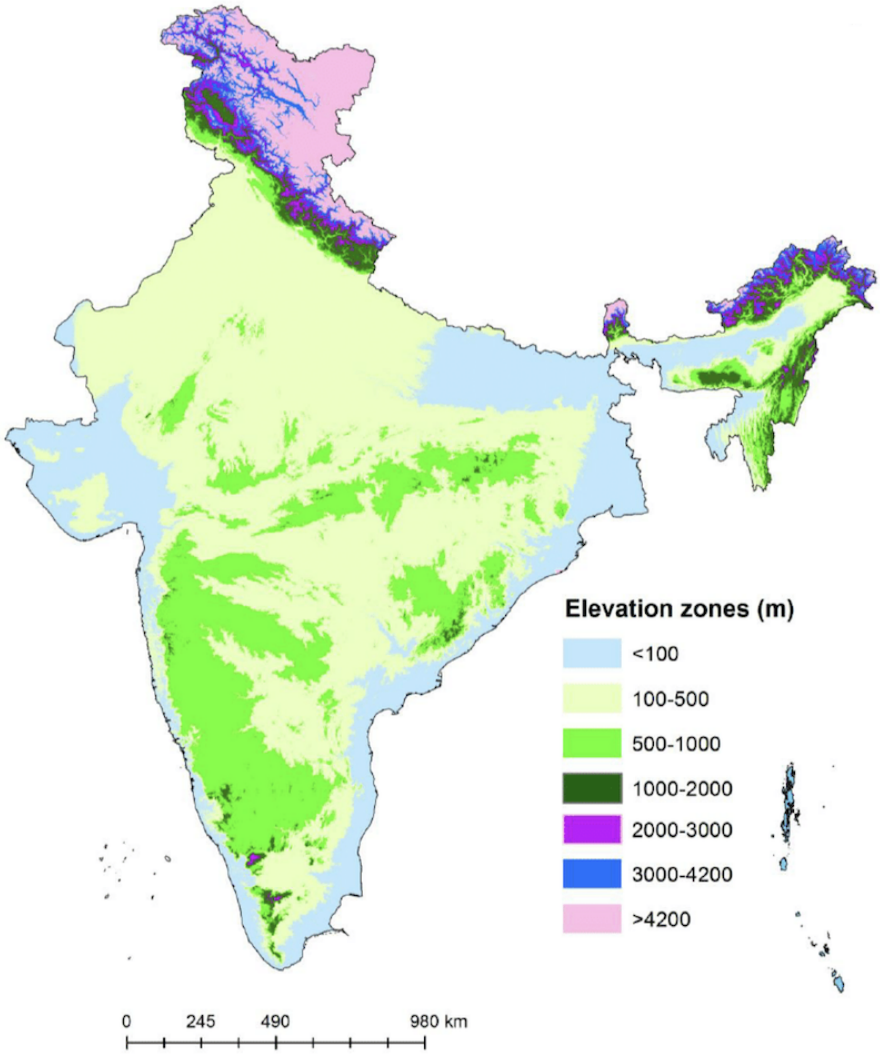
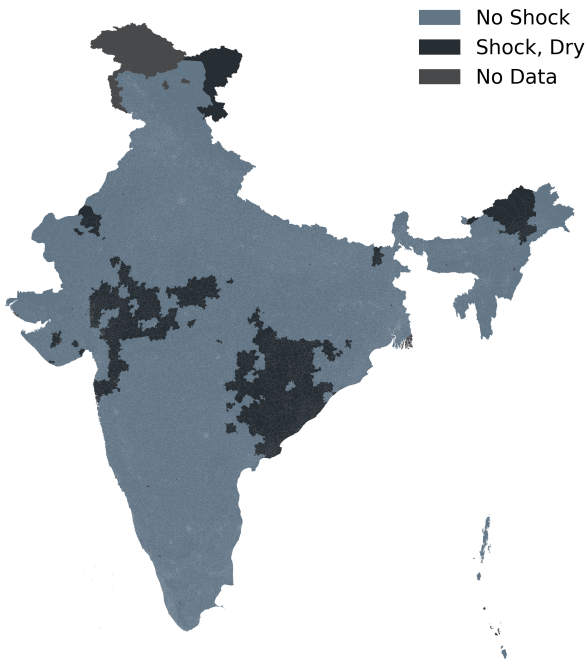
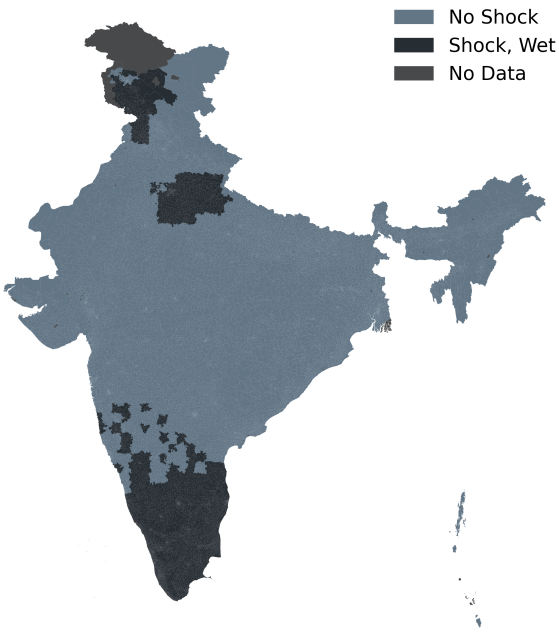


Figure A1: **Elevation.** The Figure presents the geographic distribution of the elevation profile of India, an important determinant of the weather, sourced from Chintala et al. (2015).

