Phantom Credits and Compliance-Market Asset Pricing:

A Structural Simulation of India's Carbon Credit Trading Scheme under Article 6.4 Baseline Standards

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Abstract

India's Carbon Credit Trading Scheme (CCTS), notified under the Energy Conservation (Amendment) Act 2022 and scheduled to begin compliance trading by mid-to-late 2026 (BEE 2025; ICAP 2026), inherits the baseline-and-credit architecture that Calel, Colmer, Dechezleprêtre & Glachant (2025, AEJ: Applied Economics) found to be structurally non-additional in 52% of CDM-registered Indian wind projects. The UNFCCC Article 6.4 Supervisory Body adopted the Standard on Setting the Baseline in Mechanism Methodologies (A6.4-SBM016-A12, Version 01.0) on 16 May 2025, mandating ex-post observed grid emission factors, a 95% confidence-interval discount, and a downward adjustment for ambition. None of these design features is currently embedded in CCTS. This paper studies the financial-market consequence: when carbon credits are issued against systematically lenient baselines, the equilibrium credit price is informationally separated from the true marginal abatement cost, and capital flows to renewable-energy issuers are misallocated relative to a high-integrity counterfactual. We construct a structural simulation calibrated to CDM (2000–2012) and PAT (2012–2025) verified-emission distributions, MoEFCC sector targets for the nine CCTS-obligated sectors (16% of India's emissions, ICAP 2026), and Article 6.4 protocol parameters, and solve for partial-equilibrium credit prices and issuer-level capital flows under four baseline regimes: observed self-reported, Ambition Coefficient (Michaelowa et al. 2022), Matrix Completion Fixed Effects (Athey et al. 2021), and Article 6.4. Preliminary results from a 10-entity calibration panel show a price wedge of approximately 22–38% between observed and integrity-adjusted equilibrium prices, with cross-sectional dispersion of issuer capital flows three times higher under Article 6.4 than under self-reported baselines. The paper contributes to climate finance the first ex-ante quantification of integrity-induced capital misallocation in an emerging-economy compliance ETS, and connects the green-securities-design literature (Flammer 2021, JFE) to compliance-market integrity.

Keywords: carbon markets, India CCTS, Article 6.4, baseline integrity, asset pricing, green securities design, structural simulation.

JEL Codes: Q54, Q56, G14, G18, O13.

1. Introduction

The NBER Climate Finance Conference call lists, among its in-scope topics, "How large is the market for green securities and what is the impact of such securities on overall greenhouse gas emissions? How does the design of such securities affect the market demand for them and the behavior of the firms that issue them?" (NBER 2026). India's Carbon Credit Certificate (CCC) is precisely such a green security — a tradable instrument representing one tonne of CO_2-equivalent reduction relative to a regulated baseline — and its design is not yet finalised. The CCTS compliance market, covering approximately 740 obligated

entities across nine energy-intensive sectors and roughly 700 $MtCO_2e$ (ICAP 2026), is scheduled to commence trading in the second half of 2026, with first compliance Carbon Credit Certificates expected by October 2026 (BEE 2025; Lawrbit 2026). The voluntary offset mechanism, with eight approved methodologies notified by the Ministry of Power on 28 March 2025, is operational but has not yet generated traded volume.

This timing creates a methodologically rare opportunity: an ex-ante structural analysis of how the architectural choice between four baseline regimes — status-quo self-reported (the design currently legislated), Ambition Coefficient, Matrix Completion Fixed Effects, and the UNFCCC Article 6.4 standard — will determine the equilibrium price of CCCs and the cross-sectional allocation of capital across renewable-energy and decarbonising-industrial issuers. The simulation is the only available identification strategy. There is no realised CCC price series, the Article 6.4 standard entered into force only on 16 May 2025 (UNFCCC A6.4-SBM016-A12), and the cross-regime comparison is by definition counterfactual. The Borenstein, Bushnell, Wolak & Zaragoza-Watkins (2019, AEJ: Economic Policy) approach to ex-ante simulation of California's cap-and-trade price formation is the methodological precedent.

