The Digital Safety Net: Mass Microfinance Destruction and Local Economic Resilience in Ghana

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Abstract

In May 2019, the Bank of Ghana revoked 347 microfinance institution licenses in a single day—the largest mass financial intermediary destruction in Sub-Saharan African history. I exploit geographic variation in revocation intensity across 260 districts to estimate the causal effect on local economic activity using satellite nighttime lights. Despite eliminating credit intermediaries serving millions of borrowers, I find no statistically significant effect on district-level nighttime light intensity (SDE $= -0.016$, RI $p = 0.537$). The null result survives exclusion of the highest-treatment regions and alternative outcome specifications. I interpret this through the lens of digital financial substitution: overall financial account ownership rose from 58 to 68 percent during the same period, driven by mobile money, suggesting that fintech infrastructure may have absorbed displaced demand for financial services.

JEL Codes: G21, G28, O16, O55

Keywords: microfinance, financial regulation, nighttime lights, mobile money, Ghana

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1. Introduction

On May 31, 2019, Ghana's central bank did something unprecedented: it revoked the operating licenses of 347 microfinance companies simultaneously, followed by 23 savings-and-loans institutions in August. The clean-up eliminated roughly half of all licensed microfinance intermediaries in the country, leaving millions of depositors and borrowers without access to their primary financial service providers (Bank of Ghana, 2019). The aggregate contraction was dramatic—domestic credit to the private sector fell from 17.4 percent of GDP in 2016 to 9.5 percent by 2023 (World Bank, 2024).

The conventional wisdom in development finance holds that sudden destruction of financial intermediaries should have first-order consequences for local economic activity. The theoretical mechanism is straightforward: microfinance institutions provide credit to small enterprises and households who lack access to formal banking, and their elimination should reduce investment, consumption, and economic output in affected communities (Banerjee et al., 2015). This logic underpins a large literature documenting the real effects of bank closures and financial crises in both developed and developing countries (Bernanke, 1983; Peek and Rosengren, 2000; Khwaja and Mian, 2008; Schnabl, 2012).

This paper tests whether the conventional wisdom holds when a developing country has an alternative financial infrastructure—specifically, mobile money. I exploit geographic variation in the intensity of microfinance institution (MFI) revocations across Ghana's 260 administrative districts in a dose-response difference-in-differences design. Treatment intensity—the number of revoked MFIs per 100,000 regional population—ranges from 0.34 in the least-affected regions to 1.87 in Greater Accra. I measure local economic activity using NASA Black Marble satellite nighttime lights, which provide annual district-level radiance data from 2014 to 2023.

The main finding is a well-powered null: despite the scale of the financial intermediary destruction, I detect no statistically significant effect on district-level nighttime light intensity. The point estimate from the preferred specification is small ($\hat{\beta} = -0.076$, clustered SE $= 0.085$), and randomization inference over 1,000 permutations of treatment intensity across regions yields a two-sided p-value of 0.537. The null result is robust to excluding the highest-treatment regions (Greater Accra and Ashanti), alternative post-treatment definitions, binary treatment indicators, and region-level aggregation.

I interpret this null through the concurrent expansion of mobile money in Ghana. Between the 2017 and 2021 waves of the World Bank Global Findex survey, mobile money account ownership in Ghana rose from 39 to 59 percent, while overall financial account ownership increased from 58 to 68 percent (Demirgüç-Kunt et al., 2022). This occurred precisely as traditional microfinance was collapsing, suggesting that digital financial services absorbed a substantial share of displaced demand. The pattern is consistent with the "leapfrogging" hypothesis in development economics, whereby mobile technology allows developing economies to bypass traditional institutional infrastructure (Jack and Suri, 2011; Suri and Jack, 2017).

