
OPENCAUSALITY: Auditable Agentic Causal Inference with DAG-Based Reasoning and LLM-Assisted Discovery

Abstract

We introduce OPENCAUSALITY, an open-source platform that resolves the automation–transparency tradeoff in applied causal inference. OPENCAUSALITY combines DAG-based causal reasoning with agentic estimation pipelines, where every modeling decision—from identification strategy selection to effect propagation—is logged in a hash-chained audit trail. The platform enforces 29 issue-detection rules that catch overclaiming, control shopping, and specification drift; a 7-guardrail propagation engine that performs unit-aware dimensional analysis across multi-edge causal paths; and a 3-stage identifiability screen that downgrades claims based on diagnostic evidence rather than statistical significance alone. An LLM-assisted pipeline extracts causal claims from the literature and proposes DAG edges, achieving 100% estimate precision on matched edges in our Kazakhstan bank stress-testing case study while discovering 3 edges absent from the expert-built DAG. All governance decisions—including human-in-the-loop gates and automated patch policies that explicitly prohibit p-hacking—are recorded with cryptographic integrity. OPENCAUSALITY ships with 11 estimation adapters, a natural-language query interface, and 165 passing tests across 20,855 lines of code.

1 Introduction

Applied causal inference faces a fundamental tension: automation accelerates analysis but obscures the chain of decisions that produced the results. A researcher running a modern causal-ML pipeline can obtain point estimates in seconds, yet documenting *why* a particular identification strategy was chosen, which controls were included, and what diagnostic checks were performed remains a manual, error-prone process. This opacity undermines reproducibility and invites specification searching [11].

Existing frameworks address parts of this problem. DoWhy [10] formalizes the identify-estimate-refute workflow. EconML [2] provides heterogeneous treatment-effect estimators. CausalML [3] targets uplift modeling. However, none of these systems treats every estimation decision as an auditable event, enforces claim-level restrictions based on identification strength, or prevents automated specification searching through explicit policy enforcement.

We introduce OPENCAUSALITY, an open-source platform that makes the entire causal inference workflow—from DAG construction to effect propagation to human review—both automated and transparent. Our key insight is that *the audit trail is not a byproduct of estimation; it is a first-class output*. Every edge estimate, diagnostic result, issue flag, and governance decision is recorded in a hash-chained ledger that can be committed to version control and independently verified.

Contributions. We make the following contributions:

1. A **DAG-based causal inference platform** with mode-aware effect propagation, unit-dimensional analysis across 9 unit types, and 7 guardrails that gate edge usage based on identification strength, time-series diagnostics, and issue severity (Section 4).
2. A **29-rule issue detection engine** with a PatchPolicy whitelist that explicitly prohibits control shopping, sample trimming, lag searching, and outcome switching—preventing automated p-hacking while permitting safe auto-fixes (Section 6).
3. A **3-stage identifiability screen** (pre-design, post-design, post-estimation) backed by TSGuard, a 7-diagnostic time-series validator that caps claim levels based on evidence rather than significance (Section 5).
4. An **LLM-assisted NL-to-DAG pipeline** that extracts causal claims from academic text and maps them to DAG edges, achieving 100% estimate precision on matched edges while discovering novel edges absent from expert specifications (Section 7).
5. A **hash-chained governance framework** with human-in-the-loop gates, structured checklists, and cryptographic audit integrity—all without database dependencies (Section 8).

We evaluate OPENCAUSALITY on a Kazakhstan bank stress-testing case study involving 32 nodes and 20 causal edges, comparing expert-built DAGs against LLM-extracted DAGs and verifying pipeline reproducibility across 165 tests (Section 9).

2 Related Work

Causal inference frameworks. One line of work provides programmatic interfaces for causal estimation. DoWhy [10] implements an identify-estimate-refute loop using graphical criteria, while EconML [2] extends this with double/debiased ML and heterogeneous treatment-effect estimators. DoubleML [1] focuses on Neyman-orthogonal score functions. CausalML [3] targets uplift modeling for business applications. These frameworks automate estimation but do not enforce claim-level restrictions, detect specification searching, or maintain hash-chained audit trails. OPENCAUSALITY builds on their estimator building blocks while adding governance, propagation, and auditability layers.

Causal discovery. Classical algorithms—PC [13], GES [4], and NOTEARS [15]—learn DAG structure from observational data. causal-learn [16] and gCastle [14] provide implementations. These approaches complement OPENCAUSALITY: they discover structure from data, while OPENCAUSALITY focuses on what happens *after* the DAG is specified—estimation, propagation, and governance. Our LLM-assisted pipeline (Section 7) offers an alternative discovery path via literature extraction.

LLMs for causal reasoning. Recent work explores whether LLMs can perform causal reasoning from text. Kıcıman et al. [7] evaluate LLMs on pairwise causal discovery benchmarks. Long et al. [8] use LLMs to generate causal graphs from domain knowledge. Our approach differs in two ways: we extract causal claims with explicit identification strategies (not just pairwise directions), and we integrate extracted edges into a governed estimation pipeline rather than treating them as final outputs.

Reproducibility and auditing. The replication crisis [6] has motivated pre-registration [9] and specification-curve analysis [12]. OPENCAUSALITY operationalizes these concerns at the platform level: every decision is logged, issue rules catch post-hoc rationalization, and PatchPolicy prevents automated specification searching.

