Sales Campaign Effectiveness Analysis Report

1. Introduction

This report analyzes sales revenue data to evaluate the effectiveness of a marketing campaign. The objective is to determine whether the campaign led to a statistically and practically meaningful increase in revenue, and to translate the statistical findings into actionable business recommendations.

The analysis applies core statistical concepts, including sampling theory, the Law of Large Numbers (LLN), the Central Limit Theorem (CLT), hypothesis testing using t-statistics, confidence levels, Type I error considerations, and effect size measurement through Cohen's d. All conclusions are drawn at a **95% confidence level**.

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2. Insights from the Data

2.1 Revenue Comparison Between Campaign and Non-Campaign Stores

The analysis shows a clear difference in average revenue between stores that ran the campaign and those that did not.

- **Mean revenue (campaign stores):** 8,590.06
- **Mean revenue (no-campaign stores):** 7,401.28

This represents an **absolute difference of approximately 1,188.78** in average revenue, with campaign stores outperforming non-campaign stores.

From a purely descriptive perspective, the campaign appears to be associated with higher sales revenue. However, descriptive statistics alone are insufficient to determine whether this difference is due to the campaign or random variation, necessitating formal statistical testing.

2.2 Stability of Estimates (Law of Large Numbers)

As sample sizes increased during analysis, sample mean revenue estimates became more stable and converged toward consistent values. This behavior is consistent with the **Law of Large Numbers**, which states that larger samples yield more reliable estimates of population parameters.

This provides confidence that the observed mean revenues for both campaign and non-campaign groups are not artifacts of small-sample variability.

2.3 Sampling Distribution and Normality (Central Limit Theorem)

Repeated sampling of revenue data (with sample size $n = 30$) produced a distribution of sample means that was approximately normal. This occurred despite the underlying revenue data exhibiting variability and potential skewness.

This observation aligns with the **Central Limit Theorem**, which justifies the use of parametric statistical tests such as the t-test. As a result, the inferential conclusions drawn from the analysis are statistically valid under the assumptions of independence and finite variance.

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3. Statistical Decisions

3.1 Hypothesis Formulation

The following hypotheses were tested:

- **Null hypothesis (H_0):** There is no difference in mean revenue between campaign and non-campaign stores.
- **Alternative hypothesis (H_1):** There is a difference in mean revenue between campaign and non-campaign stores.

A **two-sample Welch's t-test** was used to account for potential differences in variance between the two groups.

3.2 Test Results and Interpretation

The t-test produced the following results:

- **t-statistic:** 4.43
- **p-value:** 0.00000504

At a **95% confidence level ($\alpha = 0.05$)**, the p-value is far below the significance threshold. Therefore, the null hypothesis is rejected.

Statistical conclusion:
There is strong statistical evidence that mean revenue differs between campaign and non-campaign stores.

The large magnitude of the t-statistic indicates that the observed revenue difference is many standard errors away from zero, making it highly unlikely that the result is due to random chance.

3.3 Effect Size (Cohen's d)

To assess practical significance, **Cohen's d** was calculated:

- **Cohen's d:** 0.28

According to conventional benchmarks:

- 0.2 = small effect
- 0.5 = medium effect
- 0.8 = large effect

A Cohen's d of 0.28 indicates a **small but meaningful effect size**. This suggests that while the campaign does increase revenue on average, the magnitude of the increase is modest relative to the overall variability in sales.

3.4 Type I Error Consideration

By rejecting the null hypothesis, there is a controlled **5% risk of a Type I error**, meaning a small probability of concluding that the campaign works when it actually does not.

In a sales context, a Type I error could lead to scaling an ineffective campaign, resulting in unnecessary costs. However, the extremely small p-value substantially reduces concern about a false positive, though it does not eliminate it entirely.

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4. Business Recommendations

4.1 Campaign Effectiveness Assessment

The campaign is **statistically effective**, as evidenced by the very low p-value, and it produces a **small but positive practical impact**, as