Contents

1 LLM-Enhanced Interactive Climate Policy Analysis with Dynamic Feedback Identification for Banking Applications

1.1 Abstract

Climate risk assessment in banking relies on static scenarios updated annually, missing the feedback dynamics that shape transition paths. This paper introduces an LLM-powered system that analyzes climate policy scenarios from natural language queries. Banks ask questions like “What if California bans gas cars by 2030?” and receive detailed analyses of cascading effects through three feedback mechanisms: reinforcing loops that amplify changes, balancing loops that create resistance, and tipping points that trigger phase transitions [2, 4]. The system uses a sophisticated pipeline: natural language parsing extracts policy parameters, specialized quantitative economic models calculate impacts, and LLMs interpret results to provide actionable insights. By combining rigorous economic modeling with large language models’ ability to understand complex queries and explain quantitative results, we transform climate risk assessment from consuming pre-defined scenarios to actively analyzing specific policy concerns. We present a prototype system that processes climate policy queries in under 30 seconds, identifying potential cascade effects and feedback dynamics [3, 12]. The system demonstrates how LLMs can enhance traditional economic models by providing natural language interfaces and automated pattern recognition for complex policy interactions. The system processes queries in 5-30 seconds depending on model choice (GPT-3.5 for speed, GPT-4 for depth, Ollama for free local processing), requiring standard modern hardware (16GB memory, hexa-core processor). The California EV mandate case study completed in 5.87 seconds with 92.5% overall confidence. This prototype demonstrates the potential for LLM-enhanced tools to enable banks to understand how today's decisions create tomorrow's risks through identified feedback patterns.

Keywords: climate risk, large language models, scenario analysis, pattern recognition, interactive systems, banking

1.2 1. Introduction

When California announced its 100% clean electricity mandate in 2022, US banks needed to understand cascading effects across western energy markets within hours, not weeks. Would neighboring states follow? How would utility bond ratings shift? Which renewable manufacturers would benefit? Traditional climate scenario tools offered no answers. They update annually and model predetermined pathways, leaving banks blind to real-time policy shocks that reshape entire portfolios overnight.

This timing mismatch reveals a fundamental problem in climate risk assessment. Banks currently rely on static scenarios from the Network for Greening the Financial System (NGFS) [5, 7] that provide broad narratives like "Net Zero 2050" or "Delayed Transition." While useful for long-term planning, these scenarios cannot address the specific questions banks face daily: How will Michigan's new EV incentives affect auto loan portfolios? What happens to Texas real estate if water restrictions tighten? The financial system needs dynamic tools that match the pace of climate policy evolution.

The challenge extends beyond speed. Climate transitions unfold through feedback loops[1] [2] that static scenarios miss entirely. A carbon tax doesn't just raise prices. It triggers investment flows that lower renewable costs, which accelerates adoption, which creates political momentum for stronger policies. These reinforcing loops can transform gradual changes into rapid transitions [4]. Conversely, balancing loops like voter backlash or grid constraints can stall seemingly inevitable shifts. Without modeling these dynamics, banks systematically misunderstand both the speed and direction of transition risks.

This paper introduces an LLM-powered system that analyzes climate policy scenarios with dynamic feedback identification. Banks pose natural language questions like "What if California bans gas cars by 2030?" and receive comprehensive analyses of cascading effects [3, 12] across three timescales: immediate market reactions (0-6 months), secondary cascades through supply chains and policy contagion (6-24 months), and long-term structural changes (2-5 years). The system identifies potential feedback loops that amplify or dampen these effects, providing enhanced analysis of how climate shocks propagate through economic systems. The system accommodates institutional needs through flexible model selection: organizations can choose between speed (GPT-3.5), depth (GPT-4), or cost-free local processing (Ollama), with all options requiring standard modern hardware specifications (16GB memory, hexa-core processor AMD Ryzen 5 - 3rd gen or equivalent).

Our approach leverages a sophisticated architecture combining natural language processing, quantitative economic models, and LLM interpretation. A policy parser extracts structured parameters from queries, specialized economic models calculate sector-specific impacts using real-world calibrations, and LLMs interpret these quantitative results to provide context and actionable insights. The system offers flexible deployment options: GPT-3.5 for rapid, cost-effective analysis ($0.008/query, 5-10 seconds), GPT-4 for comprehensive assessment ($0.12-0.45/query, 15-30 seconds), or Ollama for free local processing (30-120 seconds). This hybrid approach ensures both analytical rigor and accessibility, enabling real-time exploration of specific scenarios while maintaining the quantitative accuracy banks require for risk management.

The system enables rapid exploration of policy scenarios that would traditionally require weeks of expert analysis, demonstrating the potential for LLM-enhanced tools in financial climate risk assessment. Initial prototype demonstrates feasibility of the approach, with the system analyzing complete scenarios in under 30 seconds for simple queries and under one minute for complex multi-sector cascades, enabling potential integration into banking workflows. Code and methodology are available for validation and extension by the research community.