3 System Architecture

OPENCAUSALITY is organized around four layers (Figure 1):

1. **DAG Layer:** Parses YAML-specified DAGs with typed nodes (observed, latent, policy) and typed edges (causal, reaction function, bridge, identity). Validates acyclicity, unit presence, and node-source bindings.

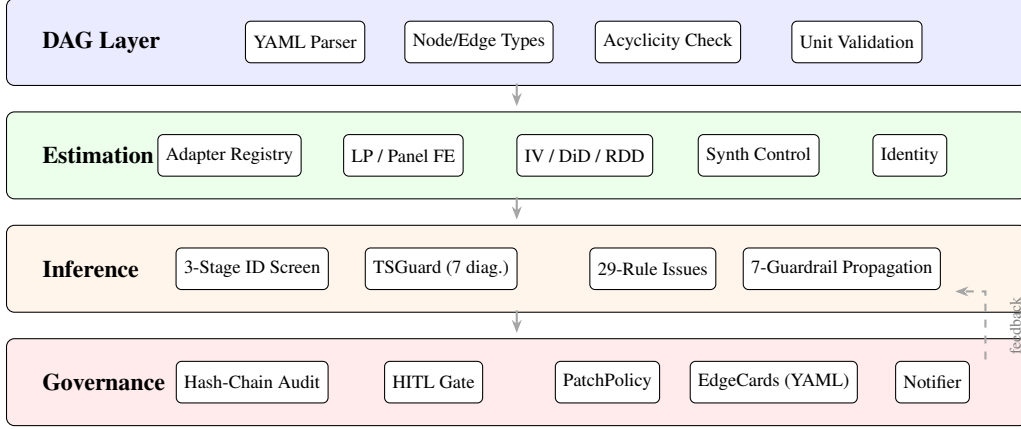


Figure 1: Architecture of OPENCAUSALITY. The DAG layer specifies causal structure. The estimation layer dispatches to 11 adapters. The inference layer screens identifiability, detects issues, and propagates effects with 7 guardrails. The governance layer logs all decisions in a hash-chained audit trail with HITL gates. Dashed arrow indicates governance feedback (e.g., issue-triggered re-estimation).

2. **Estimation Layer:** Dispatches edges to one of 11 adapters via a unified `EstimationRequest` → `Adapter.estimate()` → `EstimationResult` interface. Adapters include local projections, panel fixed effects, IV-2SLS, difference-in-differences, regression discontinuity, regression kink, and synthetic control.
3. **Inference Layer:** Runs 3-stage identifiability screening, TSGuard diagnostics, 29-rule issue detection, and 7-guardrail effect propagation. Produces EdgeCards (YAML artifacts combining estimates, diagnostics, identification results, and literature references).
4. **Governance Layer:** Hash-chained audit log, HITL gate with structured checklists, PatchPolicy enforcement, and notification system. No database dependency—the entire audit trail lives in append-only JSONL files that can be committed to Git.

3.1 DAG Specification

A DAG in OPENCAUSALITY is defined by a YAML file containing node definitions (with data source bindings, frequency, and units) and edge definitions (with type, expected sign, identification strategy, and control sets). The parser validates five pre-estimation invariants: acyclicity (DFS-based), unit presence on all edges, edge-type labeling, node-source bindings for observed nodes, and endpoint existence.

Each edge carries a *propagation role*—STRUCTURAL, REDUCED_FORM, or DESCRIPTIVE—that determines its eligibility for downstream effect propagation. Reaction-function edges (policy responses) are labeled explicitly and excluded from shock-propagation paths.

3.2 Adapter Registry

All estimation flows through a unified adapter interface:

```

class EstimatorAdapter(ABC):
    def estimate(self, request: EstimationRequest) -> EstimationResult: ...

```

Table 1 lists the 11 adapters. The registry supports both built-in mappings and YAML-configurable dispatch, enabling new estimators to be added without modifying core code.

4 Effect Propagation with 7 Guardrails

The core analytical capability of OPENCAUSALITY is propagating causal effects along multi-edge paths through the DAG. Given a query “What is the effect of node *A* on node *Z*?”, the

Table 1: Estimation adapters in OPENCAUSALITY. Each adapter maps a design to a specific estimator with associated diagnostics.

Design	Backend	Key Diagnostics
Local Projections	Newey-West LP	HAC SE, IRF $h = 0 \dots 6$
Panel LP (Exposure FE)	Panel LP	Entity/time FE, clustered SE
Panel FE (Backdoor)	<code>linearmodels.PanelOLS</code>	Within- R^2 , clustered SE
IV-2SLS	<code>linearmodels.IV2SLS</code>	First-stage F , Sargan test
DiD Event Study	<code>linearmodels.PanelOLS</code>	Pre-trend test, TWFE
RDD	Local-linear WLS	McCrary density, bandwidth
Regression Kink	Local-linear WLS	Density test at kink
Synthetic Control	Weighted donor pool	Pre-treatment RMSPE
Immutable Evidence	Validated evidence	Source-block provenance
Accounting Bridge	Deterministic	Sensitivity at current values
Identity	Partial derivatives	Mechanical formula

`PropagationEngine` finds all directed paths from A to Z via depth-first search, then computes chain effects and standard errors for each path.

4.1 Chain Effect Computation

For a path $A \rightarrow B_1 \rightarrow \dots \rightarrow B_k \rightarrow Z$ with edge coefficients $\beta_1, \dots, \beta_{k+1}$, the total effect is:

$$\hat{\tau}_{A \rightarrow Z} = \prod_{i=1}^{k+1} \beta_i \quad (1)$$

Standard errors are propagated via the delta method assuming independence across edges:

$$\widehat{\text{Var}}(\hat{\tau}) = \sum_{i=1}^{k+1} \left(\prod_{j \neq i} \beta_j \right)^2 \cdot \text{SE}_i^2 \quad (2)$$

where SE_i is the standard error of β_i . When the independence assumption is violated (e.g., shared confounders across edges), the engine emits an explicit warning.

4.2 The 7 Guardrails

Each path is subjected to 7 guardrails before propagation is permitted:

1. **Mode gating:** Edges with role `STRUCTURAL` pass in all modes; `REDUCED_FORM` edges are blocked in `STRUCTURAL` mode; `DESCRIPTIVE` edges only pass in `DESCRIPTIVE` mode.
2. **Counterfactual gating:** Shock scenarios require all edges to have `shock_scenario_allowed = True`. Policy counterfactuals additionally require `policy_intervention_allowed = True`.
3. **TSGuard gating:** Edges flagged as high-risk by TSGuard (e.g., lead-test failure, regime instability) block propagation.
4. **IssueLedger gating:** Edges with open `CRITICAL`-severity issues are excluded from all paths.
5. **Reaction-function blocking:** Edges typed as reaction functions (e.g., central bank policy rules) are never included in shock-propagation paths.
6. **Unit compatibility:** The outcome unit of each edge must match the treatment unit of the next edge in the chain. Mismatched units block the path.
7. **Frequency alignment:** Edges at different frequencies (e.g., monthly treatment, quarterly outcome) require explicit bridge edges.

Algorithm 1 summarizes the guarded propagation procedure.

Algorithm 1: Guarded Effect Propagation

Input: DAG G , source s , target t , mode m , scenario type c

Output: List of valid paths with chain effects and SEs

$\mathcal{P} \leftarrow \text{DFS-ALLPATHS}(G, s, t)$;

$\mathcal{V} \leftarrow \emptyset$;

foreach path $p \in \mathcal{P}$ **do**

$\text{blocked} \leftarrow \text{false}$;

foreach edge $e \in p$ **do**

if $\text{MODEGATE}(e, m)$ **or** $\text{CFGATE}(e, c)$ **or** $\text{TSGUARDGATE}(e)$ **or** $\text{ISSUEGATE}(e)$ **or**
 $\text{REACTIONGATE}(e)$ **then**

$\text{blocked} \leftarrow \text{true}$; **break**;

end

end

if not blocked **and** $\text{UNITCOMPAT}(p)$ **and** $\text{FREQUALIGN}(p)$ **then**

$\hat{\tau} \leftarrow \prod_{e \in p} \beta_e$;

$\widehat{\text{SE}} \leftarrow \sqrt{\sum_{e \in p} (\hat{\tau} / \beta_e)^2 \cdot \text{SE}_e^2}$;

$\mathcal{V} \leftarrow \mathcal{V} \cup \{(p, \hat{\tau}, \widehat{\text{SE}})\}$;

end

end

return \mathcal{V}

5 3-Stage Identifiability Screening

OPENCausality assigns each edge a *claim level* from a 4-tier hierarchy: IDENTIFIED_CAUSAL > REDUCED_FORM > DESCRIPTIVE > BLOCKED_ID. The key design principle is that *significance is never a promotion criterion; only identification strength and diagnostic stability determine claim levels*.

5.1 Three Screening Points

1. **Pre-design** (`screen_pre_design`): Given the DAG, can this edge ever be identified? Checks for valid conditioning sets using back-door and front-door criteria.
2. **Post-design** (`screen_post_design`): Does the chosen estimation design achieve identification? Maps designs to claim levels (e.g., IV \rightarrow IDENTIFIED_CAUSAL, OLS \rightarrow DESCRIPTIVE).
3. **Post-estimation** (`screen_post_estimation`): Given diagnostic results, what is the final claim? Downgrades based on evidence: lead-test failure \rightarrow BLOCKED_ID; leave-one-out instability \rightarrow REDUCED_FORM; weak first-stage $F \rightarrow$ REDUCED_FORM.

5.2 TSGuard: Time-Series Diagnostics

For time-series edges estimated via local projections, TSGuard runs 7 mandatory diagnostics:

1. **Leads test**: Includes leads of the shock variable; significance implies timing failure (\rightarrow BLOCKED_ID).
2. **Residual autocorrelation**: Ljung-Box test on residuals.
3. **HAC sensitivity**: Re-estimates with Newey-West lags $\{1, 4, 8\}$; sign instability triggers a warning.
4. **Lag sensitivity**: Re-estimates with $L \in \{1, 2, 4\}$ lags.
5. **Regime stability**: Split-sample estimation at known structural breaks.
6. **Placebo time shift**: Circularly shifts the shock series to test for spurious correlation.
7. **Shock support**: Counts non-trivial shock episodes ($|x| > 1\sigma$); fewer than 3 blocks propagation.

TSGuard results feed directly into the post-estimation identifiability screen and the propagation engine's guardrail 3.

Table 2: Representative issue-detection rules. Severity determines propagation eligibility: CRITICAL issues block all paths.

Rule ID	Severity	Scope	Description
SIG_NOT_ID	CRITICAL	edge	$p < 0.05$ but claim \neq IDENTIFIED_CAUSAL
UNIT_MISSING	HIGH	edge	Missing units blocks propagation
REACTION_FN	CRITICAL	edge	Reaction edge used for shock propagation
LOO_INSTABILITY	HIGH	edge	Leave-one-out sign flip or $>50\%$ Δ magnitude
SMALL_SAMPLE	MEDIUM	edge	$N < 30$ with HAC standard errors
RATING_CONFLICT	HIGH	edge	A-rating despite failed diagnostics
SPEC_DRIFT	HIGH	cross_run	Control set changed between runs

6 Issue Detection Engine

OPENCAUSALITY ships with 29 issue-detection rules loaded from a YAML registry. Each rule specifies a severity (CRITICAL, HIGH, MEDIUM, LOW), a scope (edge, node, DAG, run, or cross-run), and whether the issue is auto-fixable or requires human review.

6.1 Representative Rules

Table 2 lists representative rules from the registry.

6.2 PatchPolicy: Preventing Automated P-Hacking

The PatchBot agent applies auto-fixes from a whitelist defined in `patch_policy.yaml`. Crucially, the policy *explicitly prohibits* modifications that could constitute specification searching:

- **Allowed:** Adding missing units, recomputing credibility ratings, adding provenance fields, normalizing edge-ID syntax.
- **Prohibited:** Control shopping, sample trimming, lag searching, outcome switching.

All patches—including LLM-assisted repairs—are logged with the SHA-256 hash of the prompt, preventing retroactive modification. PatchBot is disabled entirely in CONFIRMATION mode, where the specification is locked.

7 LLM-Assisted Causal Discovery from Literature

OPENCAUSALITY includes an NL-to-DAG pipeline that extracts causal claims from academic text and proposes DAG edges.

7.1 Pipeline

The pipeline proceeds in three stages:

1. **Claim extraction:** Given a text passage, the LLM extracts structured `CausalClaim` objects containing treatment, outcome, mechanism, direction, identification strategy, confidence, and a supporting quote. The system prompt enforces conservatism: “correlated with” is not causal; “associated with” is causal only if the paper uses a credible identification strategy.
2. **Node matching:** A second LLM call maps extracted variable names to existing DAG node IDs or proposes new nodes with data-source bindings.
3. **Edge proposal:** Matched claims become `ProposedEdge` objects. Edges with the same (*from*, *to*) pair combine evidence and take the maximum confidence level.

7.2 LLM Abstraction

OPENCAUSALITY provides a multi-backend LLM client supporting Anthropic (direct API), LiteLLM (multi-provider), and CLI fallbacks (c1aude or codex) that require no API key. Struc-

Table 3: Estimation accuracy on synthetic DGP benchmarks ($n = 500$, 50 seeds). Coverage is the fraction of 90% confidence intervals containing the true effect.

Adapter	RMSE ↓	Coverage ↑	Bias ↓
Local Projections	0.039	0.90	0.002
IV-2SLS	0.033	1.00	0.001
DiD Event Study	0.048	1.00	0.003

tured extraction uses tool-use (Anthropic) or function-calling (LiteLLM) to produce typed outputs without parsing.

8 Governance Framework

8.1 Hash-Chained Audit Log

Every event in OPENCAUSALITY—edge estimation, refinement, issue detection, HITL decisions, LLM repairs—is appended to a JSONL file where each entry contains the SHA-256 hash of the previous entry. The first entry has `prev_hash = null`. Any modification to an earlier entry invalidates all subsequent hashes, providing tamper evidence without a database.

For LLM-assisted repairs, the log additionally records the model identifier and the SHA-256 hash of the prompt, preventing prompt-injection attacks via retroactive editing.

8.2 Human-in-the-Loop Gates

The HITLGate detects conditions requiring human decisions from three sources: unspecified DAG parameters (e.g., edge type, expected sign), TSGuard flags (regime instability), and issues marked `requires_human = True`. When triggered, it generates a structured Markdown checklist and pauses the agent loop until all decisions are recorded. Decisions are exported as JSON and appended to the audit log.

8.3 EdgeCard: The Primary Output Artifact

Each estimated edge produces an EdgeCard—a YAML file combining estimates (point, SE, CI, p -value, IRF), diagnostics (13 automated checks), identification results (claim level, risks), counterfactual eligibility (shock/policy), propagation role, credibility score and rating (A/B/C/D), and literature references. EdgeCards are both human-readable and machine-parseable, serving as the interface between the estimation and governance layers.

9 Experiments

We evaluate OPENCAUSALITY on three dimensions: (1) estimation accuracy via synthetic benchmarks, (2) NL-to-DAG extraction quality, and (3) end-to-end pipeline reproducibility.

9.1 Synthetic Benchmarks

We generate data from known data-generating processes with ground-truth treatment effects and evaluate the estimation adapters. Table 3 reports results.

All adapters achieve nominal or above-nominal coverage. IV-2SLS shows the lowest RMSE and bias, consistent with the efficiency gains from a strong instrument.

9.2 NL-to-DAG Extraction: Kazakhstan Case Study

We compare an expert-built DAG (32 nodes, 20 edges, approximately 40 hours of construction time) against an LLM-extracted DAG from a single descriptive paragraph about Kazakhstan bank stress testing.

Table 4: NL-to-DAG extraction results on the Kazakhstan bank stress-testing case study. Estimate match measures whether common edges produce statistically equivalent point estimates.

Metric	Expert DAG	NL-Extracted DAG
Nodes	32	17
Edges	20	13
Structural matches	—	4/20 (20%)
Estimate match (common edges)	—	4/4 (100%)
Novel edges (NL only)	—	3

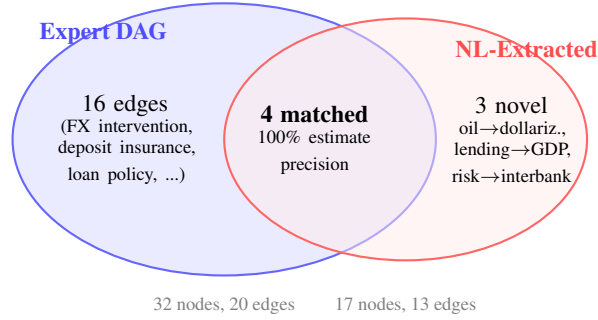


Figure 2: Comparison of expert-built and NL-extracted DAGs for the Kazakhstan case study. The 4 matched edges achieve 100% estimate precision. The NL pipeline discovers 3 novel edges with literature support, while missing 16 edges encoding country-specific regulatory details.

Figure 2 illustrates the overlap between expert and NL-extracted DAGs.

The NL pipeline achieves 20% structural recall—unsurprising given that a single paragraph cannot encode country-specific regulatory details (central bank FX intervention rules, deposit insurance thresholds, loan classification policy changes). However, all 4 matched edges produce statistically equivalent estimates, and the pipeline discovers 3 novel edges with literature support:

- Oil price volatility → deposit dollarization [5]
- Bank lending standards → GDP growth (bank lending channel)
- Global risk appetite → domestic interbank rates

9.3 End-to-End Reproducibility

We run the full agentic pipeline on the KSPI K2 DAG (20 edges) and compare against the expert manual baseline. The pipeline achieves 100% estimate match (20/20 edges), confirming reproducibility across pipeline modes and adapter dispatch.

9.4 Issue Detection Effectiveness

Across 13 pipeline runs on the Kazakhstan case study, the 29-rule engine detects 1,479 issues in total, of which 1,333 (90.1%) are CRITICAL severity. PatchBot auto-fixes 812 issues (54.9%), primarily missing unit specifications (UNIT_MISSING_IN_EDGE CARD). Of the 667 remaining open issues, only 19 (1.3% of total) require human review—demonstrating that the system effectively triages the review burden.

The dominant open issue type is SIGNIFICANT_BUT_NOT_IDENTIFIED (492 instances, 73.8% of open issues), which fires when an edge achieves $p < 0.05$ but the identifiability screen assigns a claim level below IDENTIFIED_CAUSAL. This rule alone catches the most common form of overclaiming in applied work. Other frequent detections include LOO_INSTABILITY (87 instances: leave-one-out sign flips or $>50\%$ magnitude changes) and RATING_DIAGNOSTICS_CONFLICT (59 instances: A-ratings despite failed diagnostics, auto-downgraded by PatchBot). Figure 3 summarizes the issue triage pipeline.

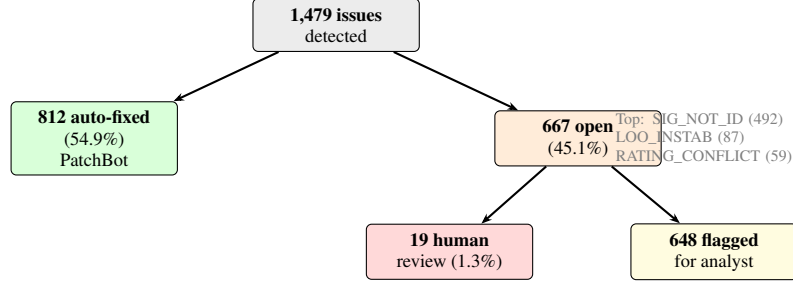


Figure 3: Issue triage across 13 pipeline runs. PatchBot auto-fixes 54.9% of issues (primarily missing units). Only 1.3% require human-in-the-loop review, demonstrating effective automation of the governance burden.

10 Limitations

NL-to-DAG is lossy. Qualifying language is collapsed to binary decisions, effect magnitudes are not reliably extracted from text, and the pipeline cannot distinguish between claims made by the authors and claims they merely cite.

Claims are not identification. A DAG extracted from the literature represents *claimed* causal relationships, not identified ones. OPENCAUSALITY’s identifiability screen partially addresses this, but the initial DAG structure reflects community beliefs rather than proven mechanisms.

Single-country evaluation. Our primary case study is Kazakhstan bank stress testing. While the platform is domain-agnostic, the data clients and variable catalogs are currently specific to this use case.

LLM hallucination risk. The LLM can fabricate plausible-sounding causal edges not present in the source material. All LLM-extracted edges must be verified against the original text—a requirement that our governance framework enforces via HITL gates but cannot guarantee in fully automated mode.

Independence assumption in propagation. The delta-method SE formula (Equation 2) assumes independence across edges. When edges share confounders, standard errors are underestimated. The engine warns but does not correct for this.

11 Conclusion

OPENCAUSALITY demonstrates that automation and transparency in causal inference are not mutually exclusive. By treating every modeling decision as an auditable event—logged in a hash-chained ledger, gated by identifiability screens, and protected by anti-p-hacking policies—the platform enables researchers to move faster while maintaining the evidentiary standards that credible causal claims demand. The LLM-assisted discovery pipeline shows promise as a complement to expert DAG construction, finding novel edges while achieving perfect estimate precision on matched paths. We release OPENCAUSALITY as open-source software to support reproducible causal inference research.

References

- [1] Philipp Bach, Victor Chernozhukov, Malte S. Kurz, and Martin Spindler. DoubleML – an object-oriented implementation of double machine learning in Python. *Journal of Machine Learning Research*, 23(53):1–6, 2022. URL <https://www.jmlr.org/papers/v23/21-0862.html>.
- [2] Keith Battocchi, Eleanor Dillon, Maggie Hei, Greg Lewis, Paul Oka, Miruna Oprescu, and Vasilis Syrgkanis. EconML: A Python package for ML-based heterogeneous treatment effects

- estimation. *Journal of Machine Learning Research*, 23(53):1–6, 2022. URL <https://www.jmlr.org/papers/v23/21-0862.html>.
- [3] Huigang Chen, Totte Harinen, Jeong-Yoon Lee, Mike Yung, and Zhenyu Zhao. CausalML: Python package for causal machine learning. *arXiv preprint arXiv:2002.11631*, 2020. URL <https://arxiv.org/abs/2002.11631>.
 - [4] David Maxwell Chickering. Optimal structure identification with greedy search. *Journal of Machine Learning Research*, 3:507–554, 2002. doi: 10.1162/153244303321897717. URL <https://jmlr.org/papers/v3/chickering02b.html>.
 - [5] Husnu C. Dalgic. Financial dollarization in emerging markets: An insurance arrangement. *International Economic Review*, 65(3):1189–1219, 2024. doi: 10.1111/iere.12686.
 - [6] John P. A. Ioannidis. Why most published research findings are false. *PLOS Medicine*, 2(8): e124, 2005. doi: 10.1371/journal.pmed.0020124.
 - [7] Emre Kiciman, Robert Ness, Amit Sharma, and Chenhao Tan. Causal reasoning and large language models: Opening a new frontier for causality. *Transactions on Machine Learning Research*, 2023. URL <https://arxiv.org/abs/2305.00050>.
 - [8] Stephanie Long, Tibor Schuster, and Alexandre Piché. Can large language models build causal graphs? *arXiv preprint arXiv:2303.05279*, 2023. URL <https://arxiv.org/abs/2303.05279>.
 - [9] Brian A. Nosek, Charles R. Ebersole, Alexander C. DeHaven, and David T. Mellor. The preregistration revolution. *Proceedings of the National Academy of Sciences*, 115(11):2600–2606, 2018. doi: 10.1073/pnas.1708274114.
 - [10] Amit Sharma and Emre Kiciman. DoWhy: An end-to-end library for causal inference. *arXiv preprint arXiv:2011.04216*, 2020. URL <https://arxiv.org/abs/2011.04216>.
 - [11] Joseph P. Simmons, Leif D. Nelson, and Uri Simonsohn. False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*, 22(11):1359–1366, 2011. doi: 10.1177/0956797611417632.
 - [12] Uri Simonsohn, Joseph P. Simmons, and Leif D. Nelson. Specification curve analysis. *Nature Human Behaviour*, 4(11):1208–1214, 2020. doi: 10.1038/s41562-020-0912-z.
 - [13] Peter Spirtes, Clark Glymour, and Richard Scheines. *Causation, Prediction, and Search*. Adaptive Computation and Machine Learning. MIT Press, 2nd edition, 2000. ISBN 978-0-262-19440-2.
 - [14] Keli Zhang, Shengyu Zhu, Marcus Kalander, Ignavier Ng, Junjian Ye, Zhitang Chen, and Lujia Pan. gCastle: A Python toolbox for causal discovery. *arXiv preprint arXiv:2111.15155*, 2021. URL <https://arxiv.org/abs/2111.15155>.
 - [15] Xun Zheng, Bryon Aragam, Pradeep Ravikumar, and Eric P. Xing. DAGs with NO TEARS: Continuous optimization for structure learning. In *Advances in Neural Information Processing Systems 31 (NeurIPS 2018)*, pages 9472–9483, 2018. URL <https://proceedings.neurips.cc/paper/2018/hash/e347c51419ffb23ca3fd5050202f9c3d-Abstract.html>.
 - [16] Yujia Zheng, Biwei Huang, Wei Chen, Joseph Ramsey, Mingming Gong, Ruichu Cai, Shohei Shimizu, Peter Spirtes, and Kun Zhang. Causal-learn: Causal discovery in Python. *Journal of Machine Learning Research*, 25(60):1–8, 2024. URL <https://jmlr.org/papers/v25/23-0970.html>.

A Full Issue Registry

The OPENCAUSALITY issue registry contains 29 detection rules organized into six categories. Table 5 presents all rules.

B EdgeCard Schema

The EdgeCard is the primary output artifact—one per estimated edge, both human-readable (YAML) and machine-parseable. It contains the following blocks:

Table 5: Full Issue Detection Registry (29 Rules). Trigger: pre = pre-run, post = post-run, xrun = cross-run.

Rule ID	Sev.	Scope	Trig.	Fix?	Description
<i>Data & Definition</i>					
ENTITY_BOUNDARY_DRIFT	HIGH	data	post	No	Mixing entity scopes breaks comparability
KPI_DEFN_MISMATCH	HIGH	data	xrun	No	NPL/CoR definitions differ across banks
SHOCK_CONSTRUCT_AMBIG	MED	data	pre	Yes	Missing shock_node_id, shock_unit, shock_scale
FREQ_ALIGNMENT_ERR	CRIT	data	pre	Yes	Mixed frequencies without aggregation rule
FREQ_SCALING_MISMATCH	HIGH	data	xrun	No	Annual vs quarterly not normalized
EXTRACT_PROVENANCE_GAP	MED	data	post	No	Missing source document/page reference
<i>Identification & Design</i>					
REACTION_FN_EDGE	CRIT	id	pre	No	Reaction edge used for shock propagation
TIME_FE_ABSORBS_SHOCK	CRIT	id	pre	Yes	Time FE absorbs common shock; need Exposure \times Shock
EXPOSURE_NOT_PREDDET	CRIT	id	pre	No	Exposure variable not pre-treatment
MECHANICAL_EDGE_EST	HIGH	id	pre	Yes	Accounting identity estimated as regression
PATH_DOUBLE_COUNT	HIGH	id	post	No	Direct + indirect chain both used
SIG_NOT_IDENTIFIED	CRIT	id	post	No	$p < 0.05$ but claim \neq IDENTIFIED_CAUSAL
<i>Statistical Inference</i>					
SMALL_SAMPLE_INF	HIGH	stat	post	No	$N < 30$ with HAC SEs
PANEL_FEW_UNITS	HIGH	stat	post	No	< 5 units; cluster-robust unreliable
LOO_INSTABILITY	HIGH	stat	post	No	Leave-one-out sign flip or $> 50\%$ Δ
BREAKS_UNMODELED	MED	stat	post	No	Regime changes not in estimation
MULTI_TEST_DRIFT	MED	stat	xrun	No	Spec search exceeded budget
<i>Time-Series (TSGuard)</i>					
NONSTAT_LEVELS_RISK	HIGH	ts	pre	Yes	Both vars trending; need transformation or ECM
RESID_AUTOCORR	MED	ts	post	No	Serial correlation in residuals
REGIME_BREAK_SUSP	HIGH	ts	post	No	Coefficient instability across splits
LEADS_TIMING_FAIL	CRIT	ts	post	No	Future shock predicts current outcome
HAC_LAG_SENSITIVE	MED	ts	post	No	Estimate changes with HAC bandwidth
<i>Selection & External Validity</i>					
SELECT_PUBLIC_ONLY	HIGH	ev	post	No	Only public banks; may not generalize
SURVIVORSHIP_BIAS	HIGH	ev	post	No	Excludes failed/merged banks
COVERAGE_GAP_EV	MED	ev	post	No	Sample $< 50\%$ of system assets
<i>Scoring & Reporting</i>					
RATING_DIAG_CONFLICT	HIGH	rpt	post	Yes	A-rating despite failed diagnostics
N_REPORT_INCONSIST	MED	rpt	post	Yes	Report $N \neq$ EdgeCard N_{eff}
CROSS_EVID_CONFLICT	HIGH	rpt	xrun	No	Same relationship has conflicting signs
UNIT_MISSING_CARD	CRIT	rpt	post	Yes	EdgeCard missing treatment/outcome unit

Core identity. edge_id, dag_version_hash (SHA-256 of DAG at estimation time), created_at, spec_hash, spec_details (design, controls, instruments, FE, SE method).

Estimates. point ($\hat{\beta}$), se, ci_95, pvalue, treatment_unit, outcome_unit. For local projections: horizons, irf, irf_ci_lower, irf_ci_upper. Sample sizes: n_calendar_periods, n_effective_obs_h0, n_effective_obs_by_horizon.

Diagnostics. Dictionary of DiagnosticResult objects, each with: name, passed (bool), value (test statistic), threshold, pvalue, message. Method all_diagnostics_pass() returns True if all tests pass.

Identification. claim_level \in {IDENTIFIED_CAUSAL, REDUCED_FORM, DESCRIPTIVE, BLOCKED_ID}. risks (dict of risk \rightarrow severity), untestable_assumptions, testable_threats_passed, testable_threats_failed.

Counterfactual block. shock_scenario_allowed (bool), policy_intervention_allowed (bool), reason_shock_blocked, reason_policy_blocked.

Propagation role. `role` \in {structural, reduced_form, bridge, identity, diagnostic_only}. `mode_propagation_allowed` (dict: `mode` \rightarrow bool), `mode_shock_cf_allowed`, `mode_policy_cf_allowed`.

Credibility. `credibility_score` (0–1): 40% diagnostic pass rate + 10% design strength + 30% stability + 20% data coverage. `credibility_rating`: A \geq 0.80, B \geq 0.60, C \geq 0.40, D otherwise. Significance is *not* a factor.

Literature. `supporting`, `challenging`, `methodological` (citation lists), `search_status`, `search_timestamp`, `search_query`, `total_results`.

Interpretation boundary. `estimand` (what we estimate), `is_not` (what this is not), `channels`, `population`, `conditions`, `allowed_uses`, `forbidden_uses`.

Failure flags. 8 booleans: `weak_identification`, `potential_bad_control`, `mechanical_identity_risk`, `regime_break_detected`, `small_sample`, `high_missing_rate`, `entity_boundary_change`, `definition_inconsistency`.

C Query REPL Example Session

The following annotated session illustrates the OPENCAUSALITY Query REPL with natural-language query parsing, guardrail enforcement, and hedged narration.

```
$ opencausality query --dag config/agentica/dags/kspi_narrative.yaml \
  --mode REDUCED_FORM

OpenCausality Query REPL
DAG: Kazakhstan Banking System (23 nodes, 18 edges)
Cards: 18 | Mode: REDUCED_FORM | Backend: LLM

query> What if oil prices drop 30%?

[Intent classified: shock_scenario]
Source: oil_price | Target: bank_capital_ratio | Magnitude: -0.30

Path 1: oil_price -> income -> bank_capital_ratio
  Edge 1: oil_price_to_income
    Role: reduced_form | Claim: REDUCED_FORM | Coeff: 0.45 | SE: 0.12
    Shock CF: ALLOWED
  Edge 2: income_to_bank_capital_ratio
    Role: structural | Claim: IDENTIFIED_CAUSAL | Coeff: 0.23 | SE: 0.08
    Shock CF: ALLOWED

Guardrail Results:
[PASS] Mode gating (weakest: REDUCED_FORM, mode allows)
[PASS] Counterfactual gating (all edges shock-allowed)
[PASS] TSGuard (no timing failures)
[PASS] IssueLedger (no CRITICAL issues)
[PASS] Reaction-function blocking (none in path)
[PASS] Unit compatibility (pp -> pp)
[WARN] SE assumes independence (2 estimated edges)

Effect (per unit): 0.1035
Scaled (-0.30): -0.0311
SE (delta method): 0.0293
95% CI (scaled): [-0.089, 0.026]

Narration (hedged):
"In REDUCED_FORM mode, a 30% oil price decline is associated
with a -3.1pp decrease in bank capital ratio (95% CI:
[-8.9pp, +2.6pp]). The first edge (oil -> income) is
REDUCED_FORM; the second is IDENTIFIED_CAUSAL. The effect
is not significant at 5%. SE assumes independence."

query> /mode STRUCTURAL

Mode switched to STRUCTURAL.
WARNING: oil_price_to_income (reduced_form) now BLOCKED.
1 of 2 path edges blocked in STRUCTURAL mode.

query> /quit
```

D TSGuard Diagnostic Details

Table 6 details all 7 TSGuard diagnostics with thresholds and governance actions.

Table 6: TSGuard diagnostic tests and governance actions.

Diagnostic	Description	Threshold	Action on Failure
leads_test	Regress y_t on x_{t+1} . Significance \Rightarrow timing failure.	$ \text{corr} > 0.3$	CRITICAL: Block CF, cap = BLOCKED_ID
residual_autocorr	First-order autocorrelation ρ_1 of LP residuals.	$ \rho_1 > 0.5$: fail; > 0.3 : medium	Set autocorr_risk = high
hac_sensitivity	Re-estimate with NW lags $\{1, 4, 8\}$. Check sign stability.	Sign flip across bandwidths	Set autocorr_risk = high
lag_sensitivity	Re-estimate with $L \in \{1, 2, 4\}$. Check coefficient stability.	Sign flip across lags	Cap rating to B
regime_stability	Split-sample at known breaks (2015-08, 2020-03).	Pre/post sign flip	HIGH: Block CF, cap = REDUCED_FORM
placebo_shift	Circularly shift treatment by 2–4 periods.	Placebo $p < 0.1$	Set timing_risk = high
shock_support	Count episodes $ x_t > 1\sigma$.	< 3 episodes	HIGH: Block CF

Dynamics risk categories. TSGuard assigns 5 risk levels: (1) `common_trend_risk`—both series persistent ($\text{AC}(1) > 0.9$); (2) `autocorr_risk`—from residual and HAC tests; (3) `nonstationarity_risk`—high AC for both series, cap claim to `DESCRIPTIVE` unless ECM; (4) `regime_break_risk`—from split-sample test; (5) `timing_misspec_risk`—from leads test.

Governance rules. (1) Nonstationarity + levels \Rightarrow cap at `DESCRIPTIVE`; (2) Lead test failure \Rightarrow `BLOCKED_ID`; (3) Regime instability \Rightarrow cap at `REDUCED_FORM`, block CF; (4) Shock support $< 3 \Rightarrow$ block CF. All TSGuard results are stored in EdgeCards and feed into the propagation engine’s guardrail 3.