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Working Paper

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SAFE Working Paper, No. 455

Provided in Cooperation with:

Leibniz Institute for Financial Research SAFE

Suggested Citation: Beyene, Winta (2025) : Disasters and lending signals: From borrower information to community characteristics, SAFE Working Paper, No. 455, Leibniz Institute for Financial Research SAFE, Frankfurt a. M., <https://doi.org/10.2139/ssrn.5435455>

This Version is available at:

<https://hdl.handle.net/10419/325484>

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SAFE Working Paper No. 455 | August 2025

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Disasters and Lending Signals: From Borrower Information to Community Characteristics

Winta Beyene¹

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Abstract

I study the informational value of community resilience in credit markets during natural disasters. Exploiting a severe flood in Germany in 2013, I combine loan-level data on car loans with a composite measure of community resilience based on structural local characteristics linked to disaster recovery capacity. After the flood, only low-income borrowers faced credit tightening, but in high-resilience areas they experienced smaller rate hikes and maintained access to credit. Resilience also predicts repayment after disasters, yet banks ignore it in normal times. This state-contingent reliance shows that community resilience enters credit pricing only in crises, when its information content beyond standard borrower characteristics is valuable enough to justify adoption.

Key words: Financial resilience; natural disasters; social capital; consumer credit

^{1*}Acknowledgement: I am grateful to Konrad Adler, Emanuela Benincasa, Tobias Berg, Martin Brown, Olimpia Carradori, Ana Mao de Fero, Manthos Delis, Sebastian Doerr, Emilia Garcia-Appendi, Florian Heider, Amra Hrustanovic, Gazi Kabas, Thea Kolasa, Christine Laudenschach, Mrinal Mishra, Steven Ongena, Alex Osberghaus, Lorian Pelizzon, Zacharias Sautner, Giuseppe Scalia, Alessandro Scopelliti, Felix von Meyerick, Alexander Wagner, Olga Balakina, Katia Vozian, and Rainer Haselmann, as well as the participants at the Brown Bag Lunch Seminar at UZH, EPFL Lausanne Research Seminar, University of Massachusetts Amherst Research Seminar, Federal Reserve Board, HEC Montreal, and Bayes Business School for helpful comments and suggestions. I gratefully acknowledge research support from the Leibniz Institute for Financial Research SAFE and financial support from the Swiss National Science Foundation and the UZH Candoc program.

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1 Introduction

Natural disasters are among the most frequent and costly shocks to local economies, and access to credit is often critical for households in their aftermath. Yet banks may restrict lending precisely when financing is most needed, as reliable information on how disasters affect borrower creditworthiness becomes costly or unavailable. When borrower information is scarce, lenders may look to community-level factors that shape recovery prospects. Because disaster response is inherently local, recovery speed and success vary substantially across communities, driven largely by underlying social and institutional factors. Recent policy initiatives increasingly stress resilience to disasters at the community level, but we know little about whether lenders incorporate such characteristics, beyond standard local economic conditions, into their credit decisions.

This paper asks whether, when disasters disrupt standard borrower information, banks turn to community resilience, capturing local capacity to recover, as an alternative signal of repayment risk. I exploit the catastrophic 2013 flood in Germany, a widespread and plausibly exogenous shock, to examine changes in household credit access using a novel loan-level dataset on car loans. To capture variation in local recovery capacity, I construct a composite Community Resilience Proxy based on pre-disaster structural social, human, and institutional factors. I find that after the flood, credit tightens sharply for low-income borrowers, but those in high-resilience counties experience smaller rate increases and higher loan origination rates. Community resilience is also predictive of post-disaster repayment performance on loans originated before the flood, yet commands no premium in normal times. These findings reveal an overlooked channel in modern credit markets: in times of crisis, when borrower signals weaken, banks rely on the resilience of local communities—rooted in social, human, and institutional capital—as an alternative signal of borrower risk.

The empirical analysis relies on the 2013 German flood as a plausibly exogenous shock to household credit, paired with loan-level data on car loans and a new proxy for community resilience. The flood was sudden, severe, and widespread, offering a rare setting to study geographic variation in lender responses. I define flood exposure as a binary county-level indicator for whether a state of emergency was declared, which applied to more than 50 of Germany’s roughly 400 counties, and show that results are robust to alternative intensity measures based on precipitation data.

To capture differences in community resilience across counties, I construct a Community Resilience Proxy (CRP), a composite measure of their ex-ante capacity to cope with and recover from disasters. The CRP aggregates pre-disaster structural characteristics of human, civic, and institutional capital—factors that proxy a community’s ability to coordinate, mobilize, and adapt effectively after a shock. It adapts the widely used Baseline Resilience Indicators for Communities (BRIC) framework to the German context, drawing on administrative and survey data and informed by forensic disaster analysis following the 2013 flood.¹

¹This framework underpins FEMA’s National Risk Index, developed following the U.S. Community Disaster Resilience Zones Act (2022), and recent resilience assessments by the European Commission. The Karlsruhe Institute of Technology’s Forensic Disaster Analysis group applied similar metrics in their evaluation of the 2013 floods in

To study lending responses, I use loan-level data on newly issued passenger car loans by banks without local branches, drawn from the European DataWarehouse, which tracks loans securitized by European banks. The dataset covers nearly 180 auto ABS transactions in Germany since 2012 and provides detailed information on loan terms and borrower characteristics. The consumer car loan market is particularly well-suited for studying disaster effects on household credit for a number of reasons. Because auto loans have short maturities relative to the return period of floods, lenders are unlikely to adjust pricing for expected flood-related collateral losses. Moreover, vehicles financed in Germany are typically insured against catastrophic flooding, ruling out concerns about incomplete insurance markets. Car ownership is highly sensitive to credit conditions, making auto lending a strong proxy for household credit access and an important margin of financial inclusion, particularly for low-income households facing income volatility (Parker, Souleles, Johnson, & McClelland, 2013; Di Maggio et al., 2017; Pástor & Veronesi, 2013; Skrastins, Gomes, Doornik, & Schoenherr, 2023). Finally, because most car loans are originated through auto retailers or online platforms, the analysis focuses on non-local banks with no disaster exposure and no private local information about borrowers.

I compare lending in counties placed under emergency during the sudden 2013 flood to unaffected counties before and after the event, and allow these responses to vary with a pre-disaster Community Resilience Proxy (CRP). The design includes county, auto-model, and bank \times state \times year fixed effects with standard county-time controls; event studies show no differential pre-trends. On pricing, loan rates rise in affected counties (≈ 28 bps), with increases concentrated among low-income borrowers (≈ 70 bps), but high-CRP counties see materially smaller hikes (≈ 60 bps less per 1 s.d. CRP). On the extensive margin, the post-flood contraction in originations and volumes is attenuated in more resilient counties ($\approx 5\text{--}6\%$ per 1 s.d. CRP). For loans originated before the flood, higher CRP predicts fewer arrears post-disaster, while resilience carries no premium in normal times, consistent with a crisis-contingent informational channel.

To assess robustness, I test whether the resilience effect reflects a general feature of credit markets or a context-specific response to disaster-driven uncertainty. I first show that resilience is not priced in normal times: placebo and falsification tests reveal no effect outside the disaster context, consistent with resilience operating as a conditional signal activated only under stress. I then examine whether the observed effects are driven by local economic fundamentals or debtor stress. Horserace specifications confirm that resilience retains explanatory power beyond these factors, and only in the aftermath of disasters. Finally, I extend the analysis to the 2010 and 2017 German floods using a stacked difference-in-differences design, which again shows that resilience is priced after disasters. These findings reinforce the interpretation that lenders attend to community-level signals only when borrower-specific information becomes less reliable.

To understand how lenders use community signals, I examine whether the effect of community

Germany, which also informs the design of this index. See Appendix for variable definitions and sources.

resilience varies systematically with long-run disaster risk and with lender experience. First, I test whether resilience matters more in counties with greater ex-ante hazard exposure, consistent with higher salience of disaster risk. Second, I exploit cross-bank variation in portfolio exposure to the 2013 flood to ask whether directly affected lenders adjust pricing more aggressively afterward, as would be expected if banks learn from their own losses.

Related Literature — This paper contributes new insights to the broad literature on how banks adjust credit supply in response to crises. Credit supply is central to both policy and research, yet the factors driving household lending decisions remain poorly understood beyond what standard borrower scorecards capture, particularly in the face of downside risk. Most empirical work focuses on observable borrower characteristics, bank balance sheets, or average macroeconomic indicators for credit risk assessment (e.g., Bellotti and Crook 2009; Güngör 2021), offering limited insight into how lenders respond when conventional signals break down. When borrower risk is difficult to observe, models of credit under asymmetric information predict that lenders rely on group or geographic characteristics as screening tools (Kurlat & Stroebe, 2015; Stiglitz & Weiss, 1981; Bartlett, Morse, Stanton, & Wallace, 2022). Empirical evidence from contexts where formal borrower data is scarce similarly shows that lenders draw on social networks and community-based signals to guide lending decisions (Banerjee and Duflo 2010; Karlan 2007. brownpaper). Recent work shows that even when standard borrower information is available, lenders adjust credit supply based on local economic expectations (Ma, Paligorova, & Peydro, 2021), and that the quality of bank information varies with the cycle (Becker, Bos, & Roszbach, 2020; Weitzner & Howes, 2023). This paper shows that in the aftermath of disasters, lenders respond to community-level characteristics as latent signals of repayment capacity. While these characteristics add little predictive value in normal times, they reveal borrower repayment capacity not captured by standard scorecard metrics when disaster strikes. The findings provide new evidence that local expectations, informed by community-level signals, shape credit supply in distressed environments and help explain persistent unmet demand in disaster-hit areas.

This paper also contributes to a growing body of work on how credit markets respond to natural disasters. One strand of this literature intersects with research on bank structure and information frictions. Local banks, with superior monitoring and access to soft information, are more likely to sustain lending after disasters (Cortés, 2014; Koetter, Noth, & Rehbein, 2020; Bolton, Freixas, Gambacorta, & Mistrulli, 2016; Berger et al., forthcoming), while multi-market banks often reallocate credit across regions to manage risk and returns (Cortés & Strahan, 2017; Blickle, Hamerling, & Morgan, 2021). I extend this literature by studying a large dataset of post-disaster car loans issued by non-local banks engaged in transaction lending that is, thus lending based on hard information without prior borrower relationships. This setting captures the dynamics of a growing segment of consumer finance where credit risk remains elevated and the absence of borrower relationships may limit effective screening (Di Maggio & Yao, 2021).

Several studies show that the aggregate effects of natural disasters on credit supply mask important heterogeneity. Banks typically restrict lending to high-risk borrowers, such as low-income

households and small businesses, while expanding credit to safer borrowers (Berg & Schrader, 2012; Collier & Ellis, 2023; Billings, Gallagher, & Ricketts, 2022). Limited access to credit can in turn amplify income shocks and slow local recovery (Love, 2003; Brown, Fazzari, & Petersen, 2009; Levine & Zervos, 1998; Beck & Levine, 2004; Duqi, McGowan, & Giuseppe Torluccio, 2021). Even access to high-cost credit, such as payday loans, can improve household welfare in the aftermath of a disaster (Morse, 2011). While prior work shows that lenders tighten credit more for vulnerable borrowers and adjust pricing as disaster risk becomes more salient and measurable, consistent with rational updating (Garmaise & Moskowitz, 2009; Xu & Xu, 2023; Correa, He, Herpfer, & Lel, 2023; Nguyen, Ongena, Qi, & Sila, 2022), I show that variation in post-disaster credit access also reflects pre-existing community resilience, not just borrower risk or disaster severity. Unlike studies that emphasize learning or belief updating in response to disasters, I find no evidence of such dynamics. Instead, I propose signal substitution: when borrower-specific information becomes noisy after a shock, lenders shift weight toward observable community resilience signals.

