

Causal Impact Methodology

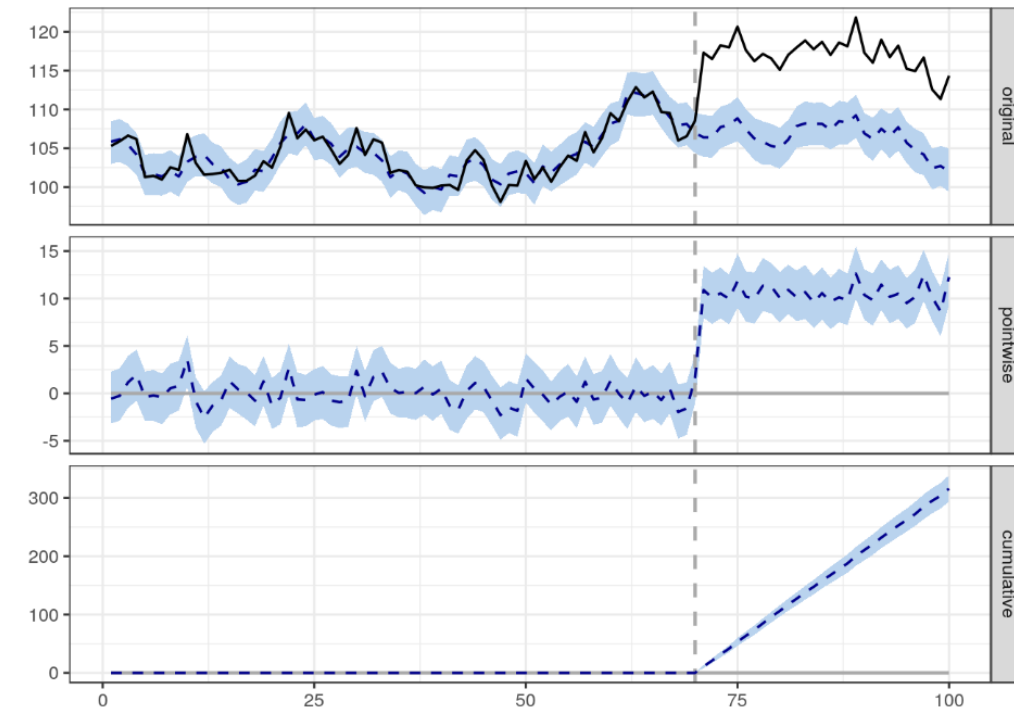
Problem Statement: Understanding the incremental impact on GMV for B2C programs such as Account Management (AM) and Pro Trader (PT).

Why Causal Impact:

- While Causal Impact is not better than A/B testing or (RCTs) but it is better than the traditional methodologies such as Diff-in-Diff and Pre vs. Post analysis. It offers a more conservative approach when A/B testing is unfeasible.
- In AM & PT we have limited number of eligible sellers, and we target all the sellers to maximize coverage and ROI.

How does Causal Impact Work:

1. **Identifying Target and Comparable Groups:** The evaluation begins by identifying AM/PT sellers as the target group. Then, a comparable group is identified to establish a baseline for comparison.
2. **Pre-Period Analysis:** Historical data from the 52-week pre-period is utilized to examine trends of both the target and comparable groups. This provides a stable basis for measuring any observed changes post-intervention.
3. **Causal Impact Algorithm:** Using a **Bayesian Time-Series model**, the causal impact algorithm predicts the expected performance of the target group based on the behavior of the comparable group during the pre-period.
4. **GMV Lift Calculation:** The incremental impact of the AM/PT programs on GMV is computed by comparing the actual GMV performance of the target group against the predicted values.