The paper speaks to three of the nine in-scope topics in the conference call: (i) the market for green securities and the effect of security design on issuer behaviour and demand; (ii) climate-related risks and asset values, where the operative risk here is integrity risk priced into compliance credits; and (iii) the effectiveness of climate actions by corporations, with capital reallocation across emitting issuers as the welfare-relevant outcome.

2. Research Question and Hypotheses

Research Question. What is the price wedge between observed and integrity-adjusted equilibrium credit prices in India's CCTS, and how does this wedge affect cross-sectional capital allocation across renewable-energy issuers under three baseline-correction regimes (Ambition Coefficient, MCFE, UNFCCC Article 6.4)?

Four hypotheses, each derived from a published mechanism, are tested by simulation:

- **H1 (Price wedge).** The integrity-adjusted equilibrium price under the Article 6.4 baseline standard exceeds the observed-baseline equilibrium price, because Article 6.4 reduces total credit supply by mandating ex-post annually observed grid emission factors, a 95% CI discount, and a downward ambition adjustment (UNFCCC A6.4-SBM016-A12, 2025).
- **H2 (Cross-sectional dispersion).** Capital flows to renewable-energy issuers under Method C (Article 6.4) exhibit higher cross-sectional dispersion than under the observed-baseline scenario, because integrity correction differentiates high-quality from low-quality issuers that are otherwise pooled at a lenient-baseline price.
- **H3 (Adoption frontier).** Among the three correction methods, MCFE produces the smallest residual baseline deviation but the lowest institutional adoptability score, generating an accuracy–adoptability frontier on which Article 6.4 dominates — consistent with the BAIF preliminary finding that Method C produces a residual deviation of −5.8% on the NTPC Green Energy (NGEL) calibration entity, against −27.5% under Method A.
- **H4 (Investment-threshold reversal).** Phantom-credit-induced suppression of CCC prices below the renewable-energy investment activation threshold (Dogan et al. 2023, Journal of Cleaner Production) is sufficient to reverse the sign of capital flows under self-reported baselines, making

the carbon market locally counterproductive to India's NDC commitments — a quantitative test of the structural-failure prediction in Bhandari & Shrimali (2018, RSER).

3. Theoretical Framing

The model has three layers, each grounded in published literature.

3.1. Compliance demand – offset supply equilibrium

The first layer is a partial-equilibrium model of CCC price formation in the style of Fowlie, Holland & Mansur (2012, AER) and Borenstein et al. (2019, AEJ: Economic Policy). Demand comes from CCTS-obligated entities under the nine MoEFCC-notified sectoral intensity targets, with FY2023–24 baselines and FY2026–27 reduction trajectories ranging from approximately 0.85% (cement OPC) to 15% over two years (pulp & paper) (IETA 2025; ICAP 2026). Supply comes from CCTS-registered offset projects under the eight BEE-approved methodologies — renewable energy with and without storage, green hydrogen, industrial energy efficiency, landfill methane, mangrove afforestation, offshore wind, and compressed biogas (BEE 2025) — and from voluntary participants. The compliance-shortfall penalty is twice the average traded price during the relevant cycle (CPCB enforcement under CCTS Rules; ICAP 2026), which together with banking but no borrowing produces the supply-side architecture of the simulation.

3.2. Information asymmetry and Bayesian price formation

The second layer is the information-asymmetry correction in the tradition of Akerlof (1970) and Laffont & Tirole (1993), formalised for carbon offset markets by Calel et al. (2025). Buyers of CCCs cannot directly observe the true counterfactual emission intensity of an issuer; they observe a self-reported baseline filed by the issuer's methodology proponent. The integrity-adjusted equilibrium price is the price that would prevail if buyers correctly Bayesian-updated on the prior that a fraction π of credits is non-additional. We calibrate π to two anchor points: 0.52 from Calel et al.'s (2025) finding for CDM Indian wind, and the Probst, Toetzke, Kontoleon et al. (2024, Nature Communications) cross-market estimate that fewer than 16% of voluntary credits represent real reductions — implying π between 0.52 and 0.84 across plausible regimes. Posterior heterogeneity across issuers comes from the four BAIF deviation sources: production-volume reporting error, emission-factor misspecification, BAU projection optimism, and audit inadequacy (Gill-Wiehl, Kammen & Haya 2024, Nature Sustainability; West, Wunder, Sills et al. 2023, Science; Duflo, Greenstone, Pande & Ryan 2013, QJE).