Finally, this paper contributes to the literature on the economic impacts of environmental shocks and how communities adapt to crisis. A core question is what enables recovery and sustained development after disruption. Postwar studies highlight the rapid rebuilding of not just physical and human capital, but also institutions and civic engagement (Blattman & Miguel, 2010; Bellows & Miguel, 2009). Recent work links civic capital to variation in COVID-19 outcomes (Barrios, Benmelech, Hochberg, Sapienza, & Zingales, 2021; Ding, Levine, Lin, & Xie, 2020). Rajan (2019) emphasizes the role of empowered communities in driving sustainable development, while Brunnermeier (2022) frames resilience as adaptive risk management—distinct from robustness—and highlights the importance of open, transparent, and flexible societal structures for bouncing back from shocks. Building on this literature, I show that pre-existing social, human, and institutional capital shapes local expectations of resilience to environmental shocks and mitigates financial fallout for households.

The remainder of the paper is organized as follows. Section 2 describes the car loan dataset used in this paper and the construction of community resilience proxy, institutional background and data sources. Section 3 outlines the empirical strategy and presents descriptive statistics for this purpose. Section 4.1 presents the main results on the relationship between community resilience and post-disaster credit access. Section 4.2 provides robustness checks and evaluates alternative explanations. Section 4.3 discusses the mechanism of how and when lenders incorporate community resilience into their lending decisions. Section 7 concludes.

2 Data and Variable Construction

2.1 Loan Data

To investigate changes in bank consumer lending practices following natural disasters, I use a dataset of new car loans securitized by European banks, available through the European Data Warehouse (EDW). The EDW is a centralized platform that provides standardized, asset-class-specific, loan-

level data on Asset-Backed Securities (ABS) transactions and private portfolios.² It includes detailed information on each loan’s origination characteristics, borrower attributes, and collateral, as well as updated loan performance data.

I focus on loans issued in Germany between June 2011 and June 2015 for the purchase of new passenger cars. The sample is restricted to amortizing and balloon loans, excluding leases and other non-standard car loans. I further limit the sample to individual borrowers, discarding loans to legal entities, government bodies, and partnerships. To ensure comparability, I remove observations that are clearly identified as non-passenger cars (hence motorbikes, mobile homes, ATVs, etc.). In addition, I identify brand and model for a subset of the data where possible. In regression specifications with model fixed effects, the analysis is restricted to cases where the underlying asset can be verified, thereby ensuring that the sample consists exclusively of passenger cars.³ The primary outcome variables are the loan interest rate and the loan amount. Additional covariates used in the regressions include the loan-to-value (LTV) ratio, loan term, down payment, and borrower income.

In the German car loan market, lenders fall into two main categories: manufacturer-owned captive banks and traditional consumer finance banks. I focus on banks without local branch networks, thereby minimizing the likelihood that lenders are directly affected by the disaster or hold vested interests at the county level. The resulting sample includes loans issued by captive banks and credit institutions specializing in automotive financing. In total, the dataset covers 4,660 bank–county clusters across 11 banks, each of which lent to at least 390 counties. The final sample consists of 813,886 individual loans issued between June 2011 and June 2015.

2.2 Community Resilience Proxy (CRP)

I construct a *Community Resilience Proxy* (CRP), a composite measure of the ex-ante capacity of counties to cope with and recover from natural disasters—specifically flood events. The CRP is built from pre-disaster local characteristics of German counties that capture structural factors the literature has identified as central predictors of post-disaster recovery outcomes. It does not measure realized, ex-post resilience; instead, it proxies for the underlying, place-based conditions that shape differences in recovery capacity across locations.

The CRP builds on the Baseline Resilience Indicators for Communities (BRIC) index developed by Cutter, Burton, & Emrich (2010); Cutter, Ash, & Emrich (2014) and adapts it to the German context using administrative and survey-based data. The choice of indicators is guided not only by the international resilience literature but also by the forensic disaster analysis conducted by the

²Other asset classes include credit card contracts, consumer loans, residential mortgages, loans to small- and medium-sized enterprises, and leasing contracts. The EDW dataset comprises over three billion loan observations, of which approximately 600 million relate to automotive loans. Germany is the largest national market for Auto ABS in Europe, accounting for approximately 61% of the total volume. Since 2016, about 80% of term transactions have been market-placed, on average

³The classification of car brands and models follows the approach in Beyene, Falagiarda, Ongena, & Scopelliti (2022).

Center for Disaster Management and Risk Reduction Technology (CEDIM) Task Force immediately following the 2013 flood in Germany (CEDIM Forensic Disaster Analysis (FDA) Task Force, 2013).⁴ The CRP is designed to be replicable across time and space, providing a consistent, data-driven proxy for local resilience potential. Its construction proceeds by grouping indicators into three domains—*human*, *institutional*, and *civic capital*. *Human capital* captures characteristics of physical health, demographic structure, and education—for example, the share of the pre-retirement-age population, access to physicians, and equality in educational attainment. *Institutional capital* reflects governance strength and access to resources, proxied by measures such as municipal staffing levels, fiscal capacity, and population stability. *Civic capital* measures social cohesion and engagement, including rates of volunteerism, child-care availability, and political participation. A summary of the indicators is provided in Table B.1, with detailed definitions, sources, and justifications in Appendix B.

The selected common factors are normalized and aggregated into a composite index in four steps:

1. Indicator selection, informed by the resilience literature and constrained by data availability;
2. Min–max normalization of all variables: $x'_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$;
3. Sub-index construction for each domain: $y'_i = \frac{1}{N} \sum_{i=1}^N x'_i$;
4. Final CRP score, computed as the unweighted sum across domains: $y'_{1,m} + y'_{2,m} + \dots + y'_{n,m}$.

This composite approach to measuring local resilience is widely used in planning and research. Similar indices underpin the U.S. *Community Disaster Resilience Zones Act*, the FEMA National Risk Index, and resilience assessments by the European Commission’s *Disaster Risk Management Knowledge Centre* (DRMKC). While many frameworks include local economic indicators, I restrict the CRP to human, civic, and institutional capital. This design choice has two advantages. First, resilience is not determined by economic fundamentals alone: communities with similar wealth can differ in governance, cohesion, and human capital—structural factors that shape recovery after disasters. Second, because economic fundamentals are closely tied to credit outcomes, excluding them allows the CRP to isolate resilience capacity beyond local economic conditions.

To check the robustness of the index construction, I construct six alternative versions. Most importantly, I generate a Principal Component Analysis (PCA)-based index, which is highly correlated with the baseline CRP (Pearson’s $r = 0.74$), suggesting both capture similar latent resilience characteristics. I also test alternative weighting schemes using z-scores and medians, and re-estimate the index excluding individual subcategories. Further details are provided in Appendix B.

⁴CEDIM (Center for Disaster Management and Risk Reduction Technology) is a research institute based at the Karlsruhe Institute of Technology. Its Forensic Disaster Analysis Task Force produces near-real-time assessments of disaster events that inform both research and government response.

3 Empirical Strategy

3.1 Empirical Setting

To study the impact of natural disasters and community resilience on bank lending behavior, I exploit the severe flooding in Germany in May 2013 as a plausibly exogenous shock. The floods, caused by heavy rainfall, saturated soils, and high hydraulic loads in the river system, affected local economies across a wide geographic area and caused an estimated €6–8 billion in damages. (Thieken et al., 2016) The flood’s simultaneous impact on a large number of counties across the country created wide cross-sectional variation in exposure while holding constant national conditions. I define flood exposure at the county level as a binary indicator equal to one if a county was placed under an official emergency alert due to the flooding. Figure 1 maps the counties for which a state of emergency was declared.

I use county-level variation in the Community Resilience Proxy (CRP), which measures pre-disaster local characteristics, to identify whether banks price local resilience into lending after the flood. I operationalize this with a triple interaction between flood exposure, a post-flood indicator, and the CRP. Counties not affected by the flood serve as the control group, providing a benchmark for how credit conditions in high- and low-CRP would have evolved absent the shock. Figure 2 illustrates the spatial distribution of the CRP across counties in 2012 (Panel A) and compares CRP distributions between all counties (white bars) and those affected by the 2013 flood (grey bars) (Panel B). The distributions exhibit no discontinuities or bunching across treatment status, indicating that flood-affected and unaffected counties were similar in baseline resilience.

The primary outcome is the auto loan interest rate, which most directly captures lenders’ risk pricing. Several features of the consumer auto loan market make it well-suited for studying how natural disasters affect household credit supply at the local level. First, the short maturity of auto loans relative to the long return period of natural disasters reduces concerns that lenders adjust credit based on expected flood damage to the collateral. Second, vehicles purchased with loans in Germany are typically insured against catastrophic flooding, mitigating concerns about incomplete insurance markets. Third, car ownership is highly sensitive to credit conditions, making auto lending a strong proxy for household access to credit (Parker et al., 2013; Di Maggio et al., 2017). Moreover, access to auto credit is directly tied to financial inclusion and consumption smoothing, particularly for low-income households facing income volatility (Di Maggio et al., 2017). Lastly, indirect lending prevails in the German auto loan market: most contracts are originated online or through auto retailers rather than local bank branches. My analysis focuses exclusively on loans from banks with no local branch presence, ensuring that lenders have no direct disaster exposure and no access to borrower-specific local information.

3.2 Descriptive Statistics

Table 1 provides detailed definitions for all variables used in the analysis, and Table 2 reports summary statistics. Panel A presents borrower-level characteristics for newly issued auto loans,

including interest rates, loan-to-value ratios, loan maturity, loan amounts, and borrower income. Loan variables are winsorized at the 0.1st and 99.9th percentiles. On average, borrowers pay an interest rate of 3.5 percent, with a 48-month term, an LTV of 78 percent, and a loan-to-income ratio consistent with high leverage. Panel B reports county-level statistics, including the number and total volume of auto loan originations (measured at the bank–county level), the Community Resilience Proxy (CRP), and local macroeconomic controls such as GDP per capita, unemployment, household income, and demographic indicators. Column 1 displays means and standard deviations for the full sample (covering 24 months before and after the flood), Column 2 reports the same statistics for the subset of flood-affected counties, and Column 3 presents t-tests of mean differences across the two groups.