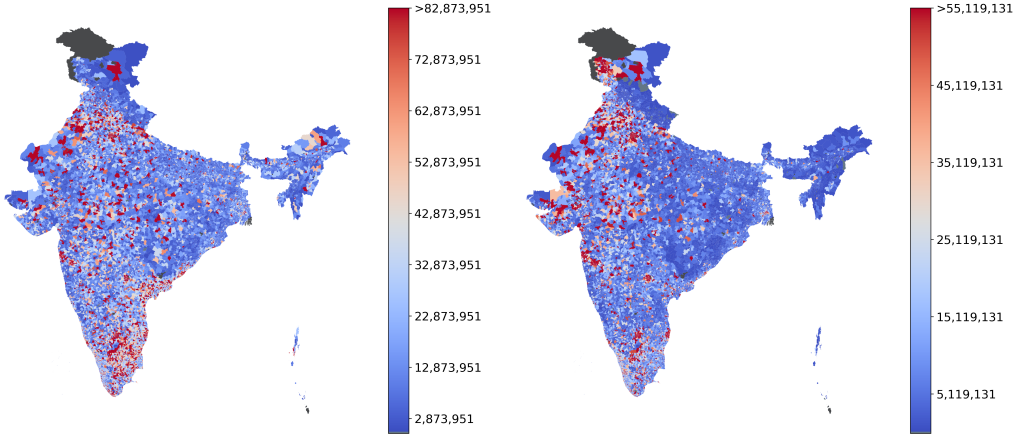


(a) Weather Shock (Dry)



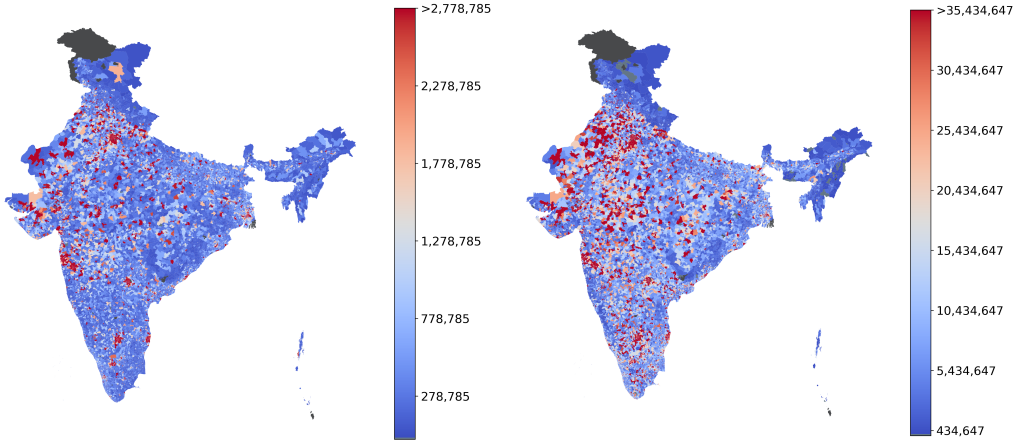
(b) Weather Shock (Wet)

Figure A2: **Weather Shock Dummies.** This figure refers to December 2020 as an example. Figure A2a shows the ZIP codes in which the SPEI is lower than the 20th percentile of the historical SPEI distribution in that ZIP code. Figure A2b shows the ZIP codes in which the SPEI is higher than the 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.



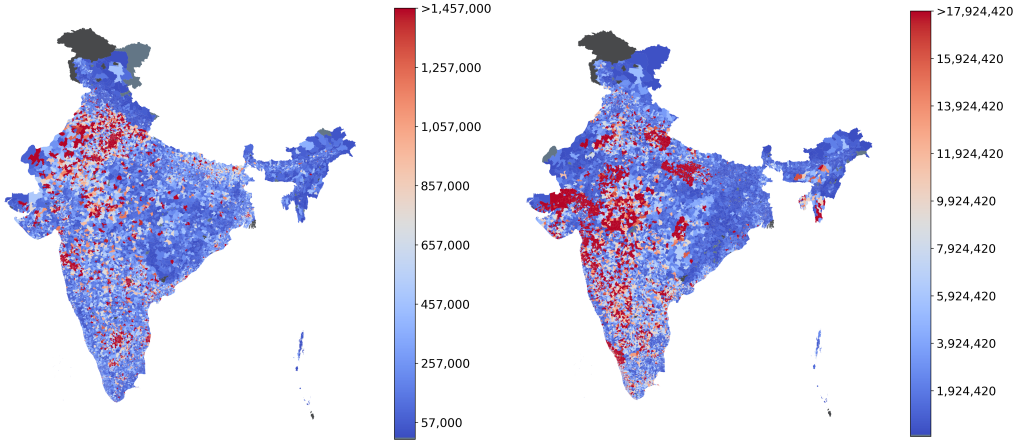
(a) Public

(b) Private



(c) Foreign

(d) NBFC



(e) Fintech

(f) Others

Figure A3: **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.

