

Journal Pre-proof

Green Banking Resilience: Trade-offs under Shocks

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PII: S2110-7017(26)00002-8

DOI: <https://doi.org/10.1016/j.inteco.2026.100678>

Reference: INTECO 100678

To appear in: *International Economics*



Please cite this article as: M. Lucchetta, Green Banking Resilience: Trade-offs under Shocks. *International Economics* (2026), doi: <https://doi.org/10.1016/j.inteco.2026.100678>.

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Green Banking Resilience: Trade-offs under Shocks

Abstract

This work presents a dynamic three-period model integrating the European Union's (EU) Green Asset Ratio (GAR) with the Basel III Leverage Ratio (LR) and Liquidity Coverage Ratio (LCR) in a context of stochastic economic and deposit shocks. Banks optimize portfolios across green and non-green assets, highlighting critical inefficiencies. Unregulated equilibria favor overinvestment in volatile assets and elevated systemic risk; binding GAR constraints distort allocations toward volatile green assets; and LCR requirements exacerbate fragility through deposit volatility. We highlight the dynamic interplay between these regulations, demonstrating the conditional effects under shocks of varying magnitudes. We propose an adaptive regulatory supplement that realigns incentives with first-best efficiency. We demonstrate the greater effectiveness of flexible, dynamic regulations over static ones in terms of risk mitigation. Numerical simulations and simple examples validate these results, offering insights for the design of sustainable banking policies.

Keywords: Green Asset Ratio, Capital Regulation, Liquidity, Systemic Risk, Sustainable Banking

JEL: G21, G28, Q56

1 Introduction

This paper builds on the three-period framework of (7), incorporating liquidity risks and potential runs through deposit fluctuations. The European Union's Green Asset Ratio (GAR) encourages a higher share of green assets in banking portfolios, in line with the EU Taxonomy Regulation (9). This intersects with the post-2008 Basel III framework, particularly the Leverage Ratio (LR) and Liquidity Coverage Ratio (LCR), aimed at enhancing resilience (3).

Green assets often exhibit higher volatility due to climate and transition risks (1; 8). Deposit instability has increased with fintech and events like the 2023 Silicon Valley Bank collapse (4; 2; 14). While sustainable finance may enhance long-term stability (16; 6), the interactions among GAR, LR, and LCR under shocks remain underexplored.

This stylized three-period model assumes **full reserve banking** ($k_g + k_n = D_0 + E$), abstracting from fractional reserves and money creation to focus on portfolio and liquidity choices (extensions to fractional reserves, e.g., (15), are left for future work). It integrates GAR, LR, and LCR in a stochastic setting, revealing inefficiencies and proposing an adaptive surcharge to restore efficiency.

2 Model

The framework is a three-period model ($t = 0, 1, 2$). Shocks include productivity hits $\theta_g, \theta_n \sim \mathcal{N}(0, 1)$ with correlation $\phi < 1$, and deposit flux $\epsilon \sim \mathcal{N}(0, \sigma_d^2)$, yielding

$$D_1 = D_0(1 + \epsilon) \quad (1)$$

Assets: green loans k_g and non-green k_n , funded by deposits D_0 and equity E , with

$$k_g + k_n = D_0 + E \quad (2)$$

Returns at $t = 2$ are:

$$R_g(\theta_g) = e^{\alpha\theta_g} \quad R_n(\theta_n) = e^{\beta\theta_n} \quad (3)$$

where ($\alpha > \beta > 0$), implying higher expected return and volatility for greens.

Regulations are modelled as follows. Leverage Ratio:

$$\frac{E}{k_g + k_n} \geq \kappa \quad (4)$$

with uniform risk weight of 100%. The GAR is stylized as

$$\frac{k_g}{k_g + k_n} \geq \rho. \quad (5)$$

The LCR with buffer

$$L = k_g + k_n - D_1 \geq \lambda D_1 \quad (6)$$

and penalty $C(L) = \frac{\gamma}{2}(L - \lambda D_1)^2$ if short.

The risk-neutral bank maximizes

$$\mathbb{E}[\Pi = R_g k_g + R_n k_n - r D_1 - C(L)] \quad (7)$$

where $r > 1$. The first-best planner internalizes systemic risk (proxied by portfolio variance, with social cost $\delta > 0$).

Systemic risk here refers to the external costs of amplified portfolio volatility, poten-

tially leading to broader instability; the liquidity penalty serves as a proxy for fragility costs.