The key identifying assumption for the baseline DiD is that, absent the disaster, loan rates in treated and control counties would have followed parallel trends. Table 2 shows some level differences in pre-flood loan characteristics, including loan rates. Figure 3, which focuses on the baseline observation window, shows no evidence of differential trends. Loan rates move similarly before the flood and diverge only afterward, with increases concentrated in low-resilience and low-income counties. Panel B of Figure 2 shows that treated counties have somewhat lower average CRP values ($\Delta\mu = 0.05 \approx 0.56\sigma$; $\sigma = 0.09$). Crucially, high- and low-resilience counties show no evidence of differential pre-trends.⁵ Panel A of Figure 3a indicates that loan rates in treated and untreated counties are indistinguishable before the flood across both resilience groups, and divergence emerges only afterward. Placebo tests in Section 4 provide additional support, showing that loans issued in flood-affected counties—and across resilience groups within them—do not differ from those in unaffected counties outside of the disaster context.

4 Main Results

4.1 Credit Market Responses to the Disaster and the Mitigating Role of Community Resilience

4.1.1 Effect on Loan Interest Rates

I examine the effect of the flood and community resilience on borrowers’ cost of credit by estimating a triple-differences specification at the individual loan level:

$$Y_{iclm} = \alpha_c + \alpha_m + \alpha_{lmt} + \beta_1(\text{Flood}_c \times \text{Post}_t) + \beta_2(\text{Flood}_c \times \text{Post}_t \times \text{Resilience}_c) + X_{ct}\gamma + Z_i\delta + \varepsilon_{iclm}, \quad (1)$$

⁵Moreover, Table B.3 reports correlations between CRP and ex-ante flood hazard measures, precipitation intensity, and related risk indicators. The correlations are close to zero, mitigating concerns that resilience is simply proxying for flood exposure.

The dependent variable, $Y_{iclm,t}$, is the interest rate on loan i issued to borrower i in county c , by lender l , for auto model m , in month–year t . $Flood_c$ is an indicator equal to one for counties that declared a flood-related emergency in 2013, and $Post_t$ is an indicator for the 24 months after the flood (with a symmetric 24-month pre-period). CRP_c is the county-level Community Resilience Proxy, measured in 2012, prior to the flood. Since both $Flood_c$ and CRP_c are time-invariant at the county level, they are absorbed by the county fixed effects (α_c) and enter the specification only through their interactions. The coefficient of interest, β_2 , captures the differential change in loan pricing after the flood between counties with high versus low CRP. County fixed effects (α_c) control for all time-invariant local characteristics, including baseline credit conditions and long-run disaster risk. Car model fixed effects (α_m) absorb persistent differences in vehicle value and collateral risk. Lender–state–year fixed effects (α_{lst}) capture time-varying lender-specific characteristics within states, which absorb persistent differences across lenders as well as state-level variation in credit supply conditions. All regressions also include loan type fixed effects (amortizing vs. balloon loans) Z_i denotes borrower-level controls, primarily income, and X_{ct} includes county–time controls for local economic fundamentals (GDP per capita and average household income, along with their growth rates), household debt constraints (the debtor ratio, measuring the share of the population in arrears, and the Population Vulnerability Index, PVI, capturing broader over-indebtedness risk), and demographics (total population and population density). Standard errors are clustered at the county level.

Table 3 reports the baseline regression results. Panel A, Column (1) shows that interest rates in flood-affected counties rose significantly after the 2013 disaster. Loan pricing increased by about 28 basis points relative to unaffected counties. This pattern is consistent with a tightening of local credit supply following the shock. Panel B, Column (1) adds the interaction with county-level resilience. The coefficient on the triple interaction is negative and statistically significant, implying that more resilient counties experienced smaller post-flood increases in loan rates.

To assess whether the effects of the flood and community resilience vary with borrower quality, we split the sample into income tertiles based on the pre-flood county income distribution, and report results separately for the top and bottom thirds in Columns (2) and (3). Panel A shows that the post-flood increase in loan rates is concentrated among low-income borrowers: loan pricing rose by about 70 basis points in treated counties, while no significant effect is observed among high-income borrowers. Panel B shows that resilience mitigates this effect. The triple interaction is negative and significant at the 5 percent level, and the magnitude is economically meaningful. In flood-affected counties, a one-standard-deviation increase in CRP (0.09 points; see Table 2) corresponds to a reduction of close to 60 basis points in loan rates for low-income borrowers. No comparable effect is found for high-income borrowers. These results highlight the role of community resilience in cushioning financially constrained households against post-disaster credit tightening.

I next estimate a dynamic version of Equation (1), replacing the post-flood indicator with event-time dummies for years relative to the disaster. Figure 4 plots the coefficients from $Flood_c \times Years\ to\ Flood \times CRP_c$, estimated separately for low- and high-income borrowers. CRP is standard-

ized, so each coefficient reflects the change in the treated–control interest rate gap associated with a one–standard-deviation higher CRP. For low-income borrowers, coefficients are close to zero before the flood and turn negative afterward; three years post-flood, the treated–control gap is about 79 basis points smaller in more resilient counties, and the gap remains sizeable in subsequent years. No comparable effect is found for high-income borrowers.

Figure 5 plots the change in loan rate spreads between low- and high-income borrowers from before to after the flood, separately for counties above and below the median in community resilience. The estimates come from regressions of loan rates on a three-way interaction between income group, flood exposure, and the post-flood period, with county fixed effects, so the gap reflects within-county differences between low- and high-income borrowers. The income group indicator equals one for borrowers in the bottom third of the pre-flood county income distribution and zero for those in the top third; middle-tercile borrowers are excluded. The figure shows that in flood-affected, low-resilience counties, the loan rate gap widens after the disaster—consistent with increased pricing inequality—while in high-resilience counties and in counties not affected by the flood, the gap remains unchanged.

4.1.2 Effect on Loan Origination Volume and Count

To examine how the CRP moderates the effect of the flood on loan origination, I use as dependent variables the log difference in the number of car loan originations (total count of new auto loans) and in total loan volume (aggregate amount of auto loans) between the pre- and post-shock periods.

The baseline regression estimates:

$$\begin{aligned} \Delta Y_{l,c} = & \alpha_{1,s} + \alpha_r + \beta_1 Flood_c + \beta_2 Resilience_c + \beta_3 (Flood_c \times Resilience_c) + \\ & \Gamma X_c + \epsilon_{l,c} \quad , \text{ where} \\ \Delta Y_{l,c} = & \ln(Y_{l,c,[2013:5-2015:6]}) - \ln(Y_{l,c,[2011:6-2013:5]}) \end{aligned} \quad (1)$$

$\Delta Y_{l,c}$ denotes the change in credit supply (log loan count or log loan volume) by lender l to county c between the post-flood and pre-flood periods. To account for baseline activity levels, the specification controls for pre-flood lending counts and volumes at the bank–county level, which capture differences in both market size and market structure (e.g., many small loans versus fewer large loans). The vector X_c includes county-level characteristics measured in 2012: log GDP per capita, log average household income, the debtor ratio (share of the population in arrears), the Population Vulnerability Index (PVI), log total population, and log population density, as well as growth rates of household income and GDP per capita between 2011 and 2012 to capture short-run pre-trends. Disaster-risk covariates include flood hazard, time since the last major flood, and a composite hazard index combining storm and landslide risk. Regional fixed effects (α_r) absorb spatially correlated demand shocks, and bank–state fixed effects ($\alpha_{l,s}$) capture persistent differences across lenders and state-level variation in lending strategies. Standard errors are clustered at the county level.

Table 4 reports the effect of flood exposure and local resilience on local credit supply. Panel A

shows results for the change in log loan counts, and Panel B for the change in log loan volumes. Column (1) presents the baseline specification with pre-flood lending levels, county characteristics, and disaster-risk controls; Column (2) adds a horserace with economic fundamentals (gdp, average income and debtortrate); Column (3) adds a horserace with the flood hazard measure.

Across both panels, the interaction between flood exposure and resilience is positive and statistically significant. This implies that community resilience mitigates the post-disaster contraction in credit supply. The point estimates are economically meaningful: in Panel A, a one-standard-deviation increase in resilience corresponds to a 6.1 percent increase in loan counts; in Panel B, the comparable effect is a 5.4 percent increase in loan volumes. These magnitudes are sizeable when benchmarked against average credit growth in the sample: counties above the median in resilience received about 9 percent more new loans than equally exposed counties below the median

Table 5 interacts the flood-resilience effect with an indicator for used-car loans. The estimates show no differential effect for used-car loans, indicating that the decline in credit supply reflects a general contraction rather than a shift in loan type.

Real effects: Car purchases - The reduction in loan origination volumes and counts in low-resilience counties naturally raises the question of real effects: do these credit shocks translate into consumption outcomes? Durable goods provide a useful test case. Unlike non-durables, car purchases typically require external financing and are highly sensitive to credit supply (Célerier & Matray, 2019; Di Maggio et al., 2017). As a result, durable consumption often responds sharply to financial constraints even though it represents only a small share of overall spending (Dossche, Forsells, Rossi, & Stoevsky, 2018). Using county-level car registration data from Germany’s Federal Motor Transport Authority, Figure 6 shows that new car purchases fell more sharply and persistently in flood-affected, low-resilience counties compared to high-resilience ones. This divergence, visible both at the median (Subfigure A) and at the lower and upper ends of the resilience distribution (Subfigure B), closely mirrors the earlier patterns in credit supply. By contrast, used-car transfers (re-registrations) remain stable (Subfigure C), consistent with households in low-resilience counties shifting toward cheaper, less credit-intensive vehicles. While alternative explanations cannot be ruled out, the consistent evidence across lending and consumption suggests that community resilience shapes the real effects of financial shocks.

4.1.3 Resilience Is Predictive of Default Risk

To test whether a county’s ex ante community resilience mitigates credit losses once the flood strikes, I focus on loans originated before the 2013 disaster that were still outstanding when the flood occurred. Because these contracts were priced without knowledge of the impending shock, this sample is immune to contemporaneous bank-selection bias.

For each county c , origination year y , and calendar year-month t_m , I compute the share of loans

in arrears, defined as the fraction of outstanding loans that are at least 90 days past due:

$$NPE_{cyt_m} = \frac{Loans\ in\ arrears_{cyt_m}}{Total\ loans_{cyt_m}}.$$

I estimate

$$NPE_{cyt_m} = \beta_1 Flood_c + \beta_2 CRP_c + \beta_3 (Flood_c \times CRP_c) + \Gamma_{ct} + \alpha_s + \alpha_y + \alpha_{t_m} + \varepsilon_{cyt_m},$$

where $Flood_c$ equals one for counties subject to a 2013 flood-emergency declaration, and CRP_c is the county's pre-flood Community Resilience Proxy. Γ_{ct} collects time-varying county controls. Fixed effects include state (α_s), origination year (α_y), and calendar month (α_{t_m}). Including both origination-year and current-month fixed effects is crucial, as it aligns loans of comparable age and maturity profiles, thereby ruling out mechanical differences in default risk across vintages. The coefficient of interest is β_3 . Theory predicts $\beta_3 < 0$, as more resilient communities should recover faster, limiting delinquency.

Table 6 presents the results. Columns (1) and (2) use loans originated before June 2013 and track their arrears status over the 12 months following the flood (June 2014–May 2015). Column (3) shifts the observation window forward by one year (June 2015–May 2016), providing a check that the results are not mechanically driven by the maturity structure of loans in the immediate aftermath of the flood. By conditioning on loans originated prior to the disaster, all specifications compare contracts of similar age and maturity, ensuring that estimated differences in arrears reflect resilience rather than loan vintage effects.