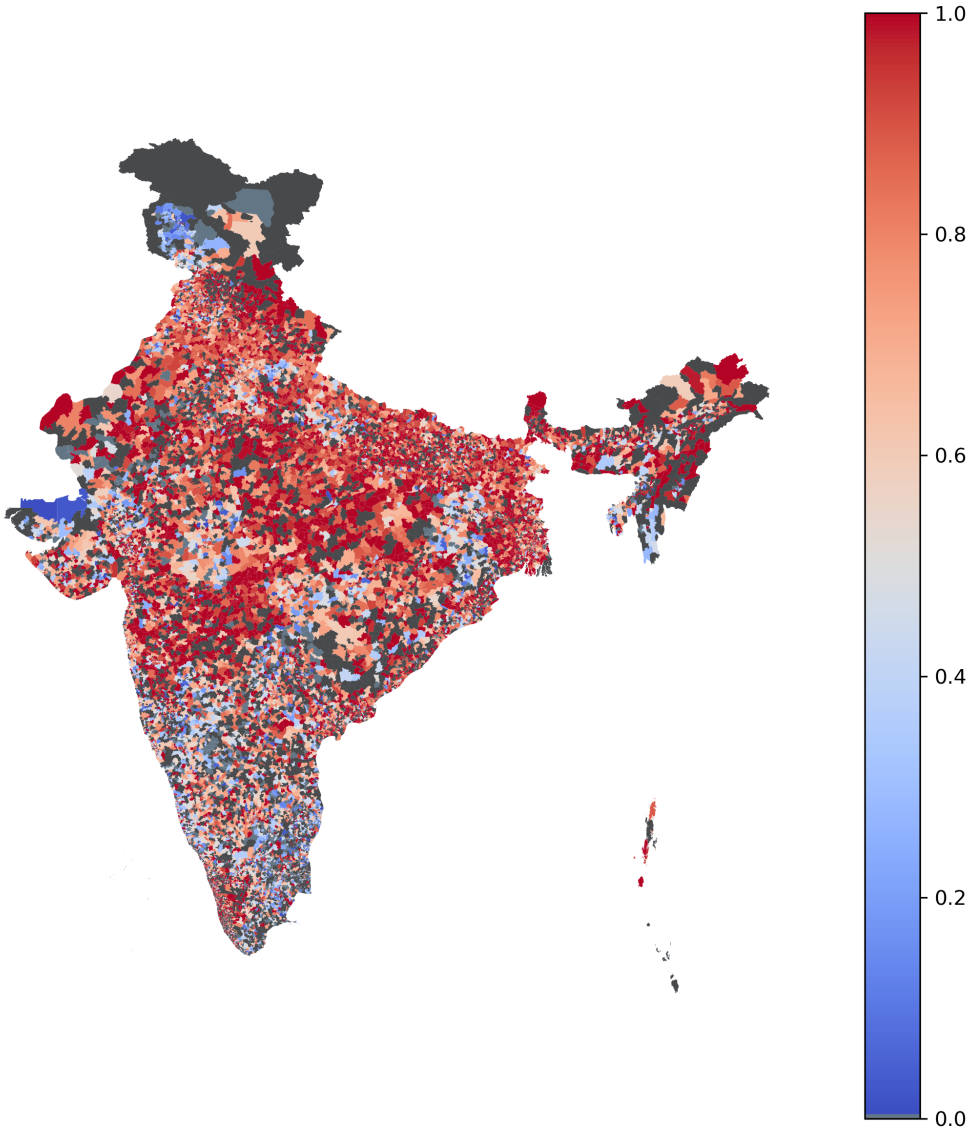


Figure A4: **UPI Index.** This figure reports the cross-sectional UPI index on the ZIP-level, constructed as described in Section 2. Light gray indicates zero, dark gray indicates missing.