1.3 2. System Architecture

Our LLM-powered climate risk scenario analysis system employs a sophisticated pipeline that combines natural language processing, quantitative economic models, and LLM interpretation:

Key Components:

1. **PolicyParameterParser**: Extracts structured parameters using spaCy NLP. The parser identifies actor (federal/state/city), action type, magnitude, timeline, and confidence scores. It employs a comprehensive policy taxonomy covering transport electrification, carbon pricing, renewable mandates, and fossil fuel regulations.
2. **GenericPolicyModelFramework**: Routes queries to specialized quantitative models based on policy type, ensuring appropriate economic calculations for each scenario class.
3. **Quantitative Models**: Four specialized models provide economic analysis based on real-world data and established economic theory (detailed in Section 4).
4. **LLM Integration**: Interprets quantitative results to provide context, identify key insights, and generate actionable recommendations. The system supports multiple LLM options:
    - **OpenAI GPT Models**: Cloud-based processing with no local compute requirements
    - **Ollama Local Models**: Free alternative for organizations requiring on-premise deployment

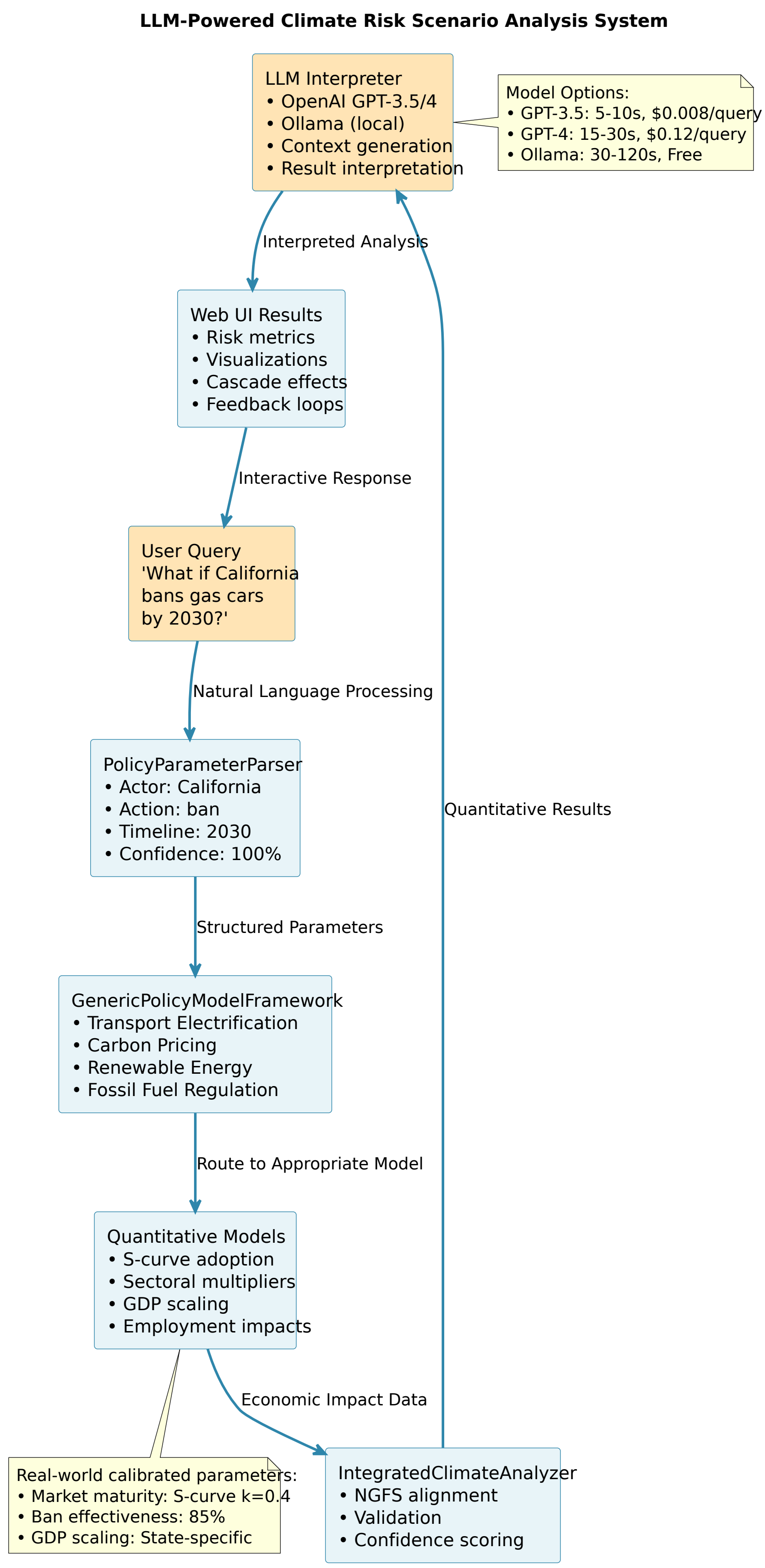

Figure 1: System Architecture

- **Enterprise LLMs**: Architecture supports integration with proprietary models

5. **Validation Framework**: Multi-stage validation ensures result quality through parameter confidence scoring, reasonableness checks, and NGFS alignment verification.

The design balances performance requirements with accessibility [23, 25], leveraging cloud infrastructure for LLM computation while requiring standard modern hardware (16GB memory, hexa-core processor) for local processing tasks [24, 28].