Table 6 shows that resilience significantly dampens post-flood arrears. Across specifications, the interaction term $Flood \times CRP$ is negative and statistically significant. In economic terms, counties one standard deviation above the mean in resilience experience roughly 8–9 basis points fewer arrears relative to less resilient counties exposed to the same flood shock. This effect is sizeable given that average arrears shares in the sample are below 5 percent. Taken together, the results indicate that community resilience not only moderates loan pricing but also predicts real credit outcomes once disaster risk materializes.

4.2 Robustness and Competing Explanations

This section is to check robustness of the results and to establish that the observed effect of community resilience on credit responses is not a general feature of credit markets, but a context-specific response to disaster-driven uncertainty. In particular, we test whether resilience is priced in normal times, and whether the observed resilience premium is driven by flood exposure, socioeconomic composition, or unobserved county characteristics. I begin by establishing that community resilience is not priced into loan terms during normal times, and that the observed effects are not driven by confounding factors. First, I conduct a placebo test to confirm that resilience is unrelated to loan pricing in the absence of disaster shocks. Across a series of placebo and falsification tests,

we find no evidence that resilience influences loan pricing outside the disaster context, reinforcing the view that resilience operates as a conditional signal activated under stress. We also test competing mechanisms, including whether resilience merely proxies for flood risk, low-income share, or long-run disaster exposure. The results consistently show that resilience has explanatory power beyond these controls, and only in periods of elevated uncertainty. Next, I perform empirical horseraces by including potential confounding variables to ensure that the results are not attributable to correlated county-level characteristics. I also turn to additional flood events—specifically the 2010 and 2017 floods—using a stacked difference-in-differences (DiD) approach. The results show that resilience is priced after these events, consistent with the main findings. These findings support the interpretation that lenders condition their attention to community-level signals on the informational environment they face post-disaster.

4.2.1 Placebo Tests

As a robustness check, I conduct placebo tests to verify that the estimated resilience effects are not driven by spurious correlations. Table 7 shows that resilience has no predictive power outside the disaster context.

Re-dated floods. Panels A and B re-date the disaster to 2017 and 2011 and recompute resilience with the corresponding pre-period data. In both falsified timelines, the triple interaction between flood, post-flood, and resilience is small and statistically insignificant. This holds in the full sample (Column 1) and across income groups (Columns 2–3). This contrasts with the baseline results, where effects are concentrated among low-income borrowers.

Unaffected neighbors. Panel C assigns treatment to counties bordering the 2013 flood zone but not directly affected. If resilience merely proxies for flood risk, one would expect significant effects here as well. Instead, the triple interaction is close to zero and insignificant across all borrower groups, again in contrast to the baseline where low-income borrowers in affected counties experience sizable increases in loan pricing.

4.2.2 Horserace with Potential Confounders

To assess whether the estimated effect of resilience is driven by correlated local characteristics, I conduct a horserace regression including potential confounders alongside the resilience measure. Specifically, I add pre-flood income, historical flood risk, infrastructure quality, and population density to the baseline specification. Population density is used rather than total population, as it better captures local urbanization and infrastructure intensity; results are unchanged if total population is used instead. As shown in

Table 8, the coefficient on resilience remains statistically significant and economically meaningful across all specifications. This suggests that resilience captures an independent dimension of ex-ante capacity to cope with the disaster, rather than proxying for these alternative factors. yes proofread this text accordingly

Flood Disaster Intensity A key difficulty is that monetary damages are not an exogenous measure of disaster severity. Reported damages reflect both the physical intensity of the event and the extent of local exposure. Communities with stronger structural characteristics may experience systematically less damage, either because they are geographically safer or because their defenses limit losses. Conditioning on damages therefore risks absorbing part of the resilience effect itself, making damages an invalid control. To address this concern, I construct an exogenous measure of disaster intensity based on extreme precipitation.

Between May 30 and June 3, 2013, heavy and continuous rainfall triggered severe flooding across Germany. To capture this shock, I use the standardized extreme precipitation indicator provided by the Copernicus Climate Data Store (ERA5 reanalysis). This indicator expresses daily rainfall relative to the local 99th percentile of wet-day precipitation, computed over the 1989–2018 baseline period. In this way, the measure reflects rainfall extremes relative to long-run local climatology rather than absolute amounts:

$$nrrXX_{pj} = \frac{RR_{ij}}{RR_{wnXX}},$$

where RR_{ij} be the daily precipitation amount on day i in period j , and let RR_{wnXX} be the XXth percentile of precipitation on wet days ($RR \geq 1.0$ mm) in the period 1989–2018. I aggregate the grid-cell values to the county (NUTS-3) level and, for each county, take the *maximum* daily value observed over the flood window (May 30–June 3). Flood intensity is then defined in quartiles based on this maximum standardized precipitation measure.

Table 9 reports estimates from Equation (1), replacing the binary flood indicator with a quartile measure of flood intensity. Panel A shows that loan rates rise most strongly in counties in the highest intensity quartile, with the effect concentrated among lower-income borrowers. Panel B examines whether the moderating role of community resilience varies with shock severity. Each intensity quartile is compared to the baseline of unaffected counties. Resilience is associated with significantly lower loan rates across different quartiles of intensity. The fact that resilience matters not only in the most severely affected areas but also under more moderate shocks indicates that lenders treat resilience as an *ex ante* signal of community strength, rather than responding mechanically to the scale of realized damages.

4.3 How Lenders Use Community Signals: Risk, Experience, and Distance

4.3.1 Heterogeneity by Flood and Other Hazard Exposure

If resilience is truly priced, it should matter more where disaster risk is higher. I test this hypothesis by examining whether the resilience premium varies with a county’s hazard exposure. To assess whether lenders value resilience more in high-risk areas, I interact the CPR with a local flood risk score. I then extend the analysis to a multi-hazard setting by incorporating storm and landslide risk, along with their interactions with the resilience index. This allows me to test whether offsetting risks—such as high wildfire but low flood exposure—dampen the average effects observed in aggregate specifications.

To capture long-run hazard exposure, I use data from the ESPON Climate Database, which provides harmonized indicators of natural hazard risk at the NUTS-3 level. Flood risk is measured as the share of land projected to flood in a 100-year riverine event, based on the JRC’s *Lisflood* hydrological model ⁶ I also use comparable county-level indicators for two additional hazards that are particularly relevant for Germany: Storm hazard, measured as the maximum three-second wind gust speed over the period 1995–2016,⁷ and Landslide susceptibility, a composite indicator of slope, soil, and land-use characteristics predictive of landslide occurrence.⁸ These variables provide time-invariant proxies for regional hazard exposure that complement the event-specific flood shock used in the main analysis.

4.3.2 Bank Learning

This section tests the mechanism that resilience is priced only after a salient disaster event, and more strongly by banks that were directly exposed to the shock. Such a pattern would be consistent with a learning interpretation, where banks update beliefs about the role of community resilience in shaping repayment risk.

Disasters generate new information: some communities recover quickly, while others do not. In theory, lenders should incorporate this information by revising their models of default risk, selectively adjusting loan pricing according to resilience. This creates a richer dynamic than simple post-disaster repricing: banks not only respond to the event, but also *learn how much resilience matters*. Importantly, this learning should be heterogeneous, depending on banks’ prior exposure to disaster risk.

To test this idea, I construct a measure of bank-level exposure to the 2013 flood:

$$\text{BankExposure}_b = \frac{\sum_{c \in \text{FloodArea}} \text{OutstandingLoans}_{b,c}}{\sum_c \text{OutstandingLoans}_{b,c}} \Big|_{\text{June 2013}},$$

the share of a bank’s outstanding auto loan portfolio located in flood-affected counties at the time of the disaster. This variable captures the extent to which each bank’s balance sheet was directly exposed to the flood shock.

5 Conclusion

I document that low-income borrowers face tightened credit access in the wake of disasters, while high-income borrowers do not—highlighting the role of asymmetric information when creditworthiness becomes harder to assess. Community resilience helps mitigate this constraint: it predicts lower

⁶<https://database.espon.eu/indicator/2191/>

⁷<https://database.espon.eu/indicator-other-data/2230/>

⁸<https://database.espon.eu/indicator/2194/>

interest rates for low-income borrowers, higher loan volumes at the county level, and fewer loans in arrears. Repayment data suggest that resilience reveals latent borrower quality not captured by conventional indicators—resilience, in effect, becomes a temporary signal of repayment capacity under stress. A battery of falsification tests confirms that this effect is not present during normal times: resilience is not priced absent a realized disaster. To probe the mechanism, I test whether pricing is stronger in areas with high disaster risk or where banks were more exposed to previous shocks.

This selective pricing reflects a broader phenomenon: lenders incorporate resilience only when conventional signals—like income—are impaired. Unlike systematic risks such as liquidity or interest rate risk, which are consistently priced across time, resilience is neither standardized nor embedded in underwriting models. It lacks regulatory benchmarks, market conventions, and is inherently local and hard to quantify. As a result, it remains a latent signal, activated only when uncertainty renders traditional metrics unreliable. The absence of bank learning may reflect the idiosyncratic nature of disasters, the cost of developing resilience metrics, or institutional inertia in underwriting practices.

These findings position community characteristics as an informational asset that lenders access only under duress—expanding the literature on how banks use information, particularly in developed economies. While prior work has focused on firm-level soft information or local bank expertise, this paper shows that community-level traits can become priced, but only contingently. It contributes to a growing understanding of how markets dynamically update in the face of uncertainty, and how informal institutions substitute when formal signals degrade. From a policy perspective, this underscores the value of investing in community resilience not just for disaster preparedness, but also as a financial stabilizer—especially for vulnerable populations that face exclusion precisely when credit matters most.

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Table 1: Variable Definitions and Sources

Variable	Description	Source
<i>Loan- and Borrower-Level Data</i>		
Loan rate	Annual percentage rate (APR) at origination	EDW
Loan-to-value	Loan-to-value ratio at origination	EDW
Down payment	Down payment amount in EUR at origination	EDW
Loan term	Loan term in months at origination	EDW
Loan amount	Original principal balance	EDW
In arrears	Dummy indicating if loan is in arrears	EDW
Borrower income	Gross annual income of primary borrower (EUR)	EDW
<i>County-Level Data</i>		
Resilience	Composite measure from ex-ante local social factors	Sec. 2
Car registrations	Annual number of new car registrations	KBA
GDP per capita	Gross domestic product per capita (EUR ‘000s)	INKAR
Av. household income	Household income per inhabitant (EUR)	INKAR
Population density	Persons per square kilometer	INKAR
Private debt index	Index of individual indebtedness	Schufa
Debtor rate	Debtors per 100 adults (percent)	INKAR
Gross value added	GVA per employed person (EUR ‘000s)	INKAR
Total population	County population	INKAR
<i>Disaster-Related Data</i>		
Past floods	Dummy for past extreme flood events	HANZE
$\frac{1}{t_{\text{last flood}}}$	Inverse time distance to most recent flood	HANZE
IV	Fatalities-to-economic damage ratio	DRMKC
Flood intensity	Precipitation exceeding 99th percentile (standardized)	Copernicus
Natural hazard damage	Annual economic damage from all hazard types	ESPO
Flood exposure	Dummy for high-risk hydrogeological zones (100-year return)	DRMKC

Notes: This table reports the variable definitions and sources used in the empirical analysis. Monetary figures are in EUR unless otherwise noted. See Section 2 for construction of the Community Resilience Proxy.