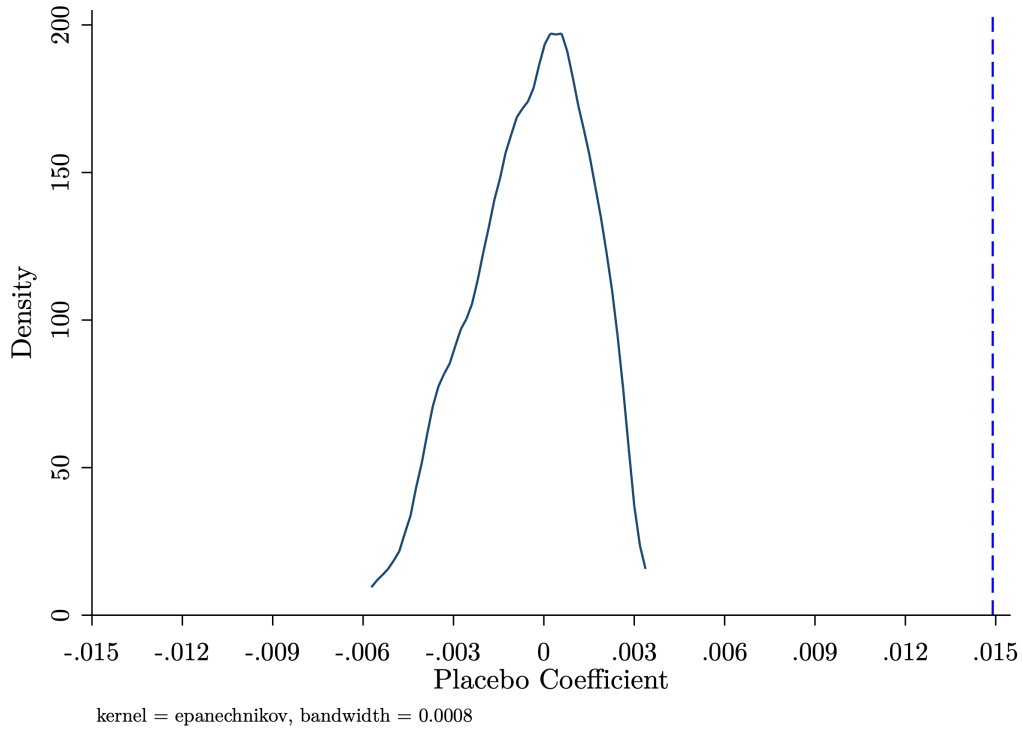


Figure A5: **Placebo Test: Random Shock Dummies.** This figure presents the results of a placebo test. We run our regression Equation 2, corresponding to Column 4 in Table 1, but replace our weather shock dummy with a dummy variable that is randomly set to one for 40% of the year-month-ZIPs. We choose 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	NBFC	Fintech	Other	Total	% Fintech
Total	22,956	22,489	2,586	44,048	8,856	7,427	108,362	8.17%
	Amounts (2021) - in billion rupees							
	Public	Private	Foreign	NBFC	Fintech	Other	Total	% Fintech
Total	4,612	3,973	218	3,137	228	1,015	13,183	1.73%
	Loan accounts (2021) - in thousands							
	Public	Private	Foreign	NBFC	Fintech	Other	Total	% Fintech
Consumption	3,572	12,826	2,579	23,176	8,338	319	50,810	16.41%
Business	112	237	2	473	135	121	1,080	12.50%
Vehicle	579	2,304	0	4,647	13	86	7,629	0.17%
Agriculture	14,350	608	0	375	2	1,305	16,640	0.01%
Gold	0	5,443	0	13,557	5	3,855	22,860	0.02%
Microfinance	73	425	0	96	0	45	639	0.00%
Other	4,270	646	4	1,724	364	1,696	8,704	4.18%
	Amounts (2021) - in billion rupees							
	Public	Private	Foreign	NBFC	Fintech	Other	Total	% Fintech
Consumption	1,161	1,361	200	794	152	90	3,758	4.04%
Business	78	202	8	222	44	49	603	7.30%
Vehicle	389	961	0	1,017	4	38	2,409	0.17%
Agriculture	1,964	269	0	145	1	243	2,622	0.04%
Gold	0	699	0	673	1	321	1,694	0.06%
Microfinance	8	36	0	3	0	9	56	0.00%
Other	1,013	444	10	282	26	266	2,041	1.27%
	Loan accounts (2021) - in thousands							
	Public	Private	Foreign	NBFC	Fintech	Other	Total	% Fintech
Super Prime	949	1,177	130	943	232	311	3,742	6.20%
Prime-Plus	3,015	3,625	549	4,049	844	783	12,865	6.56%
Prime	8,847	8,187	1,051	13,489	3,402	2,209	37,185	9.15%
Near-Prime	4,459	3,932	239	10,229	2,279	1,552	22,690	10.04%
Sub-Prime	2,214	1,624	44	5,175	764	938	10,759	7.10%
New-To-Credit	2,357	3,254	526	8,105	1,206	1,404	16,852	7.16%
	Amounts (2021) - in billion rupees							
	Public	Private	Foreign	NBFC	Fintech	Other	Total	% Fintech
Super Prime	248	286	20	107	10	42	712	1.37%
Prime-Plus	674	693	56	347	32	107	1,908	1.70%
Prime	1,874	1,462	86	1,023	99	293	4,836	2.04%
Near-Prime	887	718	18	701	50	208	2,582	1.94%
Sub-Prime	357	258	3	371	15	122	1,127	1.36%
New-To-Credit	353	313	27	414	19	152	1,278	1.47%