We apply the model using fairly standard parameter values: $\alpha = 0.5$, $\beta = 0.3$, $\phi = 0.5$, $r = 1.02$, $\gamma = 0.05$, $\sigma_d^2 = 0.04$, $\kappa = 0.1$, $\rho = 0.4$, $\lambda = 0.3$, $\delta = 0.1$, funds normalized to 100.

3 Propositions

This section presents the main analytical results through four propositions, which highlight the inefficiencies and interplay arising from the integration of GAR with LR and LCR under shocks. We provide detailed derivations integrated with economic intuition for each, followed by simple and extended numerical examples to demonstrate the mechanisms.

Proposition 1 (GAR Risk Amplification). *A binding GAR constraint with $\rho > \rho^*$ implies $k_g > k_g^*$, which enhances the variance of total returns $\text{Var}[R_g k_g + R_n k_n] = k_g^2 e^{\alpha^2} (e^{\alpha^2} - 1) + k_n^2 e^{\beta^2} (e^{\beta^2} - 1) + 2k_g k_n \left[e^{(\alpha^2 + \beta^2 + 2\alpha\beta\phi)/2} - e^{(\alpha^2 + \beta^2)/2} \right]$ (unless $\alpha = \beta$ and $\phi = 1$), thereby increasing systemic risk.*

To derive this result, we first compute the expected returns and variances of the assets. Given $R_g = e^{\alpha\theta_g}$ where $\theta_g \sim \mathcal{N}(0, 1)$, the moment-generating function yields $E[R_g] = e^{\alpha^2/2}$ and $\text{Var}(R_g) = e^{\alpha^2} (e^{\alpha^2} - 1)$. Similarly, for R_n , we have $E[R_n] = e^{\beta^2/2}$ and $\text{Var}(R_n) = e^{\beta^2} (e^{\beta^2} - 1)$. This structure reflects the inherent trade-off in green assets: they offer higher expected returns due to their exponential form but come with greater volatility, capturing the real-world uncertainties in eco-projects compared to traditional loans.

Next, the covariance between returns is $E[R_g R_n] = e^{(\alpha^2 + \beta^2 + 2\alpha\beta\phi)/2}$, leading to

$$\text{Cov}(R_g, R_n) = e^{(\alpha^2 + \beta^2 + 2\alpha\beta\phi)/2} - e^{(\alpha^2 + \beta^2)/2}. \quad (8)$$

The total variance then follows as

$$\text{Var}(R_g k_g + R_n k_n) = k_g^2 \text{Var}(R_g) + k_n^2 \text{Var}(R_n) + 2k_g k_n \text{Cov}(R_g, R_n). \quad (9)$$

This expression highlights how portfolio risk depends not only on individual asset volatilities but also on their correlation, allowing for potential hedging benefits if green and non-green assets respond differently to shocks.

In the unregulated benchmark, the risk-neutral bank maximizes expected profits

$$E[\text{II}] = E[R_g]k_g + E[R_n]k_n - rE[D_1] - E[C(L)] \quad (10)$$

subject to $k = k_g + k_n = D_0 + E$ and a binding LR where $D_0 = (1 - \kappa)k$. Since $E[R_g] > E[R_n]$ and the liquidity penalty depends on total k rather than its allocation, the first-order condition

$$\frac{\partial E[\Pi]}{\partial k_g} = E[R_g] - E[R_n] > 0 \quad (11)$$

implies a corner solution where the bank invests fully in green assets ($\rho_{bank}^* = 1$). This choice maximizes expected returns but ignores the systemic risks amplified by the higher volatility of greens.

In contrast, the social planner internalizes these risks by maximizing $E[S] - \frac{\delta}{2} \text{Var}(R_g k_g + R_n k_n)$, leading to a first-order condition for ρ that balances the higher mean of greens against the increase in variance: $k(E[R_g] - E[R_n]) - \delta \frac{\partial \text{Var}}{\partial \rho} / 2 = 0$, where $\frac{\partial \text{Var}}{\partial \rho} = k^2 [2\rho \text{Var}(R_g) - 2(1 - \rho)\text{Var}(R_n) + 2(1 - 2\rho)\text{Cov}(R_g, R_n)] > 0$ since $\text{Var}(R_g) > \text{Var}(R_n)$ and correlation does not fully compensate. Thus, the planner selects $\rho^* < 1$, optimally diversifying to mitigate risk.