EDW: European DataWarehouse. INKAR: Indicators and Maps for Spatial and Urban Development. KBA: Federal Motor Transport Authority (Germany). DRMKC RDH: Disaster Risk Management Knowledge Centre Risk Data Hub. HANZE: Historical Analysis of Natural Hazards in Europe.

Table 2: Summary Statistics

	N	Mean	Median	SD	$\mu_0 - \mu_1$
<i>Panel A: Loan-Level Variables</i>					
Interest rate (% APR)	813886	3.48	3.00	5.69	0.18***
LTV (%)	813879	78.30	80.00	20.06	0.87***
Loan maturity (month)	813886	48.55	48.00	12.14	-0.38***
ln(Loan amount)	811967	9.63	9.64	0.51	-0.02***
ln(Borrower income)	656679	10.22	10.20	0.74	0.13***
<i>Panel B: County-Level Variables</i>					
Log(Number of loans _l)	9293	3.83	3.81	1.15	0.08*
Log(Loan volume _l)	9293	13.52	13.55	1.22	0.07*
Community Resilience Proxy	9249	0.38	0.37	0.09	0.05***
Precipitation intensity	9293	0.85	0.87	0.63	-0.66***
Recency of last major flood (1/month)	9293	0.01	0.00	0.02	-0.01***
Flood hazard	7992	0.11	0.05	0.15	-0.04***
Storm hazard	9249	0.29	0.29	0.13	0.01***
Landslide hazard	9249	0.25	0.20	0.22	0.11***
Hazard Index (excluding flood)	9249	0.27	0.26	0.14	0.06***
Log(GDP per Capita)	9249	3.38	3.32	0.34	0.17***
Log(Unemployment Rate)	9249	1.77	1.79	0.50	-0.25***
Log(Average Household Income)	9249	7.40	7.40	0.12	0.07***
Log(Gross Value Added - Industries)	9249	3.97	3.96	0.16	0.11***
Log(Key Fiscal Transfers)	9249	5.66	5.87	1.02	-0.02
Log(Population Vulnerability Index)	9205	6.89	6.90	0.25	0.01
Log(Total Population)	9249	11.86	11.91	0.85	-0.06**
Log(Population Density)	9249	5.54	5.23	1.09	0.41***

Notes: This table presents summary statistics for key variables across the full sample. The final column reports the mean difference, $\mu_1 - \mu_0$, based on two-sided t-tests of equality between counties treated by the 2013 flood and control counties. Stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel A includes loan-level variables and Panel B county-level variables. Monetary values are in EUR. APR = annual percentage rate. CRP = Community Resilience Proxy. See Table ?? for variable descriptions.

Table 3: Effects of Disaster and Resilience on Auto Loan Rates by Borrower Income

	Dependent Variable: Interest Rate		
	Full Sample (1)	High-Income (2)	Low-Income (3)
Panel A. Flood Effect			
Flood \times Post-flood	0.275 (0.239)	0.179 (0.221)	0.702** (0.304)
Adj. R2	0.413	0.432	0.402
Observations	254648	70654	88853
Panel B. Flood \times Resilience Effect			
Flood \times Post-flood \times CRP	-4.026* (2.152)	-1.248 (1.517)	-6.403** (3.240)
Adj. R2	0.414	0.432	0.402
Observations	254648	70654	88853
Controls			
Lower-order interactions	✓	✓	✓
Borrower income	✓	✓	✓
County-level variables	✓	✓	✓
Fixed Effects			
Auto Model	✓	✓	✓
Bank \times State \times Year	✓	✓	✓
County	✓	✓	✓
Loan type	✓	✓	✓

Notes: This table reports estimates from Equation (1); dependent variable is the APR of individual auto loans. Column (1) uses the full sample; Columns (2)–(3) restrict to the top and bottom thirds of the pre-flood income distribution. Panel A reports the difference-in-differences effect (Flood \times Post-flood). Panel B reports the triple-differences effect (Flood \times Post-flood \times CRP). All specifications include borrower income, county-level controls (GDP per capita, household income, their growth rates, debtor ratio, population, population density), and all lower-order interaction terms. The sample period is June 2011 to June 2015. Standard errors are clustered at the county level. *t*-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effects of Disaster and Resilience on Local Credit Supply

	(1)	(2)	(3)
Panel A.	Dep. Var.: $\Delta \log(\text{Loan Count}_{l,c})$		
Flood	-0.319** (0.135)	1.644 (2.509)	-0.318** (0.136)
CRP	0.080 (0.148)	0.087 (0.147)	0.080 (0.148)
Flood \times CRP	0.575* (0.316)	0.666** (0.335)	0.577* (0.324)
Adj. R2	0.77	0.77	0.77
Observations	3930	3930	3930
Panel B.	Dep. Var.: $\Delta \log(\text{Loan Amount}_{l,c})$		
Flood	-0.312** (0.147)	1.693 (2.641)	-0.313** (0.149)
CRP	0.086 (0.153)	0.092 (0.152)	0.087 (0.153)
Flood \times CRP	0.614* (0.335)	0.732** (0.360)	0.611* (0.343)
Adj. R2	0.74	0.74	0.74
Observations	3930	3930	3930
Controls			
Pre-flood lending level	✓	✓	✓
County-level variables	✓	✓	✓
Disaster hazard variables	✓	✓	✓
Horseshoe econ fund. vars.		✓	
Horseshoe flood hazard			✓
Fixed Effects			
Bank \times State	✓	✓	✓
Region	✓	✓	✓

Notes: This table reports regression estimates of the effect of flood exposure and community resilience on credit supply. The dependent variable is the log change in loan counts (Panel A) or loan volumes (Panel B) between the pre- and post-flood periods. The sample covers lender–county pairs observed from 2011 to 2015. Controls include pre-flood lending levels (loan counts and volumes), 2012 county characteristics (GDP per capita, household income, population, debtor ratio, PVI, total population, population density), short-run growth rates of income and GDP, and disaster-risk covariates (flood hazard, time since last major flood, hazard index). Specifications also include bank–state and region fixed effects. Standard errors are clustered at the county level.

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of Disaster and Resilience on Local Credit Supply - Used cars

	(1)	(2)	(3)
Panel A:	$\Delta \log(\text{Loan Count}_{l,c})$		
Flood	-0.286** (0.124)	1.292 (1.847)	-0.293** (0.126)
CRP	0.185 (0.143)	0.194 (0.143)	0.190 (0.143)
Flood \times CRP	0.587* (0.303)	0.669** (0.317)	0.560* (0.307)
Used car	-0.086** (0.038)	-0.086** (0.038)	-0.086** (0.038)
Flood \times Used car	0.125 (0.092)	0.124 (0.092)	0.125 (0.092)
CRP \times Used car	0.141* (0.081)	0.141* (0.081)	0.141* (0.081)
Flood \times CRP \times Used car	-0.380 (0.250)	-0.379 (0.251)	-0.380 (0.250)
Adj. R2	0.69	0.69	0.69
Observations	7907	7907	7907
Panel B:	$\Delta \log(\text{Loan Amount}_{l,c})$		
Flood	-0.273** (0.133)	0.981 (1.970)	-0.278** (0.135)
CRP	0.135 (0.147)	0.141 (0.147)	0.138 (0.147)
Flood \times CRP	0.580* (0.315)	0.711** (0.337)	0.562* (0.318)
Used car	-0.486*** (0.044)	-0.486*** (0.044)	-0.486*** (0.044)
Flood \times Used car	0.133 (0.104)	0.133 (0.104)	0.133 (0.104)
Used car \times CRP	0.293*** (0.092)	0.293*** (0.092)	0.293*** (0.092)
Flood \times Used car \times CRP	-0.454 (0.284)	-0.453 (0.284)	-0.454 (0.284)
Adj. R2	0.64	0.64	0.64
Observations	7907	7907	7907
Controls			
Pre-flood lending level	✓	✓	✓
County-level variables	✓	✓	✓
Disaster hazard variables	✓	✓	✓
Horseshoe econ fund. vars.		✓	
Horseshoe flood hazard			✓
Fixed Effects			
Bank \times State	✓	✓	✓
Region	✓	✓	✓

Notes: This table reports regressions of the log change in loan counts (Panel A), loan volumes (Panel B), and loan counts with an interaction for used-car loans (Panel C) between the pre- and post-flood periods. The sample covers lender-county pairs from 2011–2015. All models control for pre-flood lending levels, 2012 county characteristics (income, GDP per capita, debtor ratio, PVI, population, density), short-run growth rates of income and GDP, and disaster-risk measures (flood hazard, time since last major flood, hazard index). Standard errors are clustered at the county level.

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of Disaster and Resilience on Payments in Arrears

Period	Dependent variable: Share in arrears		
	2014m6–2015m5 (1)	2014m6–2015m5 (2)	2015m6–2015m6 (3)
Flood	0.0195** (2.40)	0.0422*** (2.94)	0.0369** (2.19)
CRP	0.0199* (1.78)	0.0271 (1.41)	-0.0238 (-1.10)
Flood \times CRP	-0.0417** (-2.10)	-0.0936*** (-2.94)	-0.0851** (-2.14)
Observations	1,790	1,790	1,789
R^2	0.119	0.207	0.099
State FE	✓		
Origination year FE	✓	✓	✓
Current month-year FE	✓	✓	✓

Notes: The dependent variable is the share of loans at least 90 days past due. Columns (1)–(2) track arrears for loans originated prior to the 2013 flood over the 12 months following the disaster (June 2014–May 2015). Column (3) shifts the observation window forward by one year (June 2015–May 2016). All specifications include origination-year and current month fixed effects, ensuring that loans are compared at the same age and maturity profile. Standard errors clustered at the county level.

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Placebo Tests: Disaster and Resilience Effects on Auto Loan Rates

	Dependent Variable: Interest Rate		
	Full Sample (1)	High-Income (2)	Low-Income (3)
Panel A. Re-dating Flood to 2017			
Flood \times Post \times CRP	-0.314 (0.203)	-0.300 (0.271)	-0.182 (0.310)
Adj. R ²	0.425	0.379	0.443
Observations	384732	88070	126724
Panel B. Re-dating Flood to 2011			
Flood \times Post \times CRP	1.513 (1.266)	3.556 (2.206)	2.428 (2.249)
Adj. R ²	0.286	0.310	0.265
Observations	111805	32107	43994
Panel C. Unaffected Neighbors in 2013			
Flood-Neighbour \times Post \times CRP	0.654 (1.895)	-1.045 (1.651)	1.479 (3.136)
Adj. R ²	0.418	0.439	0.405
Observations	217654	60654	76479
Controls			
Lower-order interactions	✓	✓	✓
Borrower income	✓	✓	✓
County-level variables	✓	✓	✓
Fixed Effects			
Auto Model	✓	✓	✓
Bank \times State \times Year	✓	✓	✓
County	✓	✓	✓
Loan type	✓	✓	✓

Notes: This table reports placebo estimates of Equation (1), where the interaction Flood \times Post \times CRP (or analogues) is redefined in three falsification settings. Panel A re-dates the flood to 2017, Panel B to 2011, and Panel C assigns treatment to counties bordering the 2013 flood zone that were not directly affected. The dependent variable is the annual percentage rate (APR) of individual auto loans. Columns (1)–(3) report estimates for the full sample, high-income borrowers, and low-income borrowers, respectively. All specifications include borrower-income controls, county-level characteristics. Standard errors are clustered at the county level.