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**

	# Obs	p25	p50	p75	Mean	SD
Panel A: Public Sector Banks						
# Loans	4,612,254	3.00	8.00	28.00	38.43	88.40
Loan Amount	4,612,254	650,000.00	1,990,000.00	6,274,334.00	6,839,081.72	13,277,819.09
12-month Default Rate	4,612,254	0.0000	0.0000	0.0000	0.0259	0.0922
36-month Default Rate	4,612,254	0.0000	0.0000	0.0909	0.0832	0.1725
# Inquiries	4,612,254	1.50	4.83	14.08	14.56	29.82
Panel B: Private Sector Banks						
	# Obs	p25	p50	p75	Mean	SD
# Loans	5,293,364	2.00	6.00	17.00	26.10	69.66
Loan Amount	5,293,364	351,598.00	1,102,453.50	3,508,765.00	4,795,975.85	11,715,634.43
12-month Default Rate	5,293,364	0.0000	0.0000	0.0000	0.0318	0.1055
36-month Default Rate	5,293,364	0.0000	0.0000	0.1250	0.1013	0.1953
# Inquiries	5,293,364	0.58	3.58	14.00	18.81	45.66
Panel C: Foreign Banks						
	# Obs	p25	p50	p75	Mean	SD
# Loans	1,065,930	2.00	4.00	12.00	18.82	53.10
Loan Amount	1,065,930	119,000.00	348,000.00	1,128,200.00	2,137,123.93	7,123,484.05
12-month Default Rate	1,065,930	0.0000	0.0000	0.0000	0.0357	0.1125
36-month Default Rate	1,065,930	0.0000	0.0000	0.1014	0.0880	0.1902
# Inquiries	1,065,930	0.00	0.00	0.17	1.05	7.35
Panel D: NBFC						
	# Obs	p25	p50	p75	Mean	SD
# Loans	5,055,554	3.00	10.00	35.00	45.15	98.57
Loan Amount	5,055,554	300,150.00	1,061,582.50	3,447,068.00	4,135,903.40	9,693,066.12
12-month Default Rate	5,055,554	0.0000	0.0000	0.0541	0.0518	0.1239
36-month Default Rate	5,055,554	0.0000	0.0335	0.1905	0.1300	0.2071
# Inquiries	5,055,554	0.08	3.92	27.83	32.40	66.14
Panel E: Fintech						
	# Obs	p25	p50	p75	Mean	SD
# Loans	1,307,221	2.00	5.00	19.00	28.76	79.03
Loan Amount	1,307,221	26,050.00	103,995.00	380,000.00	705,198.36	2,763,901.72
12-month Default Rate	1,307,221	0.0000	0.0000	0.0870	0.0787	0.1692
36-month Default Rate	1,307,221	0.0000	0.0000	0.1250	0.1111	0.2144
# Inquiries	1,307,221	0.17	4.50	22.75	27.26	58.50
Panel F: Other Financial Institutions						
	# Obs	p25	p50	p75	Mean	SD
# Loans	3,125,635	1.00	4.00	12.00	16.50	44.48
Loan Amount	3,125,635	144,900.00	500,000.00	1,590,000.00	2,114,495.08	6,227,082.97
12-month Default Rate	3,125,635	0.0000	0.0000	0.0000	0.0573	0.1834
36-month Default Rate	3,125,635	0.0000	0.0000	0.1111	0.1352	0.2749
# Inquiries	3,125,635	0.00	0.08	0.50	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**

Panel A: Consumption Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	6,069,098	3.00	9.00	29.00	42.31	99.41
Loan Amount	6,069,098	160,288.00	660,000.00	2,403,431.00	3,577,856.09	9,865,923.66
12-month Default Rate	6,069,098	0.0000	0.0000	0.0448	0.0470	0.1237
36-month Default Rate	6,069,098	0.0000	0.0000	0.1034	0.0874	0.1738
# Inquiries	6,069,098	0.42	6.50	27.75	34.06	67.75
Panel B: Business Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	1,590,155	1.00	2.00	5.00	5.59	15.83
Loan Amount	1,590,155	180,000.00	645,449.00	2,260,000.00	3,164,580.21	8,872,734.77
12-month Default Rate	1,590,155	0.0000	0.0000	0.0000	0.0546	0.1751
36-month Default Rate	1,590,155	0.0000	0.0000	0.2500	0.1675	0.2932
# Inquiries	1,590,155	0.33	1.58	5.50	6.94	19.03
Panel C: Vehicle Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	3,505,068	2.00	6.00	19.00	19.36	41.79
Loan Amount	3,505,068	575,000.00	1,671,310.00	4,861,874.00	5,386,249.19	11,263,563.74
12-month Default Rate	3,505,068	0.0000	0.0000	0.0299	0.0345	0.0933
36-month Default Rate	3,505,068	0.0000	0.0357	0.2282	0.1383	0.1997
# Inquiries	3,505,068	2.08	9.75	29.67	28.57	50.99
Panel D: Agriculture Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	3,269,797	2.00	6.00	25.00	42.17	100.36
Loan Amount	3,269,797	468,000.00	1,350,000.00	4,620,000.00	5,993,857.02	13,091,405.32
12-month Default Rate	3,269,797	0.0000	0.0000	0.0033	0.0452	0.1392
36-month Default Rate	3,269,797	0.0000	0.0016	0.2000	0.1453	0.2507
# Inquiries	3,269,797	0.00	0.67	3.83	4.99	14.48
Panel D: Gold Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	2,488,014	4.00	13.00	49.00	50.27	92.83
Loan Amount	2,488,014	237,794.00	884,500.00	3,214,600.00	3,603,792.97	8,061,805.13
12-month Default Rate	2,488,014	0.0000	0.0000	0.0000	0.0247	0.0901
36-month Default Rate	2,488,014	0.0000	0.0000	0.0311	0.0435	0.1211
# Inquiries	2,488,014	0.00	0.00	0.42	1.39	6.38
Panel E: Microfinance Loans						
	# Obs	p25	p50	p75	Mean	SD
# Loans	385,748	1.00	3.00	8.00	8.38	19.44
Loan Amount	385,748	40,000.00	169,000.00	593,000.00	708,686.67	2,958,832.10
12-month Default Rate	385,748	0.0000	0.0000	0.0000	0.0558	0.1759
36-month Default Rate	385,748	0.0000	0.0000	0.1263	0.1406	0.2816
# Inquiries	385,748	0.00	0.08	0.75	2.44	12.71
Panel F: Other						
	# Obs	p25	p50	p75	Mean	SD
# Loans	3,152,078	2.00	5.00	14.00	16.87	39.73
Loan Amount	3,152,078	185,000.00	825,000.00	3,040,891.00	4,182,848.87	10,640,875.77
12-month Default Rate	3,152,078	0.0000	0.0000	0.0000	0.0464	0.1461
36-month Default Rate	3,152,078	0.0000	0.0000	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: NBFC