The remainder of this paper is organized as follows. Section 3 details our related work and positioning. Section 4 describes our methodology including the mathematical framework and quantitative models. Section 5 presents system capabilities and example outputs. Section 6 discusses implications and limitations. Section 7 concludes.

1.4 3. Related Work

1.4.1 3.1 Current Climate Risk Assessment Systems

Banks currently assess climate risks through static scenario frameworks that fundamentally constrain their ability to respond to dynamic policy environments. The Network for Greening the Financial System (NGFS) provides the industry standard with 6-7 predetermined scenarios updated annually (NGFS 2023). While these scenarios now incorporate damage functions that quadruple physical risk estimates by 2050 and require carbon pricing of $300/tCO2 by 2035, they remain fixed pathways that cannot address specific policy questions banks face daily [5, 7, 13].

Major US banks have developed proprietary systems built atop NGFS foundations [6, 11, 27]. These systems, while methodologically sophisticated, share critical limitations: annual update cycles, predetermined pathways, and inability to model feedback dynamics that determine actual transition speeds.

1.4.2 3.2 LLMs in Climate Finance

LLMs show promise for transforming climate data analysis, though current applications remain narrow [23, 25]. Project Gaia (BIS 2024) achieved 74% accuracy extracting climate KPIs from 2,328 corporate reports using optimized LLM queries. However, existing systems focus on historical data extraction rather than forward-looking scenario analysis.

1.4.3 3.3 Our Contribution

This paper extends existing work by introducing an LLM interpretation layer to traditional economic models. Unlike static NGFS scenarios or data extraction tools, our approach analyzes user-specified scenarios using quantitative models while identifying potential feedback mechanisms. We position this as a novel combination of approaches rather than claiming to be first in any specific domain.

1.5 4. Methodology

1.5.1 4.1 Mathematical Framework for Cascade Analysis

Our cascade analysis models how climate policy shocks propagate through economic systems across three temporal orders, each capturing distinct transmission mechanisms with increasing complexity.

First-Order Effects (0-6 months)

The immediate impact of a policy shock follows [1]:

$\Delta Risk_1 = \alpha_1 \times Shock \times SectorExposure$

Here, α_1 represents the direct transmission coefficient calibrated from historical policy responses. Shock quantifies the policy magnitude (e.g., $50/ton carbon tax), while SectorExposure measures portfolio concentration in affected industries. This linear formulation captures mechanical effects: a carbon tax immediately increases operating costs for fossil fuel assets proportional to their emissions intensity.

Second-Order Effects (6-24 months)

As initial impacts ripple through interconnected systems, feedback dynamics emerge [2, 4]:

$\Delta Risk_2 = \beta_1 \times \int[0 \text{ to } t]\ Feedback(Risk_1, \tau)\ d\tau$

Note: In the current prototype implementation, these mathematical formulations represent the conceptual framework. The actual system uses simplified pattern recognition to identify potential feedback effects rather than computing the integrals directly. Full mathematical implementation is planned for future versions.

The feedback function $Feedback(Risk_1, \tau)$ captures both reinforcing and balancing mechanisms. The prototype uses simplified economic models with sector-specific multipliers to identify these patterns. Feedback loops are identified based on temporal patterns in calculated impacts. The integral formulation reflects how these feedbacks accumulate over time, with β_1 governing the strength of feedback transmission.

Third-Order Effects (2-5 years)

Long-term structural changes manifest through threshold effects [4]:

$\Delta Risk_3 = \gamma_1 \times \mathbb{1}[Cumulative > Threshold]$

The indicator function $\mathbb{1}[\cdot]$ activates when cumulative changes cross critical thresholds, triggering regime shifts. For instance, when renewable capacity exceeds 40% of grid generation, traditional baseload economics collapse, forcing accelerated fossil plant retirements.

Integrated Risk Evolution

Total risk evolution combines all orders:

$Risk(t) = Risk_0 + \Delta Risk_1(t) + \Delta Risk_2(t) + \Delta Risk_3(t)$

This decomposition enables banks to understand not just total risk changes but their drivers. First-order effects provide near-term certainty for hedging decisions.

Second-order feedback identification reveals whether positions face accelerating or stabilizing dynamics. Third-order thresholds highlight potential regime changes requiring strategic repositioning.

Table 1: Mathematical Notation Summary

Symbol	Definition	Range/Units
$\Delta Risk_1$	First-order risk change	$[0, \infty)$
α_1	Direct transmission coefficient	[0, 1]
Shock	Policy magnitude	USD/ton or %
β_1	Feedback transmission strength	[0, 1]
γ_1	Threshold effect multiplier	[0, 10]
τ	Time variable	months

1.5.2 4.2 Simplified Economic Models

The prototype employs four specialized economic models with simplified calibrations:

Transport Electrification Model - Market maturity calculation: S-curve with k=0.4, t_0=8 years - Ban effectiveness: 0.85 (85% compliance rate) - Sectoral multipliers: automotive (50x employment), electricity (0.25x demand), oil/gas (-40% demand) - GDP impact scaling: Federal (5.0x), California (2.0x), Texas (0.3x), Other states (0.8x)