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Horserace Regressions: Resilience vs. Alternative County Characteristics

	(1)	(2)	(3)	(4)	(5)
	Baseline	+ Econ fundamentals	+ Debt stress	+ Hazard exposure	Full horserace
Flood \times Post \times CRP	-6.412** (3.233)	-6.545* (3.793)	-5.952* (3.229)	-6.595** (3.152)	-7.042* (3.587)
Controls					
Lower-order interactions	✓	✓	✓	✓	✓
Borrower income	✓	✓	✓	✓	✓
County-level variables	✓	✓	✓	✓	✓
Fixed Effects					
Loan type	✓	✓	✓	✓	✓
Auto model	✓	✓	✓	✓	✓
County	✓	✓	✓	✓	✓
Bank \times State \times Year	✓	✓	✓	✓	✓
Adj. R ²	0.402	0.402	0.402	0.402	0.402
Observations	88670	88670	88670	88240	88240

Notes: Each column reports the coefficient on the triple interaction term $\text{Flood}_c \times \text{Post}_t \times \text{CRP}_c$. All specifications include borrower-level controls, pre-flood lending levels, county covariates, and the fixed effects listed above. Column (1) shows the baseline. Column (2) adds horserace interactions with economic fundamentals (average household income and GDP per capita growth). Column (3) adds debt stress measures (debtor ratio and PVI). Column (4) adds disaster risk (composite disaster hazard index). Column (5) includes one representative from each group. The coefficient on resilience remains stable across all specifications, suggesting that the resilience effect is not explained by correlated local factors.

Standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

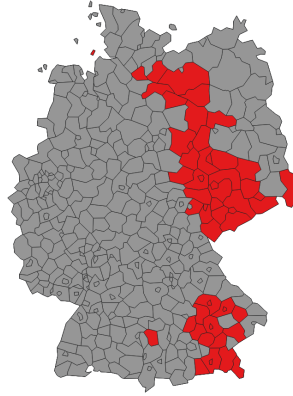
Table 9: Flood Disaster Intensity

		Loan interest rate (%)		
		Full sample (1)	High-Income (2)	Low-Income (3)
Panel A: Flood Effect				
Post-flood ×				
	Q1	0.133 (0.483)	0.261 (0.368)	0.789** (0.401)
	Q2	-0.192 (0.350)	0.226 (0.362)	-0.235 (0.531)
	Q3	0.275 (0.261)	-0.0443 (0.245)	0.858** (0.410)
	Q4	0.713** (0.323)	0.554 (0.353)	1.212** (0.471)
Adj. R2		0.467	0.516	0.465
Observations		252347	67807	88087
Panel B: Flood × Resilience Effect				
Post-flood × CRP ×				
	Q1	-8.734** (3.901)	-6.263 (4.122)	-9.477** (4.028)
	Q2	-7.936** (3.937)	-1.614 (4.438)	-16.35** (7.719)
	Q3	-4.454* (2.628)	1.360 (2.360)	-11.27*** (4.038)
	Q4	-0.728 (1.337)	-0.544 (1.575)	-1.890 (1.966)
Adj. R2		0.468	0.516	0.465
Observations		252347	67807	88087
Controls:				
Other interactions		Y	Y	Y
Loan		Y	Y	Y
Borrower income		Y	Y	Y
County		Y	Y	Y
Fixed effects:				
Bank-Brand-Model-State-Year		Y	Y	Y
County		Y	Y	Y
Loan type		Y	Y	Y
Clustered SE		County	County	County

Notes: This Table provides estimates derived from Equation (1), with the loan interest rate in percentage being the dependent variable. Column (1) shows estimates for the entire sample, while Columns (2) and (3) display estimates for borrowers in the top and bottom thirds of the income distribution before the flood. The variable 'flood' has been updated to indicate the severity of floods, rather than just being a dummy variable as in the previous specification in the baseline. In the new specification, counties affected by floods are divided into four quartiles based on the highest precipitation intensity, nrrXXpj, which was measured from May 30 to June 3, 2013.

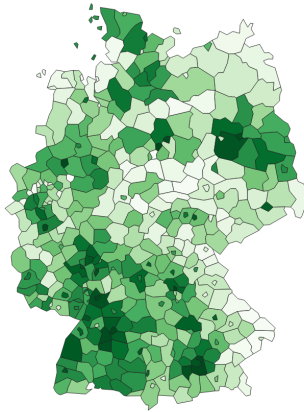
t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Flood-Affected Counties



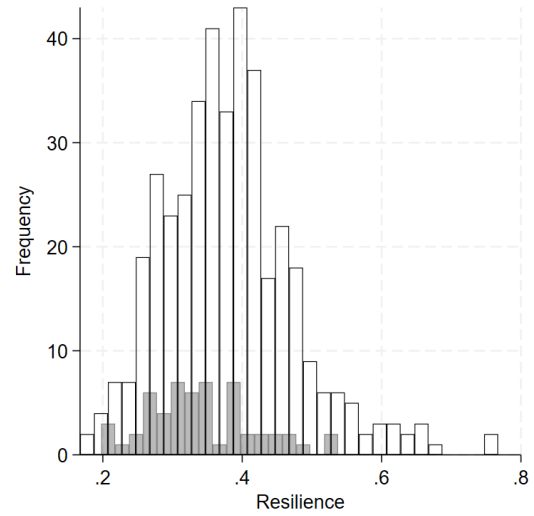
Notes: This map shows the counties declared under a state of emergency during the 2013 flooding event in Germany.

Figure 2: Community Resilience Index Across Counties: Spatial and Distributional Perspectives



(a) Spatial Distribution of the Community Resilience Proxy (CRP)

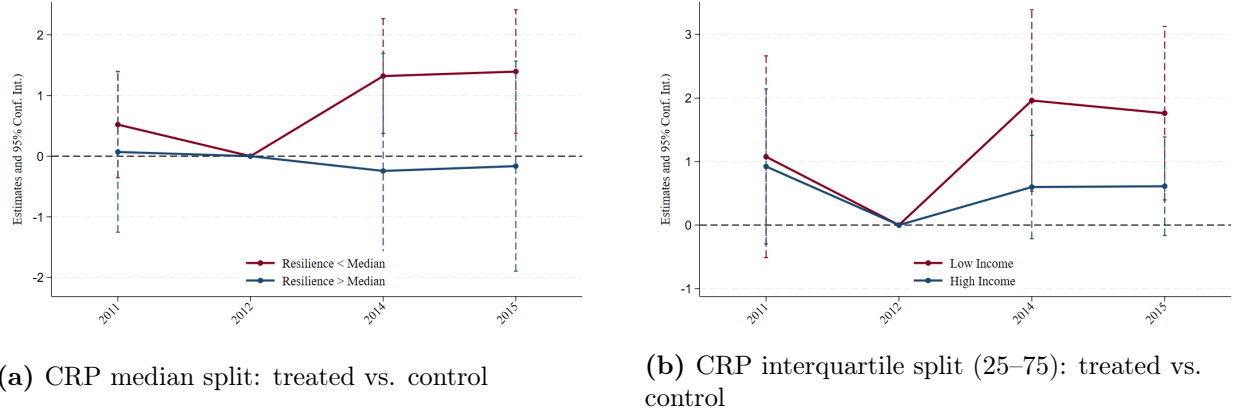
Notes: This figure displays the geographic variation in the CRP across German counties as of 2012, prior to the 2013 flood. Darker shading reflects higher resilience. There is no visible clustering or discontinuity across flood-affected and unaffected regions.



(b) Distribution of CRP Scores Across Counties

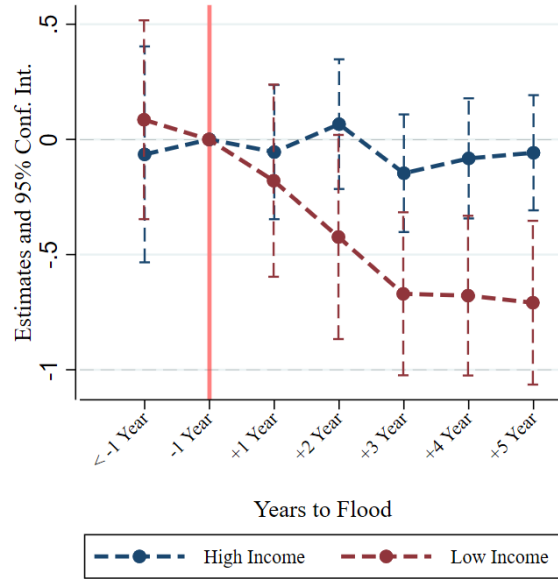
Notes: The figure plots the CRP distribution across all counties (white bars) and counties affected by the 2013 flood (gray bars). Data is from the year 2012, prior to treatment. The similar shapes indicate balance in pre-treatment resilience across treated and control counties.

Figure 3. Pre-treatment Loan Rates by Resilience/Income (Baseline Window)



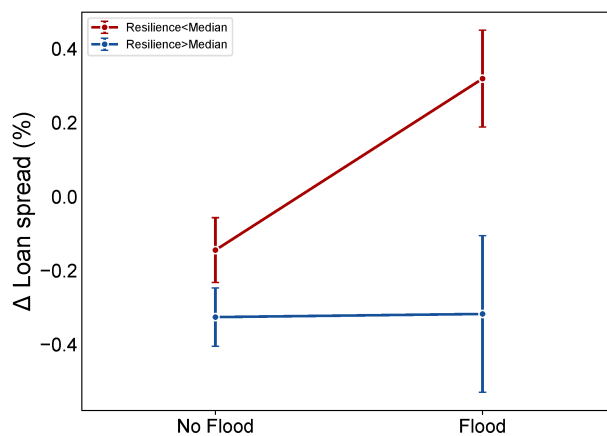
Notes: Each panel reports difference-in-differences estimates of average auto loan interest rates by treatment status relative to the 2012 base year over the baseline observation window (24 months before and 24 months after the flood). The coefficients shown correspond to the interaction between flood treatment and year dummies. Panel (A) splits counties by the Community Resilience Proxy (CRP) median; Panel (B) splits counties by income group. Treated counties are those under an official emergency alert during the 2013 flood.