	# 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**

	# 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
Panel A: Public Sector Banks																				
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
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
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
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	-				-				-				-				-			
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																				
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
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
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
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
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																				
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
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
Vehicle	-				-				-				-				-			
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	-				-				-				-				-			
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: NBFC																				
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
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
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
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
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																				
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
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
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
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
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																				
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
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
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
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
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%	1373	2001	27%	18%
5-10%	1782	2607	20%	14%
10-20%	2112	3157	17%	12%
20-30%	2454	3762	15%	10%
30-40%	2768	4348	13%	8%
40-50%	3094	4963	12%	7%
50-60%	3455	5662	11%	6%
60-70%	3887	6524	9%	6%
70-80%	4458	7673	8%	5%
80-90%	5356	9582	7%	4%
90-95%	6638	12399	6%	3%
95-100%	10501	20824	3%	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**

Dep Var: # Inquiries	(1)	(2)	(3)	(4)
FinTech × Shock	59.2412***	62.3401***	60.1413***	7.8576***
	(1.1479)	(1.0575)	(1.0403)	(1.3598)
FinTech	-27.2132***	-70.9572***	-68.7952***	
	(0.8843)	(1.3012)	(1.2845)	
Shock	28.0795***	-6.1881***		
	(0.9493)	(0.2940)		
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	0.00	0.18	0.19	0.94
Observations	3,241,414	3,241,414	3,241,414	3,241,414

Notes: This table presents Fintech inquiries after the shock, compared to other lenders. Equation 2 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. $\text{Shock}_{y,z}$ 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 Issuance – Provider Type and Credit Score**

Dep Var: LN(Amount)	Total (1)	Super-Prime (2)	Prime-Plus (3)	Prime (4)	Near-Prime (5)	Sub-Prime (6)	New-to-Credit (7)
FinTech × Shock	0.0129***	-0.0061	-0.0014	0.0059*	0.0089***	0.0155***	0.0229***
	(0.0024)	(0.0082)	(0.0046)	(0.0031)	(0.0033)	(0.0046)	(0.0038)
NBFC × Shock	0.0001	-0.0005	-0.0029	-0.0063***	0.0003	-0.0034	0.0071***
	(0.0014)	(0.0050)	(0.0028)	(0.0019)	(0.0022)	(0.0030)	(0.0022)
Private × Shock	-0.0035**	-0.0006	0.0020	-0.0029	-0.0005	-0.0047	-0.0023
	(0.0014)	(0.0047)	(0.0027)	(0.0019)	(0.0023)	(0.0032)	(0.0022)
Foreign × Shock	-0.0026	-0.0003	-0.0012	0.0019	-0.0107***	-0.0041	-0.0030
	(0.0023)	(0.0065)	(0.0037)	(0.0029)	(0.0041)	(0.0071)	(0.0037)
Other × Shock	-0.0069***	-0.0184***	-0.0035	-0.0067***	-0.0055*	0.0032	-0.0194***
	(0.0018)	(0.0066)	(0.0039)	(0.0026)	(0.0029)	(0.0036)	(0.0027)
Omitted Category	Public	Public	Public	Public	Public	Public	Public
FinTech × Shock = NBFC × Shock	0.00	0.47	0.73	0.00	0.01	0.00	0.00
FinTech × Shock = Private × Shock	0.00	0.47	0.45	0.00	0.00	0.00	0.00
FinTech × Shock = Foreign × Shock	0.00	0.49	0.97	0.25	0.00	0.01	0.00
FinTech × Shock = Other × Shock	0.00	0.19	0.70	0.00	0.00	0.02	0.00
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,060	15,468	18,821	19,007	18,940	18,601	18,968
Year-months	71	71	71	71	71	71	71
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 lender credit issuance after a shock, compared to public banks, by credit score. Equation 2 describes the regression, plus interactions for other lenders. Public banks are omitted. The data is on the year-ZIP-lender-product level. $\ln(\text{Amount})_{y,z,l,p}$ 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. $\text{Shock}_{y,z}$ 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 – Credit Score**

