Fintech to the Rescue: Navigating Climate Change

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Preliminary and incomplete – Please do not circulate

Abstract

What role can Fintech play in climate change adaptation in developing countries? Combining the census of 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 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 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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Extended Abstract

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. 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. Fintechs may be better at responding to climate shocks for two 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, the integration of technology enhances their capacity to adapt to such challenges swiftly. Although there is considerable academic and policy discourse regarding Fintechs mitigating climate-related disruptions, empirical evidence is limited.

This paper aims to shine a light on the role 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 weather data. 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 apply a granular difference-in-difference strategy, comparing loan outcomes within the same ZIP code, the same year-month, the same lender type, and the same product category.

Our first result shows that Fintech providers issue more credit in response to climate shocks than traditional banks. The response is both rapid and economically meaningful. In the month of the shock, the credit amount issued by Fintech lenders increases by 2%. The dynamic response demonstrates that Fintech lending remains higher than in the absence of a shock for the following five months. Second, we document that Fintechs primarily increase their lending to borrowers with a low and medium credit score or who are new-to-credit.[1] On the other hand, lending to high-credit-score segments does not increase. Since this is a within-lender comparison, Fintechs' loan portfolio shifts towards more risky credit. 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. We examine FinTech's

[1]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.

one- and three-year default rates and do not see economically meaningful increases. In other words, climate risk does not create ex-post risky balance sheets of Fintech lenders.

Next, we examine the underlying mechanism that allows FinTechs to respond stronger to climate shocks. We hypothesize that this could be driven either by a lower regulatory burden or a technological advantage. To test for the mechanism of lower regulatory burden, we compare how Fintech and shadow banks respond relative to traditional banks when faced with climate shocks. The underlying idea of this analysis is that if the lower regulatory burden motivates Fintechs to increase lending to segments that are inherently riskier following climate shocks, we would expect similar behavior from shadow banks, given that they also operate under a regulatory burden lower than that of traditional banks, and similar to Fintechs. However, we document that shadow banks respond similarly to traditional banks, indicating that a lower regulatory burden is unlikely to be the sole explanation for how Fintechs respond to climate events.

These findings indicate that Fintech companies stand out, and their response to climate-related disruptions might not simply be due to reduced regulatory constraints. Instead, it appears to stem from the advanced technology and alternative data these lending platforms utilize. It enables them to promptly react to such disruptions and identify underserved segments not reached by traditional banks. By analyzing proprietary data from two Fintech firms, we demonstrate that their technological edge indeed drives this outcome. Specifically, Fintechs can leverage alternative data sources such as social connections and digital transaction records to extend more credit to individuals with limited or no credit history in a timely fashion following a climate shock.