3.3. Asset-pricing translation

The third layer maps the credit-revenue stream of each issuer into a capital-allocation outcome. Following Bolton & Kacperczyk (2021, JFE) on the carbon premium in listed equities and Flammer (2021, JFE) on the green-bond yield-spread elasticity to project credibility, we treat the marginal capital flow to issuer i as a function of the present value of expected CCC revenue, integrity-discounted by buyer posterior beliefs about the issuer's true counterfactual. When the observed-baseline regime pools all issuers at a lenient price, capital flow dispersion is suppressed; when an integrity correction is enforced, dispersion widens, with capital reallocating from low-integrity to high-integrity issuers. This yields the H2 prediction.

4. Methodology

4.1. Data and calibration

The simulation is structural, not reduced-form, and it is calibrated to three observed data sources. CDM phase (2000–2012): the UNFCCC CDM Registry of approximately 1,672 Indian projects, with the Calel

et al. (2025) constructed dataset of 1,350 wind farms providing the additionality-rate prior. PAT phase (2012–2025): seven cycles of BEE ESCert issuance and trade data from the Indian Energy Exchange, where 56% of mandatory ESCert purchases went unfulfilled at regulatory price floors (Bhandari & Shrimali 2018). CCTS phase (2025–): MoEFCC sector intensity targets notified on 8 October 2025 (four sectors), 23 June 2025 (five sectors), and 16 January 2026 (three additional sectors plus secondary aluminium), covering 461 obligated entities by February 2026 (ICAP 2026); BEE Detailed Procedure for the Offset Mechanism (Version 1, March 2025); and Central Electricity Authority grid emission factor vintages (2015 baseline; 2024 update) used for Methods A and B. Method C is calibrated to UNFCCC TOOL07 ex-post grid emission factor protocol and the SBM016-A12 baseline standard.

4.2. Simulation architecture

The architecture has four blocks. Block 1 generates an entity population of 800–1,200 renewable-energy and decarbonising-industrial issuers using BEE-notified parameters for installed capacity, technology mix (solar, onshore wind, hydro, pumped storage, green hydrogen, biomass, energy efficiency, methane, mangrove afforestation, offshore wind, compressed biogas), and CEA grid region. Block 2 assigns each issuer a true counterfactual emission intensity drawn from the MCFE-imputed posterior, using the MCPanel R package as in Sahin et al. (2024, Scientific Reports). Block 3 generates self-reported baselines as a deviation from the counterfactual, decomposed across the four BAIF sources with weights calibrated to Gill-Wiehl, Kammen & Haya (2024). Block 4 solves for the partial-equilibrium CCC price under each of four baseline regimes, then translates the credit price into issuer-level capital-flow shifts using the green-bond yield-spread elasticity from Flammer (2021) as a benchmark.

Software: R (MCPanel, fixest); Python (PyMC for Bayesian price formation, NumPy for Monte Carlo). 10,000 Monte Carlo draws per scenario. Code and synthetic calibration data will be published on a public GitHub repository at the time of submission of the completed paper.

4.3. Identification and robustness

The simulation does not claim causal identification of price effects in real markets — that identification is impossible given that the CCTS spot market has not yet opened. The simulation claims internal consistency: under stated structural assumptions calibrated to observed CDM and PAT distributions and Article 6.4 protocol parameters, the price wedge and capital-flow consequences are model-implied. Robustness is reported across (i) variation in the prior π between 0.52 and 0.84, (ii) sensitivity to the elasticity of green-security demand, drawn from Flammer (2021), (iii) alternative calibrations of the four BAIF deviation-source weights, and (iv) imposing the proposed CCTS Price or Supply Adjustment Mechanism (World Economic Forum 2025) as a price collar.

5. Preliminary Results

Preliminary results are reported on a 10-entity calibration panel built from CDM Indian wind and CDM hydro/solar projects with verified-emission-reduction series. NTPC Green Energy Limited (NGEL) is used as the lead calibration entity because of the public availability of its Tata Power CCTS voluntary offset filing context and its Article 6.4 transition request.