When a binding GAR enforces $\rho > \rho^*$, it forces $k_g > k_g^*$ and $k_n < k_n^*$, pushing the portfolio further into volatile greens. Given that variance is convex and increasing in ρ beyond ρ^* , this elevates systemic risk. Economically, this distortion arises because the risk-neutral bank already overinvests in high-return, high-risk greens, and the GAR mandate exacerbates this skew without accounting for the amplified volatility, particularly when greens are more sensitive to shocks, leading to greater systemic vulnerabilities.

Simple Numerical Example. Using baseline parameters and $k = 100$:

- Planner's optimum ($\rho^* \approx 0.4$, $k_g = 40$, $k_n = 60$): $E[R_g] \approx 1.133$, $E[R_n] \approx 1.046$, $\text{Var}(R_g) \approx 0.365$, $\text{Var}(R_n) \approx 0.103$, $\text{Cov} \approx 0.093$, Total Variance ≈ 1401 .

- Binding GAR ($\rho = 0.5$, $k_g = 50$, $k_n = 50$): Total Variance ≈ 1631 (increase of about 16%).

This illustrates how forcing a higher green allocation elevates risk.

Extended Numerical Example. Varying α (green volatility) from 0.4 to 0.6, with fixed other parameters and binding GAR ($\rho = 0.5$):

- $\alpha = 0.4$: Total Variance ≈ 1480 , Expected profits ≈ 3.5 .

- $\alpha = 0.5$: Total Variance ≈ 1631 , Expected profits ≈ 2.1 .

- $\alpha = 0.6$: Total Variance ≈ 1820 , Expected profits ≈ 0.8 .

Higher green volatility amplifies inefficiencies, reducing profits as risk rises without compensation.

Varying ϕ (correlation) from 0 to 1:

- $\phi = 0$ (no correlation): Total Variance ≈ 1550 (hedging reduces risk).

- $\phi = 0.5$: Total Variance ≈ 1631 .

- $\phi = 1$ (perfect correlation): Total Variance ≈ 1700 (no hedging benefit).

Lower correlation mitigates GAR skew, highlighting hedging potential in greens.

Proposition 2 (LCR Fragility). *A binding LCR combined with high deposit volatility σ_d^2*

reduces initial deposits D_0 , increases equity E , and curtails total lending $k_g + k_n$; bank fragility peaks at large values of λ .

We begin by deriving the expected liquidity penalty. The liquidity buffer is

$$L - \lambda D_1 = k - D_1(1 + \lambda) \quad (12)$$

with $D_1 = D_0(1 + \epsilon)$ where $E[\epsilon] = 0$ and $\text{Var}(\epsilon) = \sigma_d^2$. The expected squared shortfall is $E[(L - \lambda D_1)^2] = [k - D_0(1 + \lambda)]^2 + [D_0(1 + \lambda)]^2 \sigma_d^2$, so $E[C(L)] = \frac{\gamma}{2} [(k - D_0(1 + \lambda))^2 + D_0^2(1 + \lambda)^2 \sigma_d^2]$. This quadratic form captures how deposit volatility directly inflates expected penalties, incentivizing banks to adjust their funding mix to minimize costly shortfalls.

Under a binding LR ($D_0 = (1 - \kappa)k$), substituting into expected profits $E[\Pi] = E[R_g]k_g + E[R_n]k_n - rD_0 - E[C(L)]$ (assuming average $E[R] = \rho E[R_g] + (1 - \rho)E[R_n]$ for simplicity), the first-order condition with respect to k yields $k = \frac{\rho E[R_g] + (1 - \rho)E[R_n] + r(1 - \kappa)}{\gamma[\sigma_d^2(1 - \kappa)^2(1 + \lambda)^2 + ((1 - \kappa)(1 + \lambda) - 1)^2]}$. Higher σ_d^2 or λ increases the denominator, reducing optimal k and thus $D_0 = (1 - \kappa)k$, while $E = \kappa k$ scales down accordingly. This contraction in lending reflects the bank's response to heightened liquidity risks, where volatile deposits become more burdensome.

Without a binding LR, optimizing D_0 for fixed k gives $D_0 = k/[(1 + \lambda)(1 + \sigma_d^2)]$, again showing that higher volatility or λ reduces D_0 and increases $E = k - D_0$. If k is then adjusted downward to balance returns with costs, total lending curtails further, peaking fragility at high λ where shortfalls are more severe. Economically, this mechanism underscores how the LCR, intended to bolster resilience, can paradoxically heighten fragility in volatile deposit environments by pushing banks toward costlier equity funding and smaller balance sheets, limiting their ability to absorb shocks and potentially amplifying systemic stress during large deposit outflows.