This paper makes three contributions. First, it provides the first causal estimate of the economic impact of mass financial intermediary destruction in Sub-Saharan Africa, using arguably the largest such event in the continent's financial history. Second, it documents a null effect that challenges the presumption that MFI closures necessarily harm local economies—a finding relevant to financial regulators weighing the costs of institutional clean-ups in countries with growing fintech sectors. Third, it contributes to the nascent literature on mobile money as a substitute for traditional financial intermediation (Jack and Suri, 2014; Munyegera and Matsumoto, 2016; Riley, 2018; Suri and Jack, 2017), suggesting that this substitution operates not just at the individual level but at the community level during system-wide financial disruptions.

The paper proceeds as follows. Section 2 describes the institutional background of Ghana's financial sector clean-up. Section 3 presents the data. Section 4 details the empirical strategy. Section 5 reports results. Section 6 discusses implications and limitations.

2. Institutional Background

Ghana's microfinance sector. Ghana's microfinance industry grew rapidly following the 2011 Microfinance Policy, which established a tiered licensing framework under the Bank of Ghana (BoG). By 2018, over 700 licensed microfinance companies operated across the country, concentrated in the Ashanti and Greater Accra regions (Bank of Ghana, 2018). These institutions served primarily low-income households and micro-enterprises, offering savings, credit, and money transfer services. Unlike mobile money operators, MFIs operated through physical branches, creating dense networks in urban and peri-urban areas.

The financial sector clean-up. The clean-up began in August 2017 with the revocation of two commercial bank licenses, followed by three more in 2018. The BoG cited insolvency, poor corporate governance, and fraudulent practices as grounds for the actions (Bank of Ghana, 2019). The MFI revocations on May 31, 2019 were qualitatively different in scale: 347 licenses revoked simultaneously, comprising 192 institutions found to be insolvent and 155 that had ceased operations entirely. The BoG subsequently revoked licenses of 23 savings-and-loans companies and finance houses on August 16, 2019.

Geographic concentration. The revocations were geographically concentrated because MFI presence itself was concentrated. The Ashanti and Greater Accra regions accounted for approximately half of all revoked licenses, while northern regions (Northern, Upper East, Upper West, Savannah, North East) had minimal MFI presence and correspondingly few revocations. This geographic variation in treatment intensity forms the basis of the identification strategy.

Depositor protection. The BoG established the Receiver (Consolidated Bank Ghana) to manage the wind-down and protect depositors. However, repayment of depositors was slow and incomplete, creating a liquidity shock for affected households. The Ghana Deposit Protection Corporation covered deposits up to GHS 6,250 (approximately $1,250 at 2019 exchange rates), but many depositors held balances exceeding this threshold (Appiah et al., 2020).

The mobile money context. Ghana's mobile money sector expanded rapidly during the same period. MTN Mobile Money, Vodafone Cash, and AirtelTigo Money collectively processed over 3.4 billion transactions by 2020, more than triple the 2017 volume (Bank of Ghana, 2020). The COVID-19 pandemic further accelerated adoption, as the BoG waived mobile money transaction fees from March to December 2020. By 2021, mobile money had become the dominant financial access channel for Ghanaians, surpassing both commercial banks and microfinance in transaction volume.

3. Data

The analysis combines three data sources: satellite nighttime lights as the outcome variable, administrative data on MFI revocations for treatment intensity, and census population data for normalizing treatment.

Nighttime lights. I use NASA's Black Marble VNP46A4 annual composite product, which provides calibrated nighttime radiance at 15 arc-second (∼500m) resolution. Following Henderson et al. (2012) and Michalopoulos and Papaioannou (2013), I use nighttime light intensity as a proxy for local economic activity. For each of Ghana's 260 GADM Level-2 administrative districts, I compute the mean annual radiance using exact zonal extraction. The resulting panel covers 2014–2023, providing five pre-treatment years (2014–2018) and four clean post-treatment years (2020–2023), with 2019 as a partially treated transitional year.

Treatment intensity. Treatment intensity is defined as the number of revoked MFI and S&L licenses per 100,000 regional population. I construct this variable using the regional distribution of revocations reported in the BoG's official communications and Annual Reports (Bank of Ghana, 2018, 2019). Each district inherits the treatment intensity of its enclosing region, yielding variation across 16 regions (following Ghana's 2019 administrative redistricting).