Alignment on how we measure efficacy – Comparison of evaluation methodologies

	Pre-Post Analysis	Difference-in-Differences (Diff-in-Diff)	Causal Impact
Methodology:	<ul style="list-style-type: none"> Compares outcomes within the same group before and after an intervention. 	<ul style="list-style-type: none"> Compares changes in outcomes between two groups (treatment vs. control) before and after an intervention. 	<ul style="list-style-type: none"> Employs Bayesian time-series models to estimate causal effects. Compares actual post-intervention data with counterfactual predictions.
Assumption:	<ul style="list-style-type: none"> Assumes observed changes are solely due to the intervention. 	<ul style="list-style-type: none"> Assumes parallel trends between treatment and control groups in the absence of treatment. 	<ul style="list-style-type: none"> Assumes accurate representation of counterfactual outcomes.
Advantages:	<ul style="list-style-type: none"> Simple and straightforward. Useful for initial exploration. 	<ul style="list-style-type: none"> Controls for time-invariant unobserved factors. Provides a causal interpretation under parallel trends. 	<ul style="list-style-type: none"> Robust estimation of causal effects. Accounts for time-varying factors and seasonality. More conservative than A/B testing when randomization is not feasible.
Disadvantages:	<ul style="list-style-type: none"> Lacks comparison group. Susceptible to confounding factors. 	<ul style="list-style-type: none"> Relies heavily on the parallel trend's assumption. Vulnerable to bias if assumption is violated. 	<ul style="list-style-type: none"> Requires careful model specification. May be computationally intensive.
Conclusion	<ul style="list-style-type: none"> Simple yet lacks comparison group for causal inference. 	<ul style="list-style-type: none"> Useful for group comparisons but relies on strong assumptions. 	<ul style="list-style-type: none"> Offers robust estimation and causal inference, suitable when A/B testing is not feasible.

FAQ – Causal Impact

1. What is Causal Impact? - Causal Impact is a statistical methodology for estimating the causal effect of an intervention or treatment on a target outcome.

2. What are the key assumptions underlying Causal Impact?

- a. Stationarity: The relationship between variables remains stable over time.
- b. Parallel Trends: Treated and control groups follow similar trends in the absence of intervention.
- c. No Spillover Effects: The intervention only affects the treated group.
- d. Covariate Independence: Other variables being controlled for in the analysis are not influenced by additional interventions.

3. How does Causal Impact differ from other causal inference methods?

- a. Bayesian Framework: Causal Impact uses Bayesian statistics for causal estimation.
- b. Time-series Modeling: It accounts for temporal dependencies and seasonality.
- c. Counterfactual Predictions: Estimates what would have happened without the intervention.

4. What data is required for conducting a Causal Impact analysis? - Causal Impact typically requires pre-intervention and post-intervention time-series data for both the treated and control.

5. How is the effectiveness of an intervention assessed using Causal Impact? - The effectiveness of an intervention is evaluated by comparing the actual outcomes post-intervention with the counterfactual predictions generated by the model. The difference between the observed and predicted outcomes represents the causal effect of the intervention.

6. What are some potential challenges or limitations of using Causal Impact?

- a. Model Specification: Crucial for accurate estimation.
- b. Assumption Validation: Ensuring validity of assumptions.
- c. Interpretation: Requires domain expertise to account for confounding factors.

7. Is cannibalization factored into the methodology? - Cannibalization, or other negatively impacting intervention, is not explicitly factored into the Causal Impact but careful control group selection can mitigate potential effects.

8. What is the cannibalization for B2C sellers for Big-3 geographies in eBay? - **US:69%, UK:48% & DE:48%**(DE is assumed similar as UK). **Blended** Cannibalization for **Big-3** is **61%**. [Reference](#)

9. What if a control group is unavailable for analysis? - Considered using proxy control groups or statistical techniques like synthetic control methods.

10. How do we interpret results without a control group? - Carefully considered alternative explanations and conducted sensitivity analysis.

11. References for Causal Impact: Causal Impact Package details: [here](#) & “Inferring causal impact using Bayesian Structural Time-Series Models” Original paper [here](#)

12. How do we address potential bias from account managers selecting sellers likely to grow GMV? - Account manager bias can be mitigated by ensuring randomized seller assignments or incorporating propensity score matching to balance groups based on growth potential.

13. How are Ads team and Greater China measuring the incrementality?

- Ads Team uses Pre/Post, A/B test or Holds-out group (RCT) for measurement [deck](#)
- Greater China has never evaluated incremental GMV as 80% of GMV is managed in Greater China and rest of the sellers are small and risky

14. How is the comparable group for AM sellers created? - Non-test B2C sellers with GMV within 15% and SI within 25% of the test seller are considered. The top 2% closest are chosen.

15. What happens if a test seller has no comparable sellers? - Outlier test sellers are excluded from lift calculations to ensure conservative iGMV estimation, mitigating bias.