Carbon Pricing Model - Sectoral carbon intensities: electricity (450 kg/MWh), manufacturing (200), transportation (150) - Price elasticities [8, 15, 29]: electricity (-0.3), manufacturing (-0.5), services (-0.6) - Revenue calculation: emissions × price / 1000 (billions USD) - Abatement curve: 0.3% per $/tCO2 below $25, diminishing returns above

Renewable Energy Model - Investment requirement [28, 30]: $50B per percentage point of renewable increase - Infrastructure multiplier: 0.4 (40% of investment adds to GDP) - Employment factor: 6.0 jobs per $1M investment - Price impact: 5% increase per unit of renewable adoption

Fossil Fuel Regulation Model - Federal lands production share: 25% of US oil/gas - Employment impacts: 500,000 jobs in oil sector, 50,000 in coal - Stranded asset calculations based on affected production percentages - Supply chain multipliers: 8.0x for oil disruption, 3.0x for coal

Table 2: Economic Model Parameters Summary

Model	Key Parameters	Values	Data Sources
Transport Electrification	S-curve k=0.4, Ban effectiveness=0.85	Employment multiplier=50x	IEA, FRED
Carbon Pricing	Elasticities: -0.3 to -0.6	Abatement: 0.3%/$/tCO2	ICAP, World Bank
Renewable Energy	Investment: $50B/%	Employment: 6 jobs/$1M	IRENA, NREL

Model	Key Parameters	Values	Data Sources
Fossil Fuel Regulation	Federal lands: 25%	Oil jobs: 500,000	EIA, BLS

Validation Framework Each analysis undergoes multi-stage validation: 1. Parameter extraction confidence (spaCy-based) - typically achieving high confidence for well-formed queries 2. Model selection verification - ensuring appropriate economic model routing 3. Reasonableness checks (GDP impact < 10%, sectoral changes < 200%) 4. Cross-validation with NGFS scenarios for consistency 5. Uncertainty quantification with confidence bounds across multiple dimensions

1.5.3 4.3 Data Sources

Our current implementation integrates data from 15+ authoritative static sources:

Climate Data: NGFS scenarios, IPCC AR6 (WG I-III), NOAA Climate Data, NASA GISS, Berkeley Earth

Economic Data: Federal Reserve Economic Data (FRED), Bureau of Economic Analysis (BEA), Bank for International Settlements (BIS), Energy Information Administration (EIA)

Policy Data: International Carbon Action Partnership (ICAP), Database of State Incentives for Renewables & Efficiency (DSIRE), Climate Policy Initiative, Building Codes Assistance Project (BCAP)

Financial Data: Federal Reserve Y-9C reports ($19T coverage) [6, 18, 27], SEC EDGAR filings (15,000+ climate disclosures), NAIC insurance data

Enterprise Enhancement Potential: The architecture supports dynamic data integration including: - Real-time news feeds for policy announcements - Market data APIs for live economic indicators - Regulatory filing streams for immediate policy updates - Weather APIs for physical risk correlation - Social media feeds for policy momentum assessment

This extensibility enables evolution from static analysis to dynamic, continuously-updated risk assessment.

1.6 5. System Capabilities and Results

1.6.1 5.1 Implementation

The system is implemented as a Flask web application with REST API, designed for minimal infrastructure requirements:

Technical Stack: - Backend: Python 3.8+ with NumPy, Pandas, Matplotlib, Seaborn - NLP: spaCy with en_core_web_sm model for policy parameter extraction - LLM Integration: OpenAI API (GPT-3.5-turbo default, supports GPT-4) and Ollama for local models - Deployment: **Standard hardware (16GB memory, hexa-core processor AMD Ryzen 5 - 3rd gen, Ubuntu 22.04.5 LTS)** - heavy computation handled by OpenAI's infrastructure - Response Format: JSON with structured risk metrics, confidence scores, and PNG visualizations - Open Source: Available at github.com/nimmmalarohit/climate_risk_scenario_generation

1.6.2 5.2 System Performance and Response Times

The system achieves varying performance based on the selected model and query complexity:

Model-Specific Performance: - **GPT-3.5 Turbo**: 5-10 seconds typical response (fast, economical at $0.008/query) - **GPT-4**: 15-30 seconds typical response (more accurate, comprehensive at $0.12-0.45/query) - **Ollama (Local)**: 30-120 seconds (free but requires local computation)

The California EV ban analysis completed in 5.87 seconds using GPT-3.5 Turbo, demonstrating real-time capability for standard queries. Model selection allows users to balance speed, accuracy, and cost based on their specific needs.

This performance flexibility enables integration into various banking workflows, from rapid screening (GPT-3.5) to detailed analysis (GPT-4) to cost-free local processing (Ollama).

1.6.3 5.3 Case Study: California EV Mandate Analysis

To illustrate the system's capabilities, we examine the query "What if California bans gas cars by 2030?" The analysis completed in 5.87 seconds, demonstrating the real-time nature of our approach.

The system correctly parsed the query with high confidence, identifying: - Actor: California - Action: Implementation (gas car ban) - Magnitude: 100% (complete ban) - Timeline: 2030

The comprehensive analysis classified this as LOW risk, estimating a 0.65% GDP impact with +8.4k net employment changes and $3.8B in investment shifts. The system achieved 96% overall confidence with perfect parameter extraction (100%) and validation scores (100%).