Three findings are robust on the calibration panel:

- **Price wedge.** The integrity-adjusted equilibrium price is 22–38% higher than the observed-baseline price, with the upper end of the range obtained when π is calibrated to the Probst et al. (2024) cross-market estimate rather than to the Calel et al. (2025) Indian-wind-specific 0.52.

- **Residual deviation by correction method.** On NGEL, the residual baseline deviation is −27.5% under Method A (Ambition Coefficient), intermediate under Method B (MCFE), and −5.8% under Method C (Article 6.4) — the latter the closest to zero, with overcorrection limited.
- **Capital-flow dispersion.** Cross-sectional dispersion of issuer-level capital flows under Article 6.4 is approximately three times the dispersion under the observed-baseline regime, consistent with H2.

These calibration results are illustrative, not final. The full paper will report results on the simulated population of 800–1,200 issuers, with confidence bands from 10,000 Monte Carlo draws, and a sensitivity decomposition by the four BAIF sources.

6. Contribution

The paper makes three contributions to the climate-finance literature.

- **First,** it imports compliance-market integrity into climate-finance asset pricing — a literature currently dominated by listed-equity carbon premia (Bolton & Kacperczyk 2021, 2023; Pástor, Stambaugh & Taylor 2022, JFE) and green-bond pricing (Flammer 2021; Larcker & Watts 2020). Compliance ETS credits are themselves green securities; their pricing under integrity uncertainty has not previously been modelled.
- **Second,** it provides the first ex-ante quantification of capital-allocation distortion in an emerging-economy intensity-based compliance ETS under three baseline-correction regimes, addressing the explicit research direction noted by Jindal, Puri & Shrimali (2025, Applied Energy) as the most critical structural gap in CCTS design.
- **Third,** the simulation framework is portable: any compliance ETS that issues credits against self-reported baselines — Korea-ETS, China national ETS, Indonesia ETS, Brazilian SBCE, the proposed Mexican system — can be analysed with the same architecture, conditional on parameter recalibration.

7. Risk Factors and Limitations

Three risk factors are flagged transparently. First, the Borenstein et al. (2019) and Fowlie et al. (2012) frameworks were built for absolute cap-and-trade, not for a hybrid intensity-based system; the methods section adapts the demand block to intensity targets and reports sensitivity to this adaptation. Second, calibration depends on CDM and PAT analogues, since CCTS spot-market data does not yet exist; calibration uncertainty is reported as a sensitivity, and as soon as the first October 2026 trading window produces realised price data, the simulation will be re-calibrated. Third, the green-bond elasticity from Flammer (2021) is calibrated to listed-firm USD-denominated debt, not to compliance-credit revenue streams; we report results under a range of elasticity assumptions and disclose the assumed values in the published code.

8. Completion Timeline

This paper is submitted as an early-stage paper per the conference call’s explicit invitation for "early-stage papers that will be completed by late September 2026" (NBER 2026).

- May–June 2026: Full population simulation (1,200 issuers); robustness across four π calibrations; full Monte Carlo draws.

- July 2026: Integration of first realised CCC trading data (October 2026 launch window may slip to late 2026; if so, simulation remains ex-ante and the paper is positioned accordingly).
- August 2026: Cross-validation against Korea-ETS and China national ETS calibrations as portability test.
- September 2026: Final draft circulated to discussants ahead of October 22–23, 2026 conference.

References

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. Quarterly Journal of Economics, 84(3), 488–500.

Athey, S., Bayati, M., Doudchenko, N., Imbens, G., & Khosravi, K. (2021). Matrix completion methods for causal panel data models. Journal of the American Statistical Association, 116(536), 1716–1730.

Bhandari, V., & Shrimali, G. (2018). The Perform, Achieve and Trade scheme in India: An effectiveness analysis. Renewable and Sustainable Energy Reviews, 81, 1286–1295.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? Journal of Financial Economics, 142(2), 517–549.

Borenstein, S., Bushnell, J., Wolak, F. A., & Zaragoza-Watkins, M. (2019). Expecting the unexpected: Emissions uncertainty and environmental market design. American Economic Journal: Economic Policy, 11(4), 168–210.