16. Does the algorithm consider seller category? - Yes, SI acts as a proxy for similar GMV. It helps, especially in categories where most sellers are part of AM.

17. How is cannibalization managed in iGMV calculations? - Product team factors it separately (B2C-70%, C2C-30%) on top of iGMV.

18. Are employee costs included in ROI calculations? - Unlike AM and PT, other programs do not consider employee/resource costs in ROI.

19. What's the average profile of AM sellers? - In quarters when managed, 2% are new, and 38% have T52W_GMV > \$1M.

20. What's the category distribution for test and comparable group AM sellers? - Around 70% of test AM sellers focus on Fashion, Home & Garden, or Personal Accessories. For Comparable group it is WIP.

21. Do AM sellers represent more focus category sellers? - Hypothesized, but not yet tested.

22. Is seller tenure balanced in the analysis? - Pending analysis; it's assumed differences exist due to churn rates and newer test sellers.

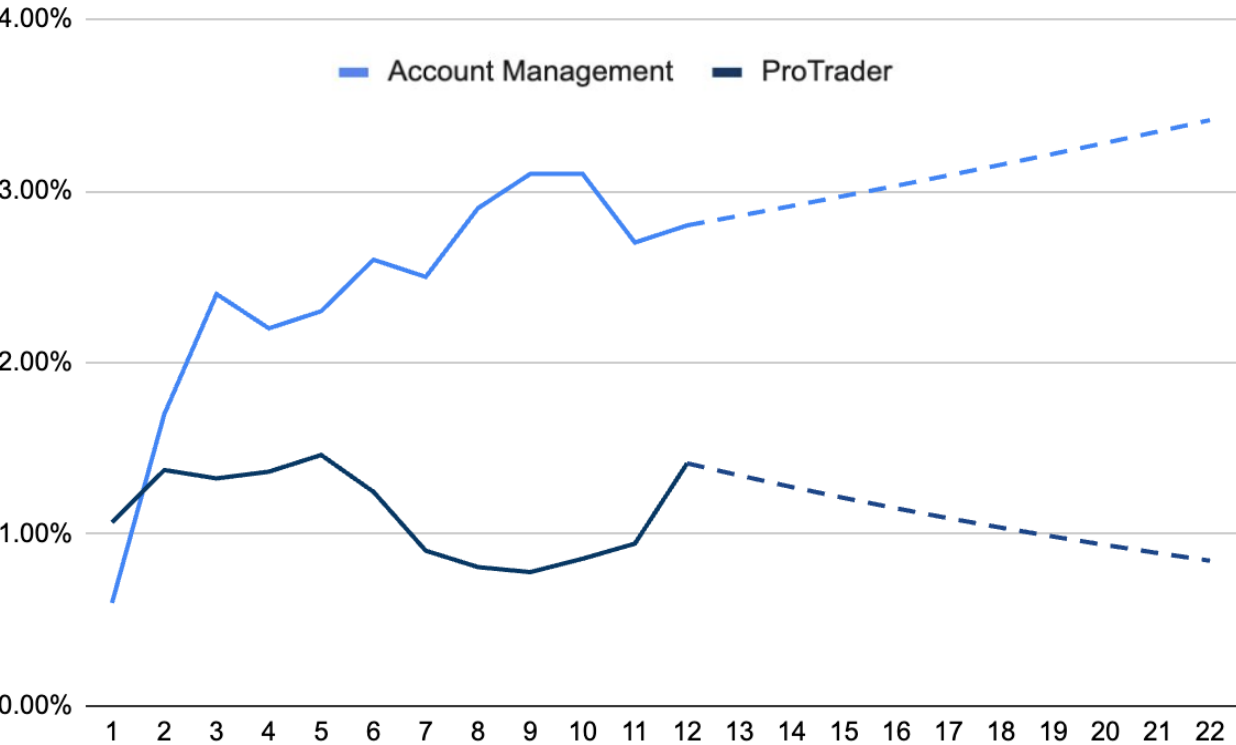
23. How are biases addressed in the program? - Despite a conservative methodology, some biases may persist, though efforts are made to minimize them.

24. How are outlier test sellers managed for AM lift calculation? - Outliers, <5% due to size and without a comparable group, are excluded from lift calculation, keeping it conservative.