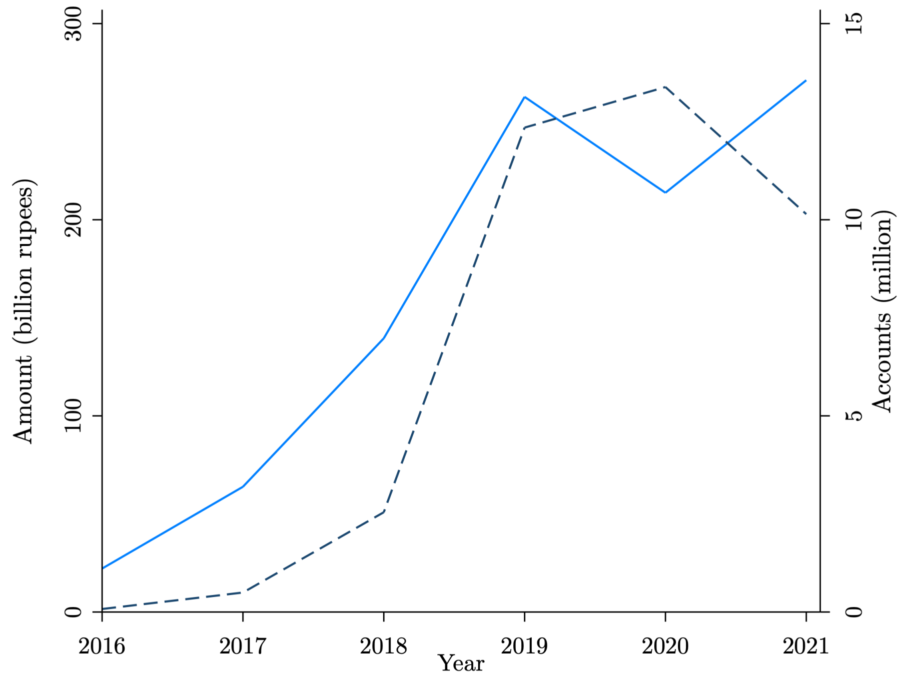

Figure 1: **Loan Amount and Number of Accounts Issued in a Given Year.** This figure shows the time series of Fintech growth between 2016 and 2021. The left-hand axis describes the aggregate loan amount in billion rupees (solid line). The right-hand axis denotes the aggregate loan accounts in millions (dashed line).

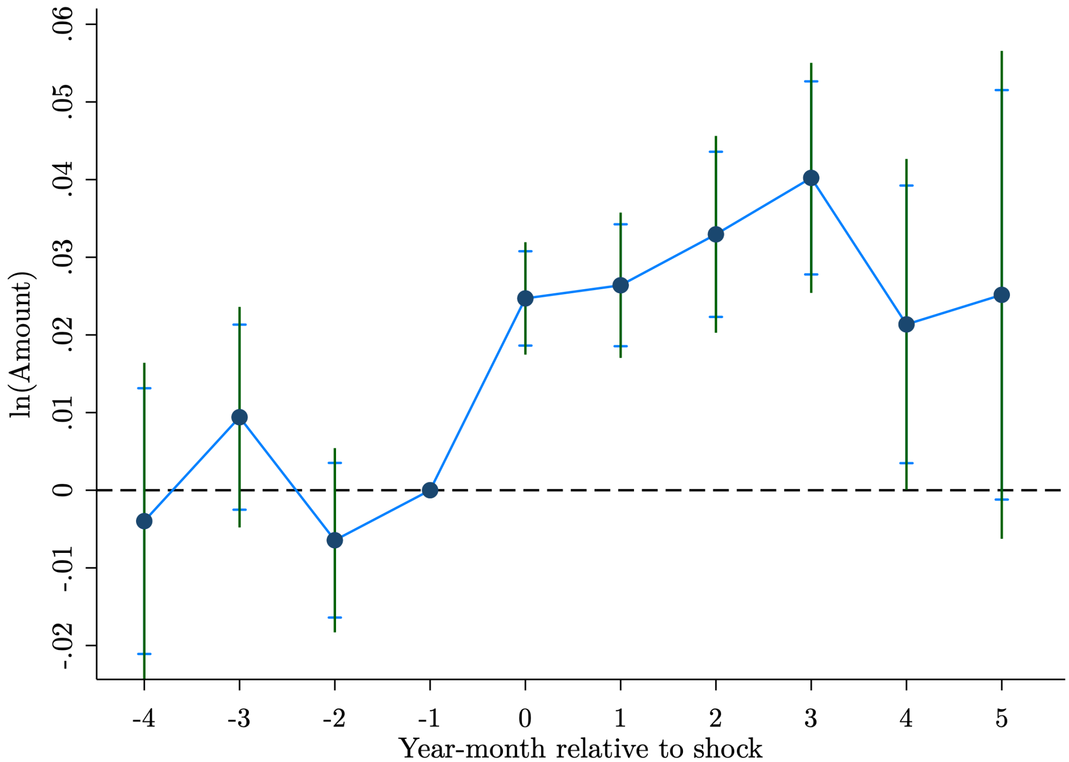

Figure 2: **Amount**. This figure shows the dynamic effects of how much more credit Fintech issues in response to a shock compared to other lenders. Equation 1 describes the regression, where t is the year-month relative to the shock and the reference period is t=-1. The data is on the ZIP-year-month-lender-product level. $\ln(\text{Amount})_{z,ym,l,p}$ 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 for if the lender is a Fintech and zero otherwise. $\text{Shock}_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. The figure shows 90% and 95% confidence intervals.