Figure 4: Dynamic Estimates of Disaster and Resilience Effects on Auto Loan Rates



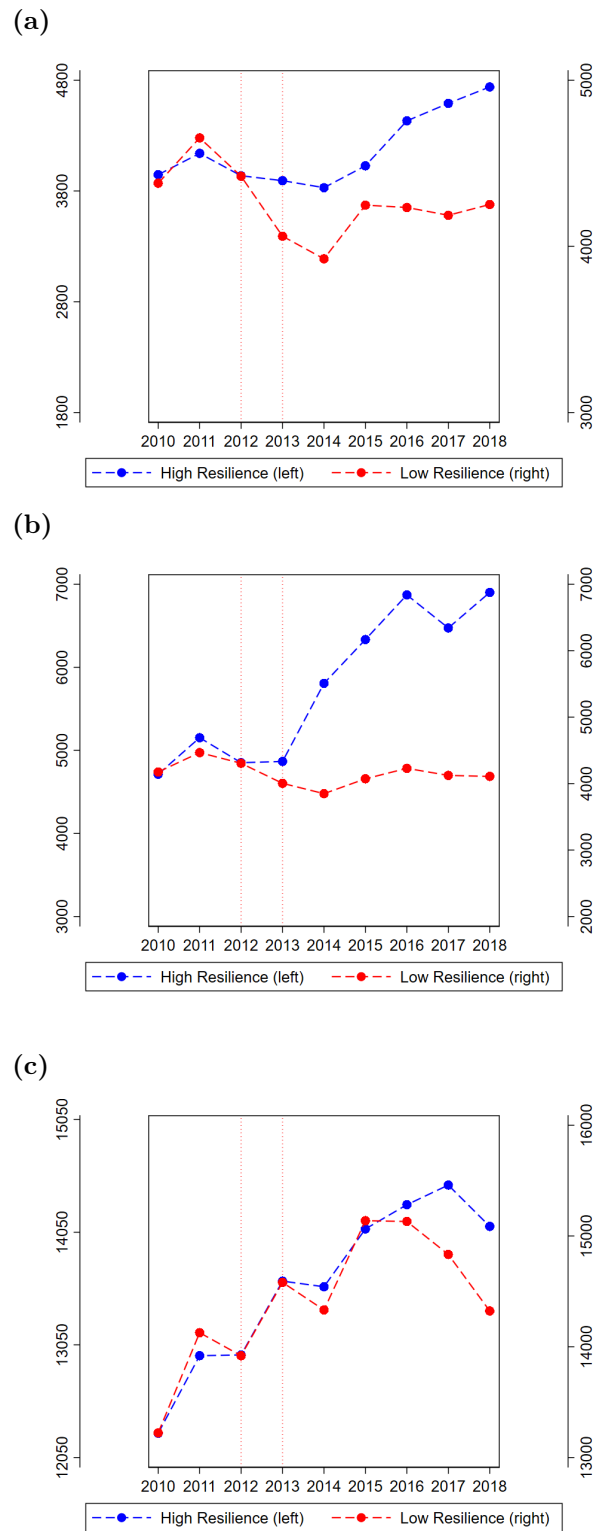
Notes: This figure plots standardized coefficient estimates and 95% confidence intervals from the event-study specification of Equation (1). The coefficients correspond to the interaction term $Flood_c \times Years\ to\ Flood \times CRP_c$. The baseline period is one year before the flood in June 2013. Model specifications include the same control variables and fixed effects as in Equation (1). Estimates are shown separately for low-income borrowers (bottom third of the pre-flood county income distribution) and high-income borrowers (top third), indicated by different colors in the figure.

Figure 5: Loan Rate Spread Between Low- and High-Income Borrowers by Community Resilience



Notes: This figure plots coefficient estimates and 95% confidence intervals for the income-group indicator (Low vs. High), conditional on the interaction of *Flood* and *Post-flood*, separately for low-resilience (below median) and high-resilience (above median) counties. The coefficients labeled “No Flood” show the change in the loan rate spread between low- and high-income borrowers from the pre- to post-flood period in unaffected counties. The coefficients labeled “Flood” show the corresponding change for flood-affected counties. The model specification follows Equation (1). The sample covers 24 months before and 24 months after the 2013 flood.

Figure 6. Median County Car Registrations (Units)



Notes: This Figure depicts the median number of car registrations at the county level from 2010 to 2018. The graph depicts these numbers split by flood-affected high and low-resilience counties. In Subfigure A, counties are split by Germany-wide median resilience, while in Subfigure B, counties that are in the 75th percentile for high resilience and below the 25th percentile for low resilience are depicted. Subfigure C shows the median county level car registrations (a re-registration occurs when a car changes hands) for high and low-resilience counties split by the median.

Appendices

A A Simple Model of Adoption and Pricing Effects of a Community-Level Risk Signal

Environment

We consider a representative competitive bank that lends for one period to borrowers i in communities c . Each borrower has observable hard attributes H_i (e.g., income, credit score, loan-to-value ratio), and each community has a resilience measure R_c (e.g., institutional capacity, disaster recovery infrastructure, social cohesion). The aggregate state is $s \in \{N, C\}$ with probabilities π_N and π_C ($\pi_N + \pi_C = 1$). In N (normal times), H_i accounts for most cross-sectional variation in repayment risk, leaving little role for R_c . In C (crisis), the predictive power of H_i declines because the shock makes it difficult to assess how borrowers will be affected and how their creditworthiness will evolve. In this environment, R_c becomes informative, capturing persistent community-level differences such as local recovery capacity or social cohesion.

The bank does not observe the true repayment probability $p_i(s) \in (0, 1)$ and instead forms a belief $\hat{p}_{i,A}(s)$ based on available information:

$$\hat{p}_{i,A}(s) = \begin{cases} f(H_i), & A = 0, \\ f(H_i, R_c), & A = 1, \end{cases} \quad \text{with} \quad \frac{\partial \hat{p}_{i,1}}{\partial R_c} > 0.$$

The predictive improvement from incorporating resilience is

$$\Phi(s) \equiv |p_i(s) - \hat{p}_{i,0}(s)| - |p_i(s) - \hat{p}_{i,1}(s)|.$$

We assume state-dependent informativeness of R_c : the predictive improvement is negligible in normal times, $\Phi(N) = 0$, and strictly positive in crises, $\Phi(C) > \underline{\phi} > 0$. Observing R_c entails a fixed cost $\kappa > 0$ (e.g., data integration, compliance).

Loan Pricing

Given its belief \hat{p} about repayment probability, the bank chooses a loan rate r to maximize expected profits. The bank incurs a constant funding cost $c > 0$ per unit lent, so per-loan expected profit is

$$\pi(r; \hat{p}) = \hat{p}r - (1 - \hat{p}) - c.$$

Borrower demand is linear,

$$D(r) = 1 - \alpha r, \quad \alpha > 0,$$

so total profit is

$$\Pi(r; \hat{p}) = (1 - \alpha r) [\hat{p}r - (1 - \hat{p}) - c].$$

Maximizing with respect to r yields the optimal interest rate

$$r^*(\hat{p}) = \frac{1 - \alpha}{2\alpha} + \frac{1 + c}{2\hat{p}},$$

with slope

$$\frac{\partial r^*}{\partial \hat{p}} = -\frac{1 + c}{2\hat{p}^2} < 0.$$

Thus, higher perceived repayment probability lowers the optimal rate, and the pass-through from beliefs to pricing is stronger when \hat{p} is low.

Adoption of Resilience

State-contingent adoption. Suppose the adoption decision is made *after* the aggregate state $s \in \{N, C\}$ is realized. If the bank adopts, it sets the rate $r^*(\hat{p}_1(s))$; otherwise it uses $r^*(\hat{p}_0(s))$. The per-state gain from adoption is

$$G(s) \equiv \Pi(r^*(\hat{p}_1(s)); p(s)) - \Pi(r^*(\hat{p}_0(s)); p(s)),$$

where $p(s)$ is the true repayment probability in state s . Adoption occurs in state s iff $G(s) \geq \kappa$.

Since $\Pi(r; p)$ is maximized when beliefs match the truth, $\hat{p} = p$, any reduction in prediction error raises profits:

$$|\hat{p}_1(s) - p(s)| < |\hat{p}_0(s) - p(s)| \Rightarrow G(s) > 0,$$

and $G(s)$ is increasing in the predictive improvement $\Phi(s)$.

Under state-dependent informativeness, $\Phi(N) \approx 0$ implies $G(N) \approx 0$, so the bank does not adopt in N . In crisis C , since $\Phi(C) > \underline{\phi} > 0$, adoption occurs iff

$$G(C) \geq \kappa.$$

Ex-ante adoption. If the bank must decide whether to adopt *before* the realization of s , the decision is based on expected rather than realized gains:

$$\mathbb{E}_s[G(s)] = \pi_N G(N) + \pi_C G(C).$$

Define the gains in each state as

$$G^{\text{pre}}(N) \equiv \Pi(r^*(\hat{p}_1(N)); p(N)) - \Pi(r^*(\hat{p}_0(N)); p(N)),$$

$$G^{\text{pre}}(C) \equiv \Pi(r^*(\hat{p}_1(N)); p(C)) - \Pi(r^*(\hat{p}_0(N)); p(C)),$$

where $G^{\text{pre}}(C)$ is the *legacy improvement in crisis*, i.e. the profit gain from having priced with R_c ex ante rather than without it.

The ex-ante adoption rule trades the certain cost κ against expected improvement:

$$(1 - \pi_C) G^{\text{pre}}(N) + \pi_C G^{\text{pre}}(C) \geq \kappa.$$

Under state-dependent informativeness with $\Phi(N) \approx 0$, this reduces to

$$\pi_C G(C) \geq \kappa \iff G(C) \geq \frac{\kappa}{\pi_C}.$$

If $\pi_C = 0$, never adopt at $t = 0$; if $\pi_C = 1$, adopt at $t = 0$ iff $G(C) \geq \kappa$. More generally, ex-ante adoption requires either (i) higher crisis likelihood π_C , (ii) greater informativeness of R_c in crises (larger $\Phi(C)$), or (iii) lower fixed cost κ .

Pricing Effects and Heterogeneity

Rate change from adoption. When the bank adopts R_c instead of relying only on H_i , the change in the optimal rate is

$$\Delta r \equiv r^*(\hat{p}_1) - r^*(\hat{p}_0) \approx -\frac{1+c}{2\bar{p}^2}(\hat{p}_1 - \hat{p}_0),$$

where \bar{p} lies between \hat{p}_0 and \hat{p}_1 . If $\hat{p}_1 > \hat{p}_0$, resilience reveals the borrower to be safer and the rate falls ($\Delta r < 0$). If $\hat{p}_1 < \hat{p}_0$, resilience reveals greater risk and the rate rises ($\Delta r > 0$).

Pricing channel and borrower heterogeneity. Resilience R_c affects loan pricing only through its impact on the bank's belief \hat{p} :

$$\frac{\partial r^*}{\partial R_c} = \underbrace{\frac{\partial r^*}{\partial \hat{p}}}_{\text{Pass-through}} \times \underbrace{\frac{\partial \hat{p}_1}{\partial R_c}}_{\text{Salience}}.$$

- *Pass-through:* $\frac{\partial r^*}{\partial \hat{p}} = -\frac{1+c}{2\hat{p}_1^2}$. The effect of a belief shift on rates is larger when \hat{p}_1 is low, i.e. for high-risk borrowers based on H_i .
- *Salience:* $\frac{\partial \hat{p}_1}{\partial R_c} > 0$ is larger when H_i is weak, i.e. when hard attributes are less informative—most often for high-risk borrowers in crises.

Borrower heterogeneity in H_i thus shapes both channels through which resilience R_c affects loan pricing. When both conditions hold, as for high-risk borrowers in crises, the two channels reinforce each other and generate the largest rate changes from resilience-based pricing.