Despite the gaps in our approach, we are driving 1-3% uplift factoring in cannibalization impact

View of output for context



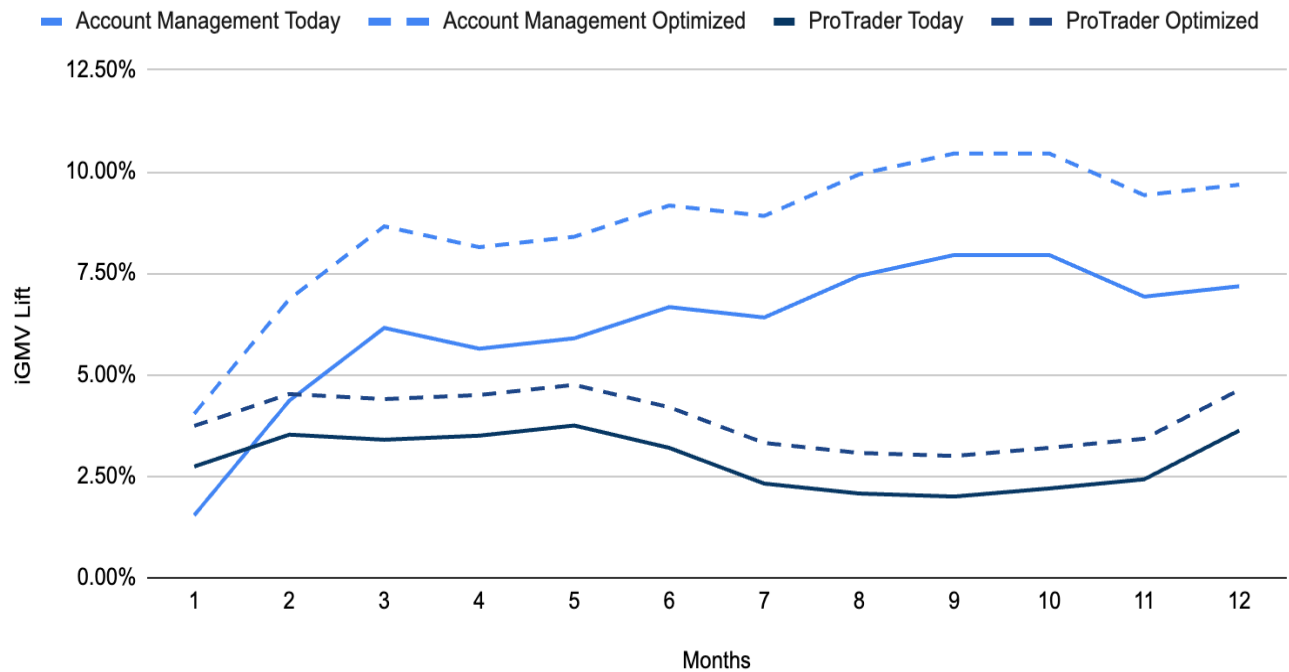
- **Full time AM are only present in Focus Categories where lift is amplified through:**
 - Product enhancements
 - Marketing investment
 - Consistent coaching for ongoing business decisions
 - Significant exposure to promotional levers with co-invest
- **Application of a more consistent playbook will allow for larger lift in these business areas**
- **Providing access to more timely seller coaching & to co-invested promotional levers will improve impact in 'Part-Time' AM businesses**

Assumed 61% cannibalization of iGMV across Big 3 in detailed model

	Full Time AM	Part Time AM(ProTrader)	iCBT Account Management
Sellers: FTE	25:1 (includes hybrid roles)	50:1 (per quarter)	95:1
GMV/Seller	\$2M	\$361K	\$1.3m
Current ROI	100%	205%	Not for FTE roles, but for AWF

Reminder: despite the gaps in our approach, we are driving 4-7% uplift with opportunity to grow impact 100-250%

View of output for context



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 - Product enhancements
 - Marketing investment
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Lift is pre-cannibalization. Assumed 61% cannibalization of iGMV across Big 3 in detailed model

	Full Time AM	Part Time AM(ProTrader)	iCBT Account Management
Sellers: FTE	20:1 (includes hybrid roles)	50:1 (per quarter)	95:1
GMV/Seller	\$2M	\$361K	\$1.3m