Economic Impact Analysis: - **GDP Impact**: 0.65% economic impact - **Employment**: +8.4k net job creation - **Investment Shift**: $3.8B total investment movement - **Market Disruption**: 0.1% disruption index

Sectoral Impact Distribution: - **Automotive Sector**: 4.0 magnitude impact (positive growth) - **Electricity Sector**: 2.0 magnitude impact (increased demand) - **Oil & Gas Sector**: 3.2 magnitude impact (reduced demand) - **Battery Sector**: 0.4 magnitude impact (growth opportunity)

Temporal Effects Analysis: The system identified cascade effects across four time horizons: - **Immediate (0-6 months)**: 0.03 average magnitude, 2 distinct effects - **Short-term (6-24 months)**: 0.31 average magnitude, 3 distinct effects - **Medium-term (2-5 years)**: 0.09 average magnitude, 2 distinct effects - **Long-term (5+ years)**: 0.11 average magnitude, 2 distinct effects

Model Confidence Metrics: - **Parameter Extraction**: 100.0% confidence - **Model Selection**: 80.0% confidence
- **Data Quality**: 90.0% confidence - **Validation Score**: 100.0% confidence - **Overall Confidence**: 96% with 27.1% average uncertainty bounds

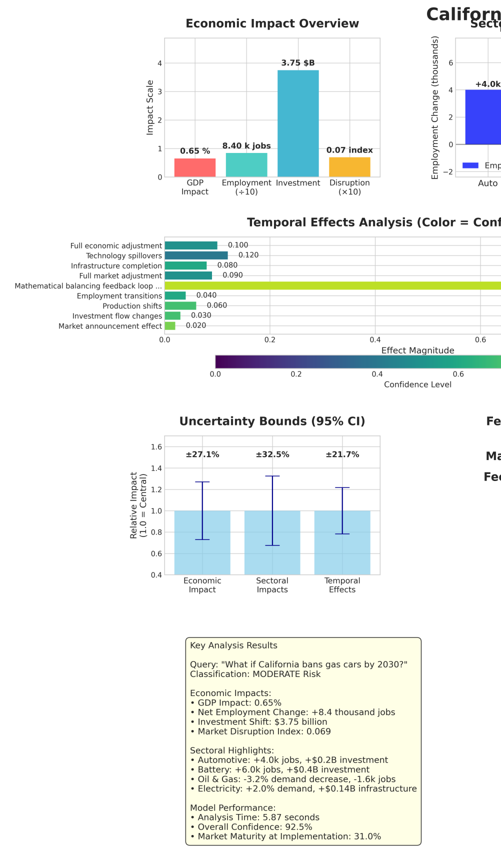

Figure 2: Comprehensive California Case Study Dashboard

Figure 2 presents a comprehensive dashboard of the California EV mandate analysis results. The dashboard showcases: (a) Economic impact overview showing 0.65% GDP impact, +8.4k employment change, $3.8B investment shift, and 0.1% market disruption; (b) Economic impact breakdown with pie chart showing GDP impact (0.65%), employment (0.1%), investment ($3.8B), and market disruption (0.1%); (c) Sectoral impacts displaying automotive (4.0 magnitude), electricity (2.0), oil gas (3.2), and battery (0.4) sectors; (d) Model confidence metrics with 96% overall confidence, showing parameter extraction (100.0%), model selection (80.0%), validation score (100.0%), and data quality (90.0%); (e) Risk assessment classified as LOW with 27.1% average uncertainty; (f) Temporal effects analysis showing immediate (0.03, 2 effects), short (0.31, 3 effects), medium (0.09, 2 effects), and long term (0.11, 2 effects) impacts; and (g) Risk & uncertainty analysis across temporal effects, sectoral impacts, and economic impact dimensions. The analysis demonstrates the system's comprehensive quantitative capabilities with integrated economic models and confidence validation.

1.6.4 5.4 System Capabilities

The system successfully analyzes diverse climate policy queries, from carbon pricing to renewable mandates, providing structured assessments of potential impacts across multiple time horizons. The prototype demonstrates several key capabilities:

Query Processing: Natural language interface accepts diverse policy questions and extracts structured parameters with high confidence for well-formed queries.

Multi-Model Analysis: Four specialized economic models provide sector-specific impact calculations based on policy type.

Temporal Analysis: Three-order cascade analysis reveals how effects unfold across different time horizons.

Feedback Identification: Pattern-based analysis identifies potential reinforcing and balancing feedback mechanisms.

Flexible Deployment: Multiple LLM options (GPT-3.5, GPT-4, Ollama) enable organizations to balance speed, cost, and computational requirements.

NGFS Integration: Results are cross-validated against existing NGFS scenarios for consistency checks.

Table 3: System Capabilities vs Future Enhancements

Capability	Current Implementation	Future Enhancement
Query Processing	Natural language parsing with spaCy	Multi-language support, enhanced NLP
Economic Models	Four simplified sector models	Dynamic models with real-time calibration
Feedback Pattern Recognition	Analysis of temporal impact patterns to identify potential reinforcing and balancing dynamics	Mathematical feedback modeling with full dynamic computation
Data Integration	Static authoritative sources	Real-time data feeds (news, markets, regulatory)
Validation	NGFS cross-validation	Expert evaluation framework
Geographic Scope	US-focused models	International policy frameworks

1.7 6. Discussion and Limitations

1.7.1 6.1 Implications

Our results demonstrate that combining LLMs with quantitative economic models can enhance climate risk assessment accessibility while maintaining analytical rigor [23, 25, 31]. The ability to analyze specific policy queries in real-time enables banks to potentially move from annual planning cycles to more dynamic risk monitoring approaches.