Empirical Implications

The model delivers three main predictions: (i) Adoption of the resilience signal should rise during crises, when it provides substantial incremental information beyond H_i ; (ii) conditional on adoption,

rates fall in high-resilience communities and rise in low-resilience communities; (iii) these effects are strongest for high-risk borrowers in crises. We test these predictions in Section X.

B Community Resilience Proxy (CRP)

To construct the *Community Resilience Proxy* (CRP), I categorize indicators into three broad dimensions: **human capital**, **institutional capital**, and **civic capital**. The selected indicators for each dimension are detailed in Table B.1, including definitions, data sources, and empirical justifications drawn from the disaster recovery literature.

These social factors capture population-level attributes associated with resilience to natural hazards, particularly severe flooding events.

- **Human capital** includes characteristics related to physical capacity, education, and health, such as educational attainment equality, pre-retirement age, access to personal transportation, communication capacity, language proficiency, absence of disability, and access to physicians.
- **Institutional capital** reflects access to resources and governance capacity. Indicators include mitigation spending, flood insurance coverage, government performance, jurisdictional fragmentation, disaster aid experience, local disaster training, population stability, nuclear accident planning, and crop insurance coverage.
- **Civic capital** proxies social networks, collective action, and engagement. This includes rates of volunteerism, religious affiliation, place attachment, political participation, citizen preparedness, and density of civic organizations.

This composite measure adopts a *place-based, empirical approach* to capture the multidimensional nature of disaster resilience at the county level. All indicators are derived from observed data and selected based on prior empirical studies linking them to post-disaster recovery capacity. The index follows the methodology of Cutter et al. (2010) and is informed by the *Baseline Resilience Indicators for Communities (BRIC)* index developed by Cutter et al. (2014), which synthesizes findings from a large body of resilience scholarship (e.g., Buckle, 2006; Engle et al., 2014; Khalili et al., 2015; Rufat et al., 2015; Reuter & Spielhofer, 2017). The BRIC index has been adopted by U.S. federal agencies, including under the Community Disaster Resilience Zoning Act, and serves as a reference for similar frameworks globally.⁹

To ensure relevance and replicability in the German context, indicator selection also draws on Scherzer, Lujala, & Rød (2019); Fekete (2009) and post-event analyses conducted by the Center for Disaster Management following the 2013 Elbe flood. Emphasis is placed on comparability across counties and over time.

⁹See NAPS Foundation (2021): <https://experience.arcgis.com/experience/376770c1113943b6b5f6b58ff1c2fb5c/page/BRIC/>

<https://experience.arcgis.com/experience/376770c1113943b6b5f6b58ff1c2fb5c/page/BRIC/>

Table B.1. Variables Used in the Construction of the Community Resilience Index

Dimension	Factor	Indicator	Justification (Literature)	Data Source
Human Capital	Educational Equality	Abs. difference between college grads and % < high school	Linked to recovery via adaptive capacity and opportunity gaps (Cutter et al., 2010, 2014)	INKAR
	Pre-Retirement Age	% of population under 65 years	Younger populations recover faster, more mobile (Cutter et al., 2010)	INKAR
	Transport Access	Passenger cars per 1,000 persons	Enhances mobility and access to resources (Cutter et al., 2010)	INKAR
	No Special Needs	% without sensory/physical/mental disability	Healthier populations have higher functional capacity post-crisis (Cutter et al., 2010)	INKAR
	Physician Access	Physicians per 10,000 persons	Access to healthcare supports recovery speed (Cutter et al., 2010)	INKAR
Civic Capital	Political Engagement	% of voters participating in elections	Proxy for civic trust and engagement (Cutter et al., 2010)	INKAR
	Voluntary Engagement	% of population volunteering	Linked to mutual aid and civic cohesion (Cutter et al., 2010)	FWS
	Migration Retention	Inverse abs. in-/out-migration % of pop.	Low turnover = social cohesion, networked recovery (Burton 2015; Singh 2014)	INKAR
	Child Care Access	Preschools per 10,000 people	Indicates care infrastructure and family support (Scherzer, 2019)	INKAR
	Creative Employment	% of workforce in creative sectors	Proxy for adaptability and innovation (Scherzer, 2019)	INKAR
Institutional Capital	Municipal Staff	Local gov. employees per 10,000 persons	Reflects service delivery capacity (Taarup-Esbensen, 2022)	INKAR
	Fiscal Capacity	Operating surplus as % of gross revenue	Strong budgets support local recovery (Datola, 2019; Holand, 2011)	INKAR
	Population Stability	Net pop. change over past 10 years	Stable population supports planning and service continuity (Moghadas, 2019)	Eurostat
	Political Fragmentation	Number of municipalities per district	High fragmentation may reduce coordination (Cutter et al., 2010)	Destatis (2016)

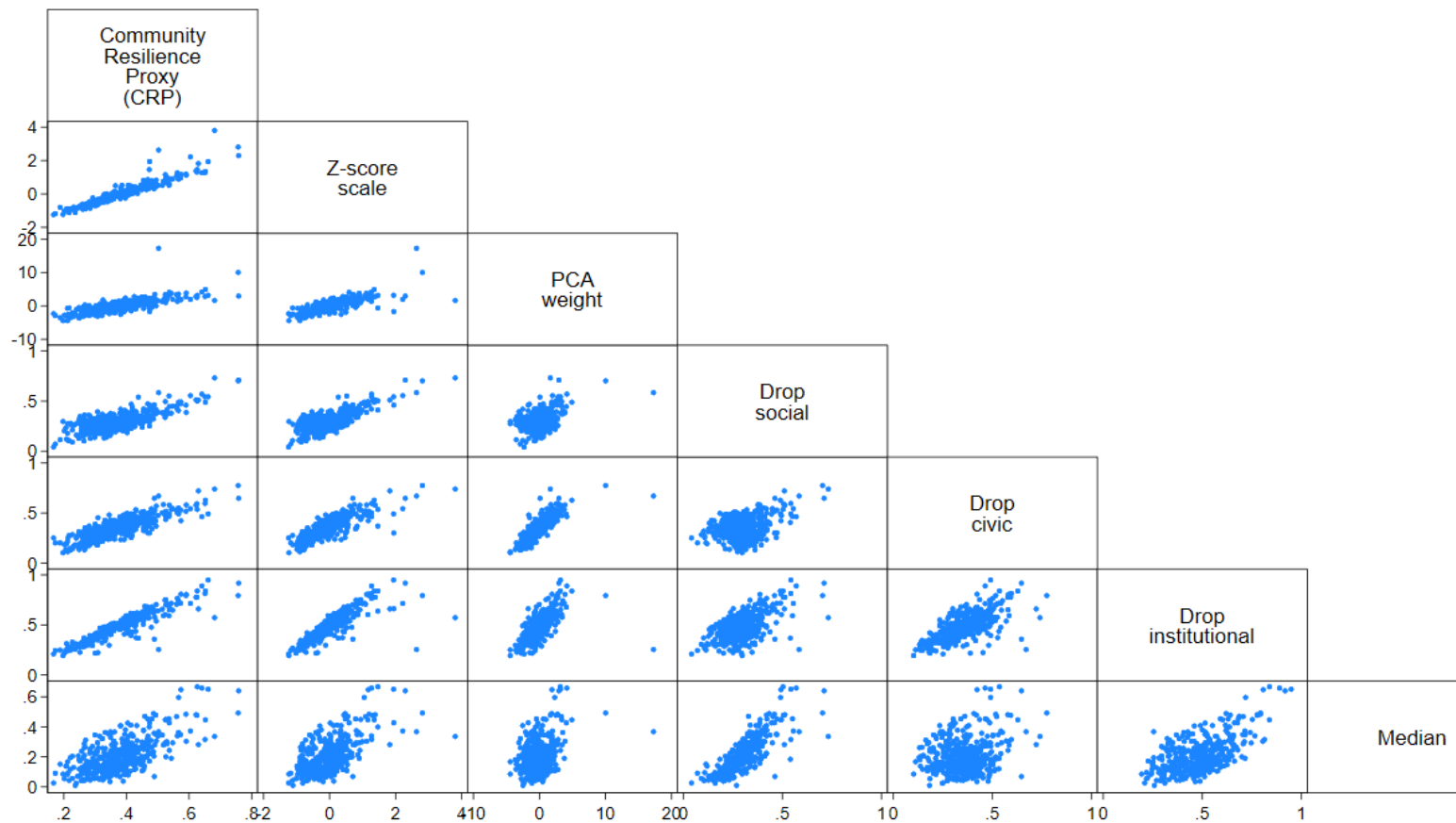
Table B.2: Pairwise correlations of resilience indices

	CRP	Zscore	PCA	NoSoc	NoCiv	NoInst	Median
CRP	1.00	0.94	0.75	0.76	0.84	0.92	0.66
Zscore	0.94	1.00	0.75	0.74	0.82	0.83	0.61
PCA	0.75	0.75	1.00	0.42	0.83	0.64	0.35
NoSoc	0.76	0.74	0.42	1.00	0.40	0.58	0.81
NoCiv	0.84	0.82	0.83	0.40	1.00	0.69	0.25
NoInst	0.92	0.83	0.64	0.58	0.69	1.00	0.63
Median	0.66	0.61	0.35	0.81	0.25	0.63	1.00

Table B.3: Pairwise correlations of county-level characteristics

	CRP	Precipitation	LastFlood	FloodHazard	StormHazard	LandslideHazard	HazardIndex	GDPpc	HHIncome	PVI	Population	PopDensity
CRP	1.00	0.05	-0.02	0.03	-0.11	0.10	0.03	0.50	0.51	-0.44	0.17	0.39
Precipitation	0.05	1.00	0.11	-0.17	0.17	0.20	0.24	-0.01	0.15	-0.48	-0.13	-0.21
LastFlood	-0.02	0.11	1.00	0.02	-0.16	0.03	-0.05	0.08	-0.08	0.05	0.11	0.13
FloodHazard	0.03	-0.17	0.02	1.00	-0.22	-0.37	-0.40	0.23	-0.10	0.26	-0.05	0.25
StormHazard	-0.11	0.17	-0.16	-0.22	1.00	0.20	0.64	-0.19	0.09	-0.22	-0.04	-0.37
LandslideHazard	0.10	0.20	0.03	-0.37	0.20	1.00	0.88	0.04	0.40	-0.31	-0.15	-0.01
HazardIndex	0.03	0.24	-0.05	-0.40	0.64	0.88	1.00	-0.06	0.36	-0.35	-0.14	-0.19
GDPpc	0.50	-0.01	0.08	0.23	-0.19	0.04	-0.06	1.00	0.40	-0.03	0.07	0.63
HHIncome	0.51	0.15	-0.08	-0.10	0.09	0.40	0.36	0.40	1.00	-0.58	0.01	0.18
PVI	-0.44	-0.48	0.05	0.26	-0.22	-0.31	-0.35	-0.03	-0.58	1.00	-0.04	0.26
Population	0.17	-0.13	0.11	-0.05	-0.04	-0.15	-0.14	0.07	0.01	-0.04	1.00	0.23
PopDensity	0.39	-0.21	0.13	0.25	-0.37	-0.01	-0.19	0.63	0.18	0.26	0.23	1.00

Figure B.1: Scatter-Plot Matrix of Alternative Community Resilience Indices



Axes are standard-deviation units.
N = 394

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