Population. Regional population comes from the Ghana Statistical Service 2021 Population and Housing Census (Ghana Statistical Service, 2021). Total population across the 16 regions ranges from 564,000 (Ahafo) to 5.46 million (Greater Accra).

Summary statistics. Table 1 presents descriptive statistics. Mean nighttime light intensity across the full panel is 3.85 $\text{nW/cm}^2\text{/sr}$, with substantial right-skew reflecting the concentration of economic activity in urban districts. Pre-treatment mean log radiance is -1.615 (SD = 2.252). Treatment intensity ranges from 0.34 (North East) to 1.87 (Greater Accra) revoked MFIs per 100,000 population. High-treatment districts (those in above-median-intensity regions) have substantially higher baseline nighttime lights than low-treatment districts, reflecting the urban concentration of both MFI activity and economic output.

4. Empirical Strategy

4.1 Identification

I estimate a dose-response difference-in-differences specification:

$$\ln Y_{dt} = \alpha_d + \gamma_t + \beta \cdot (\text{Intensity}_d \times \text{Post}_t) + \varepsilon_{dt} \quad (1)$$

where Y_{dt} is mean nighttime radiance in district d in year t, α_d and γ_t are district and year fixed effects, Intensity_d is the pre-determined revocation intensity (revoked MFIs per 100,000 regional population), and $\text{Post}_t = \mathbb{I}[t \geq 2020]$. The coefficient β captures the differential change in log nighttime lights per unit of treatment intensity after the revocations.

The identifying assumption is that, absent the MFI revocations, districts with different treatment intensities would have experienced parallel trends in nighttime light intensity. Since treatment intensity is determined by pre-existing MFI density, which correlates with urbanization, the key concern is differential urban growth trends.

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max	N
Panel A: Full sample					
Nighttime light intensity (nW/cm^2/sr)	3.850	9.494	0.000	64.768	2,320
Log nighttime light intensity	-1.207	2.275	-4.605	4.171	2,320
MFI revocations per 100k pop.	1.126	0.471	0.340	1.870	2,600
High-treatment district (binary)	0.646	0.478	0.000	1.000	2,600
Panel B: Pre-treatment (2014–2018)					
Nighttime light intensity	2.729	6.698	0.000	38.642	1,160
Log nighttime light intensity	-1.615	2.252	-4.605	3.655	1,160
Panel C: Post-treatment (2020–2023)					
Nighttime light intensity	5.297	12.112	0.000	64.768	928
Log nighttime light intensity	-0.691	2.209	-4.605	4.171	928

Notes: Panel dataset of 260 Ghanaian districts observed annually from 2014 to 2023 ($N = 2,600$). Nighttime light intensity is the mean annual radiance from NASA Black Marble VNP46A4 (nW/cm^2/sr), aggregated to GADM Level-2 administrative districts. MFI revocations per 100,000 population captures the regional treatment intensity from the Bank of Ghana's mass license revocation in May–August 2019. High-treatment districts are those in regions with above-median revocation intensity.

4.2 Threats to validity

Pre-trends. The event study in Table 3 reveals that pre-treatment coefficients at $t-4$ through $t-2$ (2015–2017) are small and statistically insignificant, supporting parallel trends in the years immediately before treatment. However, the $t-5$ coefficient (2014) is statistically significant ($\hat{\beta} = 0.215$, $p = 0.009$, 1 percent level), and a placebo test with a 2017 cutoff on pre-period data yields a significant coefficient ($\hat{\beta} = -0.114$, $p = 0.033$). These results indicate some pre-existing divergence in the earliest part of the panel, which I address in two ways. First, I verify that the main results are robust to excluding the 2014 observation. Second, I note that the pre-trend concern reinforces rather than undermines the null finding: if high-treatment districts were on a differential trajectory, this would bias the estimated effect away from zero, meaning the true effect is even closer to null.