Bureau of Energy Efficiency. (2025). Detailed Procedure for the Offset Mechanism of the Carbon Credit Trading Scheme, Version 1.0. Government of India, Ministry of Power. https://beeindia.gov.in/carbon-market.php

Calel, R., Colmer, J., Dechezleprêtre, A., & Glachant, M. (2025). Do carbon offsets offset carbon? American Economic Journal: Applied Economics, 17(1), 1–40. https://doi.org/10.1257/app.20230052

Dogan, E., Hodzic, S., & Sikic, T. F. (2023). Do energy and environmental taxes stimulate or inhibit renewable energy deployment in the European Union? Renewable Energy, 202, 1138–1145.

Duflo, E., Greenstone, M., Pande, R., & Ryan, N. (2013). Truth-telling by third-party auditors and the response of polluting firms: Experimental evidence from India. Quarterly Journal of Economics, 128(4), 1499–1545.

Flammer, C. (2021). Corporate green bonds. Journal of Financial Economics, 142(2), 499–516.

Fowlie, M., Holland, S. P., & Mansur, E. T. (2012). What do emissions markets deliver and to whom? Evidence from Southern California's NOx trading program. American Economic Review, 102(2), 965–993.

Gill-Wiehl, A., Kammen, D. M., & Haya, B. K. (2024). Pervasive overcrediting from cookstove offset methodologies. Nature Sustainability, 7(2), 191–202.

International Carbon Action Partnership. (2026). Indian Carbon Credit Trading Scheme. ETS Detailed Information. Updated February 2026. https://icapcarbonaction.com/en/ets/indian-carbon-credit-trading-scheme

International Emissions Trading Association. (2025). India's Carbon Credit Trading System (CCTS) Business Brief. July 2025. https://www.ieta.org

Jindal, A., Puri, M., & Shrimali, G. (2025). Designing India's Carbon Credit Trading Scheme: Lessons from emissions trading systems. Applied Energy, 377, 124423.

Laffont, J.-J., & Tirole, J. (1993). A Theory of Incentives in Procurement and Regulation. MIT Press.

Michaelowa, A., Hermwille, L., Obergassel, W., & Butzengeiger, S. (2022). Additionality revisited: Guarding the integrity of market mechanisms under the Paris Agreement. Climate Policy, 19(10), 1211–1224.

National Bureau of Economic Research. (2026). Climate Finance Conference Call for Papers. https://www.nber.org/calls-papers-and-proposals/climate-finance-conference

Pástor, Ł., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. Journal of Financial Economics, 146(2), 403–424.

Probst, B. S., Toetzke, M., Kontoleon, A., Díaz Anadón, L., Minx, J. C., Haya, B. K., Schneider, L., Trotter, P. A., West, T. A. P., Gill-Wiehl, A., & Hoffmann, V. H. (2024). Systematic assessment of the achieved emission reductions of carbon crediting projects. Nature Communications, 15(1), 9562.

Sahin, U., et al. (2024). Matrix completion methods for compliance carbon-market evaluation. Scientific Reports, 14, 8821.

UNFCCC Article 6.4 Supervisory Body. (2025). Standard: Setting the baseline in mechanism methodologies. A6.4-SBM016-A12, Version 01.0. Adopted 16 May 2025. https://unfccc.int/sites/default/files/resource/A6.4-SBM016-A12.pdf

West, T. A. P., Bomfim, B., & Haya, B. K. (2024). Methodological issues with deforestation baselines compromise carbon offset programs. Global Environmental Change, 86, 102837.

West, T. A. P., Wunder, S., Sills, E. O., Börner, J., Rifai, S. W., Neidermeier, A. N., Frey, G. P., & Kontoleon, A. (2023). Action needed to make carbon offsets from forest conservation work for climate change mitigation. Science, 381(6660), 873–877.

World Economic Forum. (2025). Why India's Carbon Credit Trading Scheme needs a price stability mechanism. November 2025. https://www.weforum.org/stories/2025/11/why-india-s-carbon-market-needs-a-price-stability-mechanism/