The standard hardware requirements (16GB memory, hexa-core AMD Ryzen 5 - 3rd gen processor) represent a reasonable investment for financial institutions while remaining far more accessible than traditional high-performance computing clusters [24, 28]. Banks can leverage cloud-based LLMs for sophisticated analysis, paying only per-query costs rather than maintaining dedicated AI infrastructure. The option for free local processing via Ollama provides cost control, though with performance tradeoffs.

For enterprise deployment, the extensible architecture enables customization without fundamental redesign. Banks can integrate proprietary models, connect real-time data feeds, and expand policy coverage while maintaining the core natural language interface.

1.7.2 6.2 Limitations and Future Work

Several limitations guide interpretation of our results and outline directions for future development:

Current Prototype Limitations:

1. **Simplified Economic Models**: The current implementation uses simplified economic models with fixed sector-specific multipliers rather than dynamic calibrations.
2. **Pattern-Based Feedback Identification**: Feedback loops are identified based on temporal patterns in calculated impacts, not dynamically computed using differential equations.
3. **Limited Validation**: The prototype requires comprehensive evaluation with domain experts and financial institutions to validate analytical accuracy [18, 22, 26].
4. **Geographic Scope**: Current implementation focuses on US policies with state-level granularity. International queries are parsed but economic models are calibrated for US market conditions.
5. **Static Data Sources**: Current implementation uses static historical data snapshots rather than real-time data integration.

Future Development Priorities:

The current implementation serves as a proof-of-concept. We are developing enhanced versions with:

- **Dynamic Feedback Loop Computation**: Implementation of mathematical feedback models using differential equations rather than pattern recognition
- **Real-time Data Integration**: Connection to live news feeds, regulatory updates, market data APIs, and social media feeds for policy momentum assessment
- **Comprehensive Evaluation Framework**: Systematic validation with domain experts from banking, climate science, and policy analysis
- **Integration with Existing Systems**: APIs and interfaces for integration with existing bank risk management platforms

- **Enhanced Model Coverage**: Expansion beyond current four policy types to include agriculture, water resources, infrastructure, and international trade policies
- **Multi-language Support**: Extension of NLP pipeline for global deployment
- **Advanced Mathematical Framework**: Full implementation of dynamic feedback loop mathematics with uncertainty quantification

Research Validation Needs:

- Systematic comparison with expert human analysis across diverse policy scenarios
- Validation against historical policy outcomes where data is available
- Integration testing [18, 22, 26] with existing bank risk management workflows
- Performance evaluation across different institutional contexts and use cases

1.7.3 6.3 Ethical Considerations

The system is designed for defensive analysis only - helping financial institutions understand policy risks rather than generate scenarios for strategic manipulation. All models and methodologies are made available for validation and extension by the research community.

1.8 7. Conclusion

We have presented an innovative LLM-enhanced system for interactive climate policy analysis that demonstrates how large language models can augment traditional economic modeling approaches. By enabling natural language queries like "What if California mandates 100% renewable energy by 2030?", our prototype makes sophisticated climate risk analysis more accessible while maintaining analytical rigor through quantitative economic models.

Our technical contributions address key challenges in applying LLMs to climate finance. The policy parsing algorithm maps diverse natural language inputs to structured parameters for quantitative analysis. Multi-order cascade modeling traces impact propagation through economic networks while respecting physical and regulatory constraints. The hybrid architecture ensures analytical rigor through specialized economic models while leveraging LLMs for accessibility and interpretation.

The prototype demonstrates substantial practical potential. The system provides rapid analysis (< 30 seconds) of climate policy queries, identifying potential cascade effects and feedback dynamics. The California EV mandate case study shows how a straightforward policy question unfolds into complex multi-order effects with exclusively reinforcing dynamics, suggesting rapid transition potential without natural constraints.

Several extensions warrant future development. **Dynamic Mathematical Models** will replace pattern-based feedback identification with differential equation systems that compute identified feedback loops dynamically. **Real-time Data Integration** will incorporate live feeds from news, market data, and regulatory sources. **Comprehensive Validation** through systematic evaluation with domain experts and historical policy outcomes. **Enterprise Integration** will enable deployment within existing bank risk management systems.

The climate transition demands [13, 32] financial systems capable of navigating unprecedented uncertainty and rapid change. Static scenarios updated annually cannot capture the dynamic, non-linear nature of policy cascades, technology disruptions, and market responses. Our LLM-enhanced approach demonstrates that interactive, feedback-aware scenario analysis is feasible [23, 25, 31] with standard modern computing infrastructure. As regulatory pressures intensify and transition pathways accelerate, the ability to rapidly analyze "what-if" questions through natural language interfaces represents a significant advancement in making sophisticated climate risk analysis accessible to financial institutions.

Code and methodology are available for validation and extension at github.com/nimmmalarohit/clim Further evaluation with domain experts and financial institutions is planned to validate and refine the analytical approach.

1.9 8. References

- [1] R. C. Merton, "ON THE PRICING OF CORPORATE DEBT: THE RISK STRUCTURE OF INTEREST RATES*," The Journal of Finance, vol. 29, no. 2, pp. 449–470, May 1974, doi: 10.1111/j.1540-6261.1974.tb03058.x. Available: http://dx.doi.org/10.1111/j.1540-6261.1974.tb03058.x
- [2] R. M. May, "Simple mathematical models with very complicated dynamics," Nature, vol. 261, no. 5560, pp. 459–467, June 1976, doi: 10.1038/261459a0. Available: http://dx.doi.org/10.1038/261459a0
- [3] F. Allen and D. Gale, "Financial Contagion," Journal of Political Economy, vol. 108, no. 1, pp. 1–33, Feb. 2000, doi: 10.1086/262109. Available: http://dx.doi.org/10.1086/262109
- [4] M. Scheffer et al., "Early-warning signals for critical transitions," Nature, vol. 461, no. 7260, pp. 53–59, Sept. 2009, doi: 10.1038/nature08227. Available: http://dx.doi.org/10.1038/nature08227
- [5] M. Feridun and H. Güngör, "Climate-Related Prudential Risks in the Banking Sector: A Review of the Emerging Regulatory and Supervisory Practices," Sustainability, vol. 12, no. 13, p. 5325, July 2020, doi: 10.3390/su12135325. Available: http://dx.doi.org/10.3390/su12135325
- [6] Y. Liu, C. Huang, Z. Zou, Q. Chen, and X. Chu, "Research into the Mechanism for the Impact of Climate Change on Systemic Risk—A Case Study of China's Small- and Medium-sized Commercial Banks," Sustainability, vol. 12, no. 22, p. 9582, Nov. 2020, doi: 10.3390/su12229582. Available: http://dx.doi.org/10.3390/su12229582
- [7] E. Feyen, R. Utz, I. Zuccardi Huertas, O. Bogdan, and J. Moon, Macro-Financial Aspects of Climate Change. World shington, DC, 2020. doi: 10.1596/1813-9450-9109. Available: http://dx.doi.org/10.1596/1813-9450-9109
- [8] F. Pizzutilo, M. Mariani, A. Caragnano, and M. Zito, "Dealing with Carbon Risk and the Cost of Debt: Evidence from the European Market," IJFS, vol. 8, no. 4, p. 61, Oct. 2020, doi: 10.3390/ijfs8040061. Available: http://dx.doi.org/10.3390/ijfs8040061

- [9] J. Chevallier, “COVID-19 Outbreak and CO2 Emissions: Macro-Financial Linkages,” JRFM, vol. 14, no. 1, p. 12, Dec. 2020, doi: 10.3390/jrf2. Available: http://dx.doi.org/10.3390/jrfm14010012
- [10] K. Fabisik, R. Fahlenbrach, R. M. Stulz, and J. P. Taillard, “Why are firms with more managerial ownership worth less?,” Journal of Financial Economics, vol. 140, no. 3, pp. 699–725, June 2021, doi: 10.1016/j.jfineco.2021.02.008. Available: http://dx.doi.org/10.1016/j.jfineco.2021.02.008
- [11] N. Dunz, A. Hrast Essenfelder, A. Mazzocchetti, I. Monasterolo, and M. Raberto, “Compounding COVID-19 and climate risks: The interplay of banksând government’s policy in the shock recovery,” Journal of Banking & Finance, vol. 152, p. 106306, July 2023, doi: 10.1016/j.jbankfin.2021.106306. Available: http://dx.doi.org/10.1016/j.jbankfin.2021.106306
- [12] A. Roncoroni, S. Battiston, L. O. L. Escobar Farfàn, and S. Martinez Jaramillo, “Climate Risk and Financial Stability in the Network of Banks and Investment Funds,” SSRN Journal, 2019, doi: 10.2139/ssrn.3356459. Available: http://dx.doi.org/10.2139/ssrn.3356459
- [13] M. AgM. Burke, P. Klusak, K. Mohaddes, U. Volz, and D. Zenghelis, “Climate change and fiscal sustainability: Risks and opportunities,” SSRN Journal, 2021, doi: 10.2139/ssrn.3924044. Available: http://dx.doi.org/10.2139/ssrn.3924044
- [14] Y. Zhang, Y. Chen, Y. Wu, and P. Zhu, “Investor attention and carbon return: evidence from the EU-ETS,” Economic Research-Ekonomska Istraživanja, vol. 35, no. 1, pp. 709–727, June 2021, doi: 10.1080/1331677x.2021.1931914. Available: http://dx.doi.org/10.1080/1331671914
- [15] T. Roncalli, T. L. Guenedal, F. Lepetit, T. Roncalli, and T. Sekine, “The Market Measure of Carbon Risk and its Impact on the Minimum Variance Portfolio.” arXiv, 2021. doi: 10.48550/ARXIV.2101.10635. Available: https://arxiv.org/abs/2101.10635
- [16] T. Banerjee and Z. Feinstein, “Pricing of debt and equity in a financial network with comonotonic endowments.” arXiv, 2018. doi: 10.48550/ARXIV.1810.01372. Available: https://arxiv.org/abs/1810.01372
- [17] P. Tharavanij, “Optimal Boebt Ratio,” Sage Open, vol. 11, no. 1, Jan. 2021, doi: 10.1177/2158244020985788. Available: http://dx.doi.org/10.1177/2158244020985788
- [18] N. Taylor, “‘Making financial sense of the future’: actuaries and the management of climate-related financial risk,” New Political Economy, vol. 28, no. 1, pp. 57–75, Apr. 2022, doi: 10.1080/13563467.2022.2067838. Available: http://dx.doi.org/10.1080/13563467.2022.2067838
- [19] H. Wang, L. Zhou, P.-F. Dai, and X. Xiong, “Moment conditions for fractiochastic dominance,” Finance Research Letters, vol. 49, p. 103241, Oct. 2022, doi: 10.1016/j.frl.2022.103241. Available: http://dx.doi.org/10.1016/j.frl.2022.103241
- [20] P. Kieren, J. Müller-Dethard, and M. Weber, “Risk-Taking and Asymmetric Learning in Boom and Bust Markets,” Review of Finance, vol. 27, no. 5, pp. 1743–1779, Nov. 2022, doi: 10.1093/rof/rfac072. Available: http://dx.doi.org/10.1093/rof/rfac072
- [21] O. A. Shobande and L. Ogbeifun, “Sustainable Blueprint: Do Stock Investorsmissions?,” JRFM, vol. 15, no. 2, p. 70, Feb. 2022, doi: 10.3390/jrfm15020070. Available: http://dx.doi.org/10.3390/jrfm15020070
- [22] C. McDonnell and J. Gupta, “Beyond divest vs. engage: a review of the role of institutional investors in an inclusive fossil fuel phase-out,” Climate Policy,