Dep Var: # Inquiries	Total (1)	Super-Prime (2)	Prime-Plus (3)	Prime (4)	Near-Prime (5)	Sub-Prime (6)	New-to-Credit (7)
FinTech × Shock	7.8576***	0.2432***	0.7113***	1.9301***	1.0618***	0.4220**	3.1753***
	(1.3598)	(0.0243)	(0.0977)	(0.3854)	(0.2817)	(0.1919)	(0.3965)
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	3,241,414	3,241,414	3,241,414	3,241,414	3,241,414	3,241,414	3,241,414

Notes: This table presents Fintech credit inquiry after a shock, compared to other lenders, by credit score. Equation 2 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. $\text{Shock}_{y,z}$ 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 – Provider Type and Credit Score**

Dep Var: # Inquiries	Total (1)	Super-Prime (2)	Prime-Plus (3)	Prime (4)	Near-Prime (5)	Sub-Prime (6)	New-to-Credit (7)
FinTech × Shock	8.7583***	0.2202***	0.6852***	1.8084***	0.9910***	0.2610	4.3410***
	(1.2856)	(0.0263)	(0.0872)	(0.3535)	(0.2692)	(0.1893)	(0.4213)
NBFC × Shock	0.7013	-0.0308	-0.1509**	-0.8898***	-0.4421**	-0.2178*	2.3231***
	(0.8194)	(0.0233)	(0.0739)	(0.2432)	(0.1767)	(0.1126)	(0.2540)
Private × Shock	-2.4809***	-0.1343***	-0.3836***	-1.2953***	-0.7311***	-0.5407***	0.7333***
	(0.5386)	(0.0172)	(0.0500)	(0.1551)	(0.1066)	(0.0767)	(0.2127)
Foreign × Shock	1.4561	0.1625***	0.2820**	1.0846***	0.2230	-0.3422**	0.0340
	(1.2001)	(0.0495)	(0.1396)	(0.4015)	(0.2635)	(0.1707)	(0.2841)
Other × Shock	4.3313***	0.0018	0.2748***	1.2447***	0.7149***	0.2376***	1.6175***
	(0.5583)	(0.0231)	(0.0725)	(0.2025)	(0.1248)	(0.0769)	(0.1915)
Omitted Category	Public	Public	Public	Public	Public	Public	Public
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 lender credit inquiry after a shock, compared to public banks, by credit score. Equation 2 describes the regression, except that the data is at year as opposed to year-month level plus interactions for other lenders. Public banks are omitted. 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. $\text{Shock}_{y,z}$ 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 – Provider Type and Product Type**

Dep Var: # Inquiries	All (1)	Agric (2)	Busi (3)	Cons (4)	Gold (5)	MFI (6)	Vehicle (7)	Other (8)
FinTech × Shock	8.7583***	-7.1149***	7.8763***	9.1037***	-45.1334	36.2435***	0.9300	4.5223**
	(1.2856)	(2.4523)	(0.8140)	(2.9569)	(44.7461)	(5.1804)	(1.6808)	(2.2285)
NBFC × Shock	0.7013	12.8586***	-0.5426	-21.9956***	4.2509*	0.9019	6.1791***	12.6415***
	(0.8194)	(1.4284)	(1.0049)	(2.9180)	(2.3030)	(1.4685)	(1.1026)	(1.4869)
Private × Shock	-2.4809***	-7.3565***	1.6382**	-8.4339***	-0.4587	-36.3894***	-1.7488**	8.5516***
	(0.5386)	(0.9427)	(0.6937)	(1.8541)	(2.0480)	(3.4009)	(0.8560)	(1.2815)
Foreign × Shock	1.4561	-9.3277	-15.0526***	1.2966	0.0000	0.0000	9.0076***	8.5855***
	(1.2001)	(6.6384)	(3.4827)	(1.9204)	(.)	(.)	(3.1133)	(1.3504)
Other × Shock	4.3313***	-0.2709	1.4967**	10.9374***	0.0000	11.4458***	2.0258**	7.0344***
	(0.5583)	(1.1467)	(0.6165)	(1.4051)	(.)	(1.5276)	(0.8505)	(1.1853)
Omitted Category	Public	Public	Public	Public	Public	Public	Public	Public
Year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
ZIPs	19,080	18,512	18,913	19,077	8,409	16,476	19,062	19,006
Years	6	6	6	6	6	6	6	6
R-squared	0.94	0.87	0.92	0.92	0.96	0.74	0.98	0.92
Observations	3,002,434	336,592	501,262	572,726	74,471	205,095	440,135	495,945