$$y_{z,ym,l,p} = \sum_{t=-4}^{5} \beta_t \text{Shock}_{z,ym} \times \text{Fintech}_l + \text{FE}_{ym,z,p} + \text{FE}_{ym,l,p} + \text{FE}_{z,l,p} + \epsilon_{z,ym,l,p} \tag{1}$$

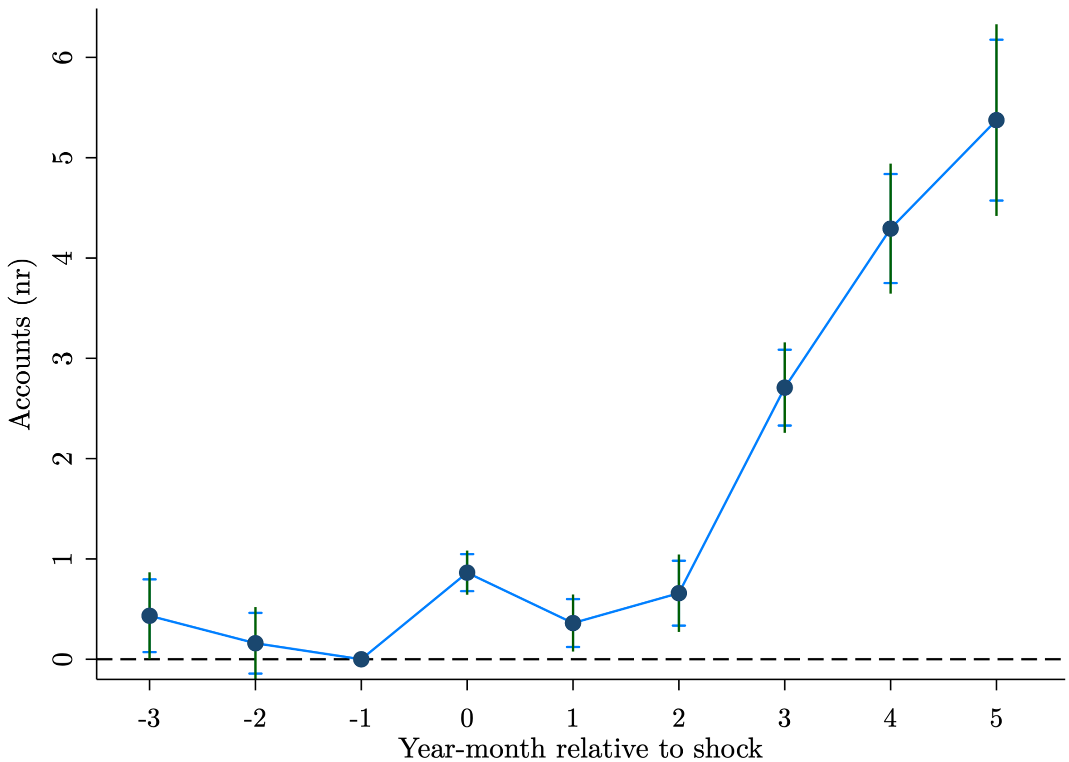

Figure 3: **Extensive Margin Effect, # of Accounts**. This figure shows the dynamic effects of how many more credit accounts Fintechs issue in response to a shock compared to other lenders. Equation 1 describes the regression, where t is the year-month relative to the shock and the reference period is t=-1. The data is on the ZIP-year-month-lender-product level. $\text{Accounts}_{z,ym,l,p}$ describes the number of loans issued. The outcome is winsorized at the 1st and 99th percentile. Fintech_{l} is a dummy equal to one for if the lender is a Fintech and zero otherwise. $\text{Shock}_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. The figure shows 90% and 95% confidence intervals.