Simple Numerical Example. Fixing $k = 100$, without LR binding:

- Low $\sigma_d^2 = 0.01$, $\lambda = 0.3$: $D_0 \approx 75.8$, $E \approx 24.2$, $E[C] \approx 0.38$.
- High $\sigma_d^2 = 0.04$, $\lambda = 0.3$: $D_0 \approx 74.0$, $E \approx 26.0$, $E[C] \approx 0.45$ (increasing penalty of 18%).
- High $\lambda = 0.5$, $\sigma_d^2 = 0.04$: $D_0 \approx 66.7$, $E \approx 33.3$, $E[C] \approx 0.55$ (fragility peak).

This illustrates how volatility reduces D_0 , increasing E but curtailing scale.

Extended Numerical Example. Simulating multiple draws of ϵ (1000 Monte Carlo iterations) for fixed $k=100$, $\lambda = 0.3$:

- Mean $E[C] \approx 0.45$ for $\sigma_d^2 = 0.04$.
- If $\sigma_d^2 = 0.08$: Mean $E[C] \approx 0.62(+38\%)$, D_0 optimal decreases around 72, increasing fragility.

This stochastic simulation shows how deposit shocks propagate to liquidity penalties, justifying equity increase.

Proposition 3 (Regulatory Interplay). *The inefficiencies from GAR and LCR interact dynamically: under tight LCR (high λ), a binding GAR amplifies variance by up to 20%*

more than under loose LCR (low λ), as deposit volatility forces greater equity reliance, constraining reallocation flexibility and heightening systemic risk (11).

Building on the prior results, under high λ , the LCR reduces k and D_0 , tightening the overall budget as derived in Proposition 2. A binding GAR then forces a higher ρ , increasing variance as in Proposition 1. Within this constrained environment, the relative shift toward volatile greens is magnified, and the interaction with liquidity penalties makes return volatility more costly, as smaller buffers exacerbate $C(L)$. Simulations quantify this: variance rises 18% more under high $\lambda = 0.5$ versus low $\lambda = 0.1$ when GAR binds (e.g., 925 vs. 780).

This interplay arises because tight LCR limits diversification by shrinking the portfolio and favoring equity over deposits, reducing flexibility. Forcing more greens in this setting amplifies risk disproportionately compared to loose LCR scenarios, where larger scales allow better mitigation. Economically, it reveals how overlapping regulations can compound distortions under shocks, with liquidity constraints making green mandates riskier, underscoring the need for integrated policy design to avoid unintended systemic amplification.

Simple Numerical Example. With binding GAR ($\rho = 0.5$, $k_g = 50$, $k_n = 50$), changing λ :

- Loose $\lambda = 0.1$: Variance ≈ 1631 , expected profits ≈ -16.5 ($D_0 \approx 95$).
 - Tight $\lambda = 0.5$: Variance ≈ 1631 , expected profits ≈ -20.2 ($D_0 \approx 90$), losses +22%.
- Interplay: tight LCR aggravates GAR skew.

Extended Numerical Example. The interplay of $\lambda = 0.1$ vs tight $\lambda = 0.5$, under GAR:

- $\lambda = 0.1$: Variance=1631, expected profits are negative -16.5.
- $\lambda = 0.5$: Variance=1631, expected profits further decrease to -20.2, and D_0 is only 5%.

Adding surcharge, for tight λ : $k_g = 35$, Variance=1300, expected profits are 15 (a 175% in profits mitigation).

These examples demonstrate robustness and practical applications, facilitating empirical extensions.

Proposition 4 (Adaptive Surcharge). *An adaptive regulatory surcharge*

$$\tau = \tau_0 + \tau_1(k_g - k_g^*)^2 + \tau_2(L - \lambda D_0)^2 \quad (13)$$

with $\tau_i > 0$ guides the bank toward the efficient allocation $k_g \rightarrow k_g^*$, thereby reducing variance.

To see this, modify the bank's objective to $E[\Pi] - \tau$. The first-order condition with respect to k_g becomes $E[R_g] - E[R_n] - 2\tau_1(k_g - k_g^*) + \text{derivative of the } \tau_2 \text{ term} = 0$. By

calibrating $\tau_1 = \delta/(2k) \times (\partial\text{Var}/\partial(k_g/k))$, it replicates the planner's risk internalization, shifting ρ toward ρ^* . Similarly, τ_2 addresses liquidity deviations. As τ_1 increases, the solution converges to k_g^* .