Notes: This table presents lender credit inquiry after a shock, compared to public banks, by product type. Equation 2 describes the regression, except that the data is at year as opposed to year-month level plus interactions for other lenders. Public banks are omitted. 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. $\text{Shock}_{y,z}$ 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: **Robustness – Absolute Specification**

Dep Var: LN(Amount)	(1)	(2)	(3)	(4)
Shock	0.0673***	0.0125***	0.0099***	0.0127***
	(0.0037)	(0.0026)	(0.0025)	(0.0022)
Year-month FE		✓	✓	
ZIP FE		✓	✓	
Product FE			✓	
Year-month × Product FE				✓
ZIP × Product FE				✓
ZIPs	19,037	19,037	19,037	19,037
Year-months	71	71	71	71
R-squared	0.00	0.33	0.53	0.69
Observations	1,353,361	1,353,361	1,353,361	1,353,361

Notes: This table presents the absolute effect of Fintech credit issuance. Equation 5 describes the regression. The data is on the ZIP-year-month-product level, conditional on Fintech. $\ln(\text{Amount})_{ym,z,l,p}$ 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.

$$y_{ym,z,p} = \beta \cdot \text{Shock}_{ym,z} + \text{FE}_{ym,p} + \text{FE}_{z,p} + \epsilon_{ym,z,p} \tag{5}$$

Table A14: **Robustness – Poisson Transformation**

Dep Var: Amount	(1)
FinTech × Shock	0.0383***
	(0.0038)
ZIP × Year-month × Product FE	✓
Year-month × Lender × Product FE	✓
ZIP × Lender × Product FE	✓
ZIPs	19,083
Year-months	71
R-squared	0.93
Observations	35,991,285

Notes: This table presents robustness for our results in Table 1, using Poisson regression. Equation 2 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. $\text{Shock}_{ym,z}$ 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 A15: **Robustness – Different Shock Splits (Wet and Dry) and Severity**

Dep Var: LN(Amount)	> 80th or < 20th Pct (1)	> 80th Pct (2)	< 20th Pct (3)	> 90th or < 10th Pct (4)	> 90th Pct (5)	< 10th Pct (6)
FinTech × Shock	0.0149***	0.0056**	0.0242***	0.0157***	0.0068**	0.0305***
	(0.0022)	(0.0026)	(0.0034)	(0.0028)	(0.0033)	(0.0048)
Year-month × ZIP × Product FE	✓	✓	✓	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓
ZIPs	19,060	19,060	19,060	19,060	19,060	19,060
Year-months	71	71	71	71	71	71
R-squared	0.84	0.84	0.84	0.84	0.84	0.84
Observations	20,459,958	20,459,958	20,459,958	20,459,958	20,459,958	20,459,958

Notes: This table presents robustness for our results in Table 1 by different splits (wet and dry) of shock. Equation 2 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. $\text{Shock}_{ym,z}$ 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 Lengths**

Dep Var: LN(Amount)	1 Month (1)	3 Months (2)	6 Months (3)
FinTech × Shock	0.0149***	0.0083***	0.0110***
	(0.0022)	(0.0023)	(0.0025)
Year-month × ZIP × Product FE	✓	✓	✓
Year-month × Lender × Product FE	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓
ZIPs	19,060	19,060	19,060
Year-months	71	71	71
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 different lengths of SPEI months. Equation 2 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. $\text{Shock}_{ym,z}$ 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 – Continuous Water Balance Measure**

Dep Var: LN(Amount)	(1)	(2)	(3)	(4)
FinTech × SPEI	0.0850***	0.0612***	0.0700***	0.0121***
	(0.0030)	(0.0026)	(0.0027)	(0.0019)
FinTech	-2.3580***	-2.5796***	-2.5821***	
	(0.0030)	(0.0026)	(0.0027)	
SPEI	0.0383***	-0.0018**		
	(0.0008)	(0.0007)		
Year-month FE		✓		
ZIP FE		✓		
Year-month × 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-Months	71	71	71	71
R-squared	0.08	0.29	0.32	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 2 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. $\text{SPEI}_{ym,z}$ 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 A18: **Fintech ABC – Days to Disbursal**

Dep Var: # Days to Disbursal	All (1)	New-to-Credit (2)	Not New-to-Credit (3)
Alternative Data × Shock	-0.1266***	-0.5521***	-0.1389***
	(0.0489)	(0.1984)	(0.0524)
Alternative Data	-0.4177***	-0.5061***	-0.4543***
	(0.0332)	(0.1358)	(0.0367)
Year-month × ZIP × Merchant Type FE	✓	✓	✓
Onboarding Channel FE	✓	✓	✓
Swipe Machine FE	✓	✓	✓
Membership in Investment App FE	✓	✓	✓
ZIPs	5,749	2,395	5,334
Year-months	16	13	16
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 4 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 A19: **Fintech ABC – Interest Rate**

Dep Var: Interest Rate	All (1)	New-to-Credit (2)	Not New-to-Credit (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
Year-months	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 4 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 A20: **Fintech ABC – Loan Default**

Dep Var: Loan Default (0 or 1)	All (1)	New-to-Credit (2)	Not New-to-Credit (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
Year-months	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 4 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.