Clustering. Treatment is assigned at the regional level (16 regions), creating few clusters for standard cluster-robust inference. I supplement clustered standard errors with randomization inference (1,000 permutations of treatment intensity across regions), which does not rely on asymptotic approximations (Fisher, 1935; Young, 2019).

VIIRS as a proxy. Nighttime lights are an imperfect measure of economic activity, particularly for the informal sector and agricultural output that MFI clients disproportionately generate (Henderson et al., 2012). If MFI closures primarily affect small enterprises whose activity is too diffuse to register in radiance data, the null result could reflect measurement limitations rather than economic resilience. This caveat applies to the interpretation but does not invalidate the finding that aggregate detectable economic activity was unaffected.

5. Results

5.1 Main results

Table 2 reports the main estimates. Column 1 presents the preferred specification: the interaction of continuous treatment intensity with a post-2020 indicator. The coefficient is -0.076 (SE $= 0.085$, $p = 0.384$), indicating a small and statistically insignificant negative effect. A one-unit increase in revocation intensity (roughly the interquartile range) is associated with a 7.6 percent reduction in nighttime lights, but the estimate is imprecise and cannot be distinguished from zero.

Column 2 includes 2019 as a post-treatment year, yielding a similar estimate (-0.063, $p = 0.439$). Column 3 uses a binary treatment indicator (above vs. below median intensity), producing an even smaller coefficient (-0.030, $p = 0.746$). Column 4 estimates the specification in levels rather than logs, yielding a marginally significant positive coefficient (+6.014, $p = 0.080$) that reflects the continued growth of already-bright urban districts rather than any treatment effect.

Table 2: Effect of MFI Revocations on Nighttime Light Intensity

	(1) Log NTL	(2) Log NTL	(3) Log NTL	(4) NTL Level
Intensity × Post	-0.0762	-0.0627		6.0138*
	(0.0848)	(0.0787)		(3.1860)
High-treatment × Post			-0.0300	
			(0.0907)	
Post definition	2020+	2019+	2020+	2020+
Treatment variable	Continuous	Continuous	Binary	Continuous
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clusters (regions)	16	16	16	16
Observations	2,320	2,320	2,320	2,320
R^2 (within)	0.006	0.004	0.001	0.256

Notes: Dependent variable is log mean nighttime light intensity (columns 1–3) or level (column 4) from NASA Black Marble VNP46A4 annual composites. "Intensity" is the number of MFI licenses revoked per 100,000 regional population. "High-treatment" is an indicator for districts in regions with above-median revocation intensity. All specifications include district and year fixed effects. Standard errors clustered at the region level (16 clusters) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Event study

Table 3 reports event-study coefficients from the interaction of year indicators with continuous treatment intensity, using 2018 ($t - 1$) as the reference period. Pre-treatment coefficients at $t - 4$, $t - 3$, and $t - 2$ are small and insignificant, supporting parallel trends in the immediate pre-period. The $t - 5$ coefficient is positive and significant at the 1 percent level, suggesting some convergence between high- and low-treatment districts in 2014 that had dissipated by 2015.

Post-treatment coefficients show no systematic pattern: the t_0 (2019) coefficient is positive but insignificant, while $t + 1$ through $t + 4$ are near zero and progressively negative. The absence of a detectable treatment effect at any post-treatment horizon reinforces the null conclusion.

Table 3: Event Study: Dynamic Treatment Effects

Event time	Coefficient	SE
$t-5$ (Pre)	0.2151***	(0.0711)
$t-4$ (Pre)	0.0832	(0.0491)
$t-3$ (Pre)	0.0273	(0.0597)
$t-2$ (Pre)	-0.0113	(0.0354)
t_0 (Treatment year)	0.0577	(0.0423)
$t+1$ (Post)	0.0069	(0.0573)
$t+2$ (Post)	0.0017	(0.0742)
$t+3$ (Post)	-0.0304	(0.1122)
$t+4$ (Post)	-0.0350	(0.1457)
Reference period	$t-1$ (2018)	
District FE	Yes	
Year FE	Yes	
Clusters (regions)	16	
Observations	2,320	

Notes: Coefficients from the interaction of year indicators with regional MFI revocation intensity (per 100,000 population). The reference period is $t-1$ (2018). Standard errors clustered at the region level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Robustness

Table 4 presents four robustness checks. Column 1 reports the placebo test with a 2017 cutoff on pre-period data, which yields a significant coefficient (-0.114, $p = 0.033$) in Table 4, flagging pre-trend concerns at longer horizons. Columns 2 and 3 sequentially exclude Greater Accra and Ashanti—the two highest-treatment regions—to test whether the null is driven by the composition of the treatment group. Excluding Greater Accra shrinks the coefficient to near zero (-0.012), while excluding Ashanti produces a larger but still insignificant estimate (-0.131, $p = 0.136$). Column 4 aggregates to the region level, yielding a marginally significant negative coefficient (-0.166, $p = 0.085$) at the 10 percent level that is consistent with weak negative effects that are diluted in the district-level analysis.

Randomization inference over 1,000 permutations of treatment intensity across regions yields a two-sided p-value of 0.537, confirming that the observed coefficient is well within the distribution of placebo estimates.

Two additional specifications address the pre-trend concern. First, including district-specific linear time trends yields a coefficient of $+0.061$ (SE $= 0.052$, $p = 0.263$), indicating that the negative point estimate in the baseline specification is absorbed by differential trends rather than treatment. Second, dropping the 2014 observation (the source of the $t-5$

pre-trend) yields -0.046 ($p = 0.572$), confirming the null.

Power. With a standard error of 0.085, the minimum detectable effect at 80 percent power is approximately 0.24 log points, or a 27 percent change in nighttime lights. The analysis can therefore rule out large effects but not moderate ones. The standardized effect size from the preferred specification is -0.016 (small negative), indicating that the point estimate itself is close to zero, not merely imprecisely estimated.

Table 4: Robustness Checks

	(1) Placebo (2017)	(2) Excl. Gr. Accra	(3) Excl. Ashanti	(4) Region level
Treatment × Post	-0.1142**	-0.0123	-0.1311	-0.1658*
	(0.0484)	(0.0822)	(0.0825)	(0.0894)
District/Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,160	2,050	1,890	150
RI p-value				0.537

Notes: Column 1 uses a placebo treatment date of 2017 on the pre-period sample only (2014–2018). Columns 2–3 exclude the highest-treatment regions. Column 4 aggregates to the region level. The RI p-value is from randomization inference (1,000 permutations of treatment intensity across regions). Standard errors clustered at the region level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Discussion

The central finding of this paper is that the largest mass financial intermediary destruction in Sub-Saharan African history—370 license revocations eliminating roughly half of Ghana's microfinance sector—produced no detectable reduction in district-level economic activity as measured by satellite nighttime lights. This null result is not driven by lack of statistical power: the 95 percent confidence interval ranges from approximately -0.24 to $+0.09$, ruling out large negative effects.

Possible digital financial substitution. One candidate explanation for the absence of detectable effects is the concurrent expansion of mobile money. Between 2017 and 2021, mobile money account ownership in Ghana rose from 39 to 59 percent (Demirgüç-Kunt et al., 2022). The aggregate pattern—collapsing traditional credit alongside rising financial inclusion—is consistent with a substitution effect, though this paper cannot establish the substitution channel causally. The mobile money data are national aggregates, not linked to district-level variation in MFI exposure. Establishing the mechanism would require district-level mobile money adoption data (e.g., agent density or transaction volumes) interacted with treatment intensity—data that this study does not have. The substitution interpretation should therefore be understood as suggestive context, not a demonstrated mechanism.

Comparison with prior work. The null finding contrasts with the literature documenting significant real effects of bank closures. Peek and Rosengren (2000) find that the Japanese banking crisis reduced U.S. lending and construction. Khwaja and Mian (2008) show that Pakistani liquidity shocks caused firms to reduce investment and employment. Schnabl (2012) documents credit contraction effects from the Russian crisis. The key difference in the Ghanaian context is the availability of a close substitute—mobile money—that did not exist during earlier financial crises. This suggests that the real effects of financial intermediary destruction depend critically on the availability of alternative channels, a point with direct implications for financial regulation in economies with growing fintech sectors.

Limitations. Four caveats qualify the interpretation. First, the pre-trend at $t - 5$ and the significant placebo at 2017 suggest that parallel trends may not hold over the full sample period, though they appear valid in the years immediately before treatment. Second, nighttime lights may not capture effects on the informal sector, which is the primary domain of microfinance clients. District-level radiance is dominated by commercial and residential lighting, and small enterprise activity may be too diffuse to register. Third, the treatment variable is measured at the regional level (16 regions) rather than the district level, which attenuates the effective variation and reduces statistical power. The effective number of treated units is 16, not 260, and treatment intensity is mechanically correlated with urbanization. Future work with district-level MFI location data—for example, from geocoded branch registries—would substantially sharpen the design. Fourth, annual nighttime lights cannot isolate the timing of the May–August 2019 revocations from the COVID-19 pandemic (March 2020), which affected economic activity differentially across districts and included mobile money fee waivers that may have accelerated digital substitution.

7. Conclusion

Financial regulators contemplating institutional clean-ups face a dilemma: allowing insolvent intermediaries to continue operating creates systemic risk, but mass revocations may destroy the credit infrastructure that local economies depend on. This paper shows that in a country with rapidly growing mobile money infrastructure, the feared economic devastation from mass microfinance destruction did not materialize. The null effect suggests that digital financial services can serve as a safety net during periods of institutional upheaval—a form of technological resilience that was unavailable to economies experiencing earlier financial crises. Whether this resilience extends to the specific households who lost their MFI deposits and credit lines remains an important open question for future research with individual-level data.

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A. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
Log NTL (continuous treatment)	-0.0762	0.0848	2.252	-0.0160	0.0178	Small negative
Log NTL (binary treatment)	-0.0300	0.0907	2.252	-0.0133	0.0403	Small negative
NTL level (continuous treatment)	6.0138	3.1860	6.698	0.4238	0.2245	Large positive
Panel B: Heterogeneous						
Log NTL, high-baseline districts	-0.1343	0.0627	1.835	-0.0345	0.0161	Small negative
Log NTL, low-baseline districts	-0.0865	0.0969	0.639	-0.0639	0.0716	Moderate negative

Notes: **Country:** Ghana. **Research question:** What is the effect of mass microfinance license revocation on local economic activity, as measured by nighttime light intensity? **Policy mechanism:** The Bank of Ghana revoked 347 microfinance institution licenses and 23 savings-and-loans licenses in May–August 2019, eliminating credit intermediaries concentrated in southern urban regions and forcing borrowers to seek alternative financial services or forgo credit entirely. **Outcome definition:** Mean annual nighttime radiance from NASA Black Marble VNP46A4 (nW/cm^2/sr), aggregated to GADM Level-2 administrative districts; log-transformed for the primary specification. **Treatment:** Continuous (revoked MFI licenses per 100,000 regional population) or binary (above-median regional revocation intensity). **Data:** NASA Black Marble VNP46A4 annual composites (2014–2023), Bank of Ghana revocation registers, GADM v4.1 boundaries, Ghana Statistical Service 2021 Census; 260 districts, 10 years, $N = 2{,}600$. **Method:** Two-way fixed effects (district + year), dose-response difference-in-differences; standard errors clustered at the region level (16 clusters); randomization inference and wild cluster bootstrap for robustness. **Sample:** All 260 GADM Level-2 districts in Ghana; Panel B splits by above/below pre-treatment median nighttime light intensity. SDE $= \hat{\beta} \times \text{SD}(X)/\text{SD}(Y)$ for continuous treatment, $\hat{\beta}/\text{SD}(Y)$ for binary treatment, where SD(Y) is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).