Table 1: **Fintech Issues More Credit Due to Shock**

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)		
Month-year FE		✓		
ZIP FE		✓		
Month-year × ZIP FE			✓	
Month-year × ZIP × Product FE				✓
Month-year × Lender × Product FE				✓
ZIP × Lender × Product FE				✓
ZIPs	19060	19060	19060	19060
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 shows how much more credit Fintech issues in the period of a shock, compared to other lenders. Equation 2 describes the regression. The data is on the ZIP-year-month-lender-product level. $\ln(\text{Amount})_{z,ym,l,p}$ 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 for if the lender is a Fintech and zero otherwise. $\text{Shock}_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

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

Table 2: **Extensive Margin Effect: Fintech Issues More Credit Due to Shock**

Dep Var: # 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)		
Month-year FE		✓		
ZIP FE		✓		
Month-year × ZIP FE			✓	
Month-year × ZIP × Product FE				✓
Month-year × 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 shows how many more credit accounts Fintech issues in the period of a shock compared to other lenders. Equation 2 describes the regression. The data is on the ZIP-year-month-lender-product level. $\text{Accounts}_{z,ym,l,p}$ describes the number of loans issued. The outcome is winsorized at the 1st and 99th percentile. Fintech_l is a dummy equal to one for if the lender is a Fintech and zero otherwise. $\text{Shock}_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 3: **Ex-Ante Risk Taking: Amount Increase for Low Score, Medium Score, and New-to-Credit Borrowers**

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)
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓
ZIPs	19060	15468	18821	19007	18940	18601	18968
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 shows how much more credit Fintech issues in the period of a shock, compared to other lenders, by credit score type. Equation 2 describes the regression. The data is on the ZIP-year-month-lender-product level. ln(Amount)$_{z,ym,l,p}$ 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 for if the lender is a Fintech and zero otherwise. Shock$_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 4: **Economically Insignificant Response in Default Rates**

Dep Var: Default Rate	1 year (1)	3 years (2)
FinTech × Shock	0.0003	0.0009**
	(0.0003)	(0.0004)
Month-year × ZIP × Product FE	✓	✓
Month-year × Lender × Product FE	✓	✓
ZIP × Lender × Product FE	✓	✓
ZIPs	19060	19060
Year-Months	71	71
R-squared	0.45	0.51
Observations	20,459,958	20,459,958

Notes: This table shows 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 ZIP-year-month-lender-product level. Default rate$_{z,ym,l,p}$ 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 for if the lender is a Fintech and zero otherwise. Shock$_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 5: **Amount Increase Concentrated in Business, Consumption, and Vehicle Loans**

Dep Var: LN(Amount)	All (1)	Agri-culture (2)	Business (3)	Con-sumption (4)	Micro-finance (5)	Vehicle (6)	Gold (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)
Month-year × ZIP × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Month-year × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
ZIP × Lender × Product FE	✓	✓	✓	✓	✓	✓	✓	✓
ZIPs	19060	18711	16549	19052	18078	11716	18962	18794
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 shows how much more credit Fintech issues 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 ZIP-year-month-lender-product level. $\ln(\text{Amount})_{z,ym,l,p}$ 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 for if the lender is a Fintech and zero otherwise. $\text{Shock}_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. $***$, ** and $*$ indicate significance at the 1%, 5% and 10% levels.

Table 6: **Mechanisms – Lower Regulatory Burden of Fintechs Unlikely Explanation, as Shadow Banks Do Not React**

Dep Var: LN(Amount)	(1)
FinTech × Shock	0.0129***
	(0.0024)
Shadow × Shock	0.0001
	(0.0014)
Private × Shock	-0.0035**
	(0.0014)
Foreign × Shock	-0.0026
	(0.0023)
Other × Shock	-0.0069***
	(0.0018)
Omitted Category	Public
FinTech × Shock = Shadow × Shock	0.00
FinTech × Shock = Private × Shock	0.00
FinTech × Shock = Foreign × Shock	0.00
FinTech × Shock = Other × Shock	0.00
Month-year × ZIP × Product FE	✓
Month-year × Lender × Product FE	✓
ZIP × Lender × Product FE	✓
ZIPs	19,060
Year-Months	71
R-squared	0.84
Observations	20,459,958

Notes: This table shows how much more credit Fintech issues in the period of a shock, compared to other lenders. 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 ZIP-year-month-lender-product level. $\ln(\text{Amount})_{z,ym,l,p}$ 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 for if the lender is a Fintech and zero otherwise. $\text{Shock}_{z,ym}$ is a dummy equal to one if the ZIP code in a given year-month experienced a weather shock. Standard errors are clustered at the ZIP code level. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels.