

Auditing Platform Competition Analytics with Causal Evidence Across Irish Organizations

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Abstract

Platform competition analytics examines network effects, pricing, participation, ranking, advertising, switching, access conditions, and strategic interaction across digital ecosystems shaped by previous product and policy choices. The article shifts attention from prediction to intervention by defining treatment, outcome, population, time horizon, and the counterfactual. It highlights confounding in historical business data and uses experiments, natural experiments, quasi-experimental designs, subgroup analysis, and operational economics to test whether recommended actions actually cause better outcomes. The Irish discussion sits within GDPR, the EU AI Act, and wider European platform and data-protection rules, making transparency, lawful processing, human oversight, and trust operational concerns. Across the analysis, business value is tied to baselines, uncertainty, subgroup effects, workflow fit, lifecycle cost, vendor accountability, scenario testing, and decision records. The overall message is that analytical performance becomes credible only when it improves real decisions under clearly defined operating and governance conditions. Independent review, common metric definitions, and periodic challenge exercises are also presented as safeguards against hidden deterioration, stale assumptions, and continued use of systems that no longer justify their cost or risk.



In Ireland, by 05 May 2026 platform competition analytics had shifted from a specialist analytics conversation to managing it as a management question. No longer was the question the one of whether or not advanced models could score, forecast, rank, or make recommendations. The focus was now on how reliable, understandable, fair and economical those outputs were when integrated into real decisions. It transformed the successful implementation of platform competition analytics from a technical success to one backed by evidence for decision quality, for organizations investing in this movement. Platform competition analytics analyzes network effects, pricing, participation, ranking, advertising, switching and strategic interaction in digital ecosystems. The importance of causal evidence is due to the influence of past product and policy decisions on platform data.

Irish institutions that are part of major online markets must separate out market effects from intervention effects. Several aspects of a platform can change at once, such as its ranking, fees, and recommendation rules, or access conditions. The auditor's focus is not on whether an analytical system predicts outcomes as it would be in a traditional audit, but rather whether recommended actions lead to better outcomes. Correlating can determine patterns, but not evidence of interventions. There are various approaches to that evidence: randomized experiments, natural experiments, quasi-experimental designs, and carefully specified causal models. A causal audit begins with making a distinction between treatment, outcome, population and time frame, and assumptions.

If interventions are ambiguous, so are the conclusions. Any recommendation for changing price, allocation, content or priority in a market requires a clear counterfactual, or what would have happened if the price, allocation, content or priority were not changed. The questions that should follow in the audit are whether

existing data can reasonably estimate the missing counterfactual. One aspect that's worthy of special mention is that business data reflects decisions that have already been made, not what they should be based on. There may be more opportunities for high dollar customers, more budget for strong markets, and better opportunities for promising employees. These previous decisions can be confused for causal effects by naive models.

Prescriptive claims are credible only following the design-based evidence or explicit adjustment strategies. Explanations can provide a means to reinforce a causal audit by revealing treatment rules, effect heterogeneity, and assumptions. It is not sufficient on its own to establish association to causation. Auditors should review to see if explanations are consistent across samples, if there are group differences in the treatment, and if the recommendations are beyond the range of support observed. The impact of the large effects in poorly supported regions should be questioned. The conclusions in audits should relate statistics to their value and operation. On average, a treatment may appear effective but it could have an average negative impact on certain subpopulations, and a treatment with a clearly positive average effect may have a small effect on these subpopulations that would not outweigh the cost of implementation.

Uncertainty, capacity, fairness, compliance and opportunity cost should be taken into account when determining decision thresholds. A causal audit is successful if it alters deployment decisions and not just provides another model score. Irish organisations operated in the rapidly-changing landscape of AI and data protection in the European Union, with GDPR requirements already coming into play whenever personal data is processed in the development or deployment of AI. The EU AI Act was adopted and came into force in August 2024, and provided a risk-based approach, with prohibitions on specific practices and extensive obligations relating to high-risk AI systems. As of early 2025, prohibited practices under AI and AI-literacy requirements started to take effect, and other elements of the regulatory timeline continued to be on the horizon.

Communication of uncertainty is also crucial to good analysis. However, when sampling is sparse or situations shift rapidly, then point estimates can give the impression of precision. Uncertainty is visible to the operational teams through the use of prediction intervals, sensitivity ranges, scenario analysis and confidence categories. Remove ambiguity language to allow proportional responses instead of automatic responses for all scores. There is an equal need to pay attention to the vendor governance since external platforms may change models, interfaces, data processing or terms without the same release cycles as the internal ones. Documentation, change notification, incident handling, security, data retention and exit arrangements should all be covered in contracts.

Independent validation required by internal teams, as vendor assurance doesn't replace organization-specific validation. Business value needs to be assessed throughout a business lifecycle. The cost of development is just the start—the cost of integration, training, monitoring, data maintenance, review time, remediation, and

retirement are also resources used. The benefits associated with those costs should be compared. A model that has to be continually hand tuned may present a spectacular picture in a pilot but fail to deliver good net value once scaled up. When the results of the monitoring process are fed back into the design of the process, organizational learning becomes a significant source of returns. When there are inconsistencies between data and front-line judgment, it can uncover missing variables, or rules that are out of date.

Errors in labels or business definitions may be identified by being replicated throughout the model. This strategy makes it possible to build a stronger decision system than just rescheduling retraining. Business unit, customer group, geography, channel, and operating regime (if it has an impact on platform competition analysis) should also be included in the segmentation of evidence. There are fewer disagreements around shared metric definitions and data dictionary, as disagreements only occur when performance starts to decline. It is important to make a baseline comparison as improvements in, say, a platform's analytics for competition can disappear if seasonal trends, policy changes or previous trends are considered. Independent review is best performed when reviewers are able to reproduce the key results, from raw inputs, documented assumptions and version controlled code or model artifacts.

A handful of indicators are relevant to decision-making as opposed to a large dashboard with no clear path for escalation. The purpose of scenario testing is to simulate adversarial scenarios prior to deployment, to uncover brittle behaviour and identify unexpected combinations, missing inputs, sudden volume changes, or unusual situations. Shared metric definitions, data dictionaries prevent conflicts that may only come to light when performance starts to suffer. Average performance and tail outcomes should both be monitored, as errors that can be severe might be more important than smaller gains in a mean statistic. Independent review is best performed when reviewers are able to reproduce the key results, from raw inputs, documented assumptions and version controlled code or model artifacts.

However, change management also requires input from actual users as workflow friction can dampen the realized value even if there are no changes to the analytical performance. The purpose of scenario testing is to simulate adversarial scenarios prior to deployment, to uncover brittle behaviour and identify unexpected combinations, missing inputs, sudden volume changes, or unusual situations. The importance of a clear retirement rule is that old models can remain in place in organisations for a long time after evidence has indicated that they should be replaced. Average and tail outcomes should be monitored as both are important; large errors can be more significant than small adjustments to a mean. Decision logs provide evidence for future review and connect recommendations and overrides, contextual reasons and actual outcomes.

Feedback from frontline users is another important aspect of change management because once workflow is hampered, realized value may decline despite a stable analytical performance. The cost sensitive evaluation is more realistic since the consequences of false positive, false negative, delayed action and unnecessary

escalation are different. The importance of a clear retirement rule is that old models can remain in place in organisations for a long time after evidence has indicated that they should be replaced. Periodic challenge exercises can be used to determine if a simpler rule or baseline or alternative model can better hold up to the incumbent system. Decision logs provide valuable evidence for retracing the steps that can be reviewed later on to connect recommendations, overrides, contextual reasons and achieved outcomes.

Additional evidence should also be broken out by business unit, customer type, geography, channel or operating regime if they impact platform competition analysis. Evaluation is made cost sensitive to enhance realism, by giving different consequences to false positives and false negatives, delayed action, and unnecessary escalation. It's important to make baselines because improvements in platform competition analysis that might appear in the data go away if you consider seasonal trends, policy changes, or past trends. Causal auditing can add credibility to platform competition analytics in Ireland, by testing if the recommended actions lead to outcomes – or if they only correlate with them. The elements of strong audits are explicit assumptions, credible counterfactuals, subgroup analysis, uncertainty, and operational economics.

That benchmark transforms analytics into evidence-based action for accountability.