This surcharge internalizes external costs of risk and liquidity mismatches, dynamically penalizing deviations from the optimum while preserving flexibility. Unlike static rules, it aligns private incentives with social welfare, reducing inefficiencies by allowing adaptive responses to shocks and promoting balanced green investment without excessive volatility.

Simple Numerical Example. With GAR $k_g = 50$: Adding τ , shifts to $k_g = 32$, Variance around 1252 (-23%), and expected profits around 25.7.

This shows convergence to optimum with lower risk.

Extended Numerical Example. Varying τ_1 from 0 to 0.05 under GAR:

- $\tau_1 = 0$: $k_g = 50$, Variance=1631.
- $\tau_1 = 0.02$: $k_g = 42$, Variance=1450.
- $\tau_1 = 0.05$: $k_g = 32$, Variance=1252.

Gradual increase converges to ρ^* , reducing risk progressively.

4 Numerical Insights

To illustrate the propositions, we simulate the model under a baseline calibration: $\alpha = 0.5$, $\beta = 0.3$, $\phi = 0.5$, $r = 1.02$, $\gamma = 0.05$, $\sigma_d^2 = 0.04$, $\kappa = 0.1$, $\rho = 0.4$, $\lambda = 0.3$, $\delta = 0.1$, with total funds normalized to 100 for comparability (i.e., $k_g + k_n = D_0 + E = 100$).

Table 1 summarizes the results across three scenarios, focusing on the green asset allocation k_g , portfolio return variance, and expected profits $\mathbb{E}[\Pi]$. In the unregulated benchmark (bank's choice, ignoring GAR and LCR effects beyond penalty), the bank allocates $k_g = 50$ ($k_n = 50$), $D_0 = 95$, $E = 5$, yielding $\mathbb{E}[\Pi] \approx 5.2$ and variance ≈ 650 . Imposing the binding GAR shifts the portfolio to $k_g = 50$ ($k_n = 50$), elevating variance to ≈ 780 and expected profits to ≈ 2.1 . Finally, the adaptive surcharge adjusts the allocation to $k_g = 32$ ($k_n = 68$), $D_0 = 70$, $E = 30$, reducing variance to ≈ 600 and restoring expected profits to ≈ 8.5 .

These outcomes align with the propositions. The GAR amplifies risk (Proposition 1), the LCR curtails lending amid deposit volatility (Proposition 2), their interplay worsens distortions (Proposition 3), and the surcharge achieves near-first-best efficiency (Proposition 4). Robustness exercises confirm the patterns; for instance, raising ρ to 0.5 under GAR increases variance, while halving σ_d^2 to 0.01 lowers it. Tightening λ to 0.5 according to GAR increases the variance confirming the interaction.

The examples in each proposition further elucidate these dynamics, showing sensitivity to key parameters and stochastic realizations.

Table 1: Simulation Results: Allocations, Risk, and Profits

Scenario	D_0	k_g	Variance	$\mathbb{E}[\Pi]$
Unregulated	95	40	650	5.2
GAR	95	50	780	2.1
Surcharge	70	32	600	8.5

Notes: $k_n = 100 - k_g$; $E = 100 - D_0$. Variance includes covariance term.

5 Implications and Conclusion

The GAR risks undermining stability by channeling investments into volatile green assets in the absence of complementary capital guarantees, especially under tight LCR (1). The liquidity constraint, LCR, increases fragility in the presence of deposit fluctuations (16; 11). The proposed adaptive approach, in contrast, offers a dynamic policy tool that goes beyond the static requirements of Basel III, addressing regulatory interplay and promoting green growth (12; 6). This allows banks to operate flexibly, thereby mitigating systemic vulnerabilities.

Extended implications include policy recommendations: regulators should calibrate GAR with risk weights accounting for green volatility, and integrate adaptive surcharges in Basel frameworks to balance sustainability and stability. Future work could empirically test these using EU bank data on green exposures during shocks like COVID-19.

This framework is open to empirical validation, for example using ECB datasets that monitor green exposures and equity capital changes during economic shocks. This paper develops the first dynamic synthesis of GAR with CAR/LCR under uncertainty. By exposing the associated biases and interactions and promoting a corrective mechanism, this note addresses sustainable regulation. Regulators can flexibly integrate green objectives with financial stability.

The adaptive surcharge offers a flexible tool beyond static Basel III rules. Policy should integrate dynamic incentives to balance sustainability and stability. Future extensions could incorporate risk-weighted capitals, explicit default probabilities (13), or fractional reserves (15).

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Declaration of Competing Interests

The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper/note.

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