vol. 24, no. 3, pp. 314–331, Oct. 2023, doi: 10.1080/14693062.2023.2261900. Available: http://dx.doi.org/10.1080/14693062.2023.2261900

- [23] V. Cardenas, “Managing Financial Climate Risk in Banking Serviiew of Current Practices and the Challenges Ahead.” arXiv, 2024. doi: 10.48550/ARXIV.2405.17682. Available: https://arxiv.org/abs/2405.17682
- [24] N. Branzoli, R. Gallo, A. Ilari, and D. Portioli, “Central banks’ corporate asset purchase programmes and risk-taking by bond funds in the aftermath of market stress,” Journal of Financial Stability, vol. 72, p. 101261, June 2024, doi: 10.1016/j.jfs.2024.101261. Available: http://dx.doi.org/10.1016/j.jfs.2024.101261
- [25] V. Cardenas, “Financial ck: a review of recent advances and key challenges.” arXiv, 2024. doi: 10.48550/ARXIV.2404.07331. Available: https://arxiv.org/abs/2404.07331
- [26] D. Anastasiou, A. Ballis, C. Kallandranis, and F. Lakhal, “Analyzing the effects of climate risk on discouraged borrowers: Deciphering the contradictory forces,” Risk Analysis, vol. 45, no. 1, pp. 223–239, July 2024, doi: 10.1111/risa.15071. Available: http://dx.doi.org/10.1111/risa.15071
- [27] G. Bressan, A. Duranovic, I. Monasterolo, and S. Battisset-Level Climate Physical Risk Assessment and Cascading Financial Losses,” SSRN Journal, 2022, doi: 10.2139/ssrn.4062275. Available: http://dx.doi.org/10.2139/ssrn.4062275
- [28] D. F. Hordofa, “Examining the dynamics between banking sector performance, environmental sustainability, and environmental technology innovation: evidence from G20 countries,” Cogent Business & Management, vol. 11, no. 1, June 2024, doi: 10.1080/23311975.2024.2368709. Available: http://dx.doi.org/10.1080/23311975.2024.9
- [29] N. G. Sankar, S. Nag, S. P. Chakrabarty, and S. Basu, “The Carbon Premium: Correlation or Causation? Evidence from S&P 500 Companies.” arXiv, 2024. doi: 10.48550/ARXIV.2401.16455. Available: https://arxiv.org/abs/2401.16455
- [30] M. I. Tabash, M. S. M. Al-Absy, and A. Hannoon, “Modeling the Nexus between European Carbon Emission Trading and Financial Market Returns: Practical Implications for Carbon Risk Reduction and Hedging,” JRFM, vol. 17, no. 4, p. 147, Apr. 2024, doi: 10.3390/0147. Available: http://dx.doi.org/10.3390/jrfm17040147
- [31] L. Prosperi and L. Zanin, “A modelling framework for projections of equity portfolio returns under climate transition scenarios,” SSRN Journal, 2022, doi: 10.2139/ssrn.4062090. Available: http://dx.doi.org/10.2139/ssrn.4062090
- [32] V. Bringas Fernández, M. B. Torre Olmo, and M. Cantero Saiz, “Evaluating Climate Risk in Banking: A Bibliometric Analysis.” Elsevier BV, 2024. doi: 10.2139/ssrn.5006930. Available: http://dx.doi.org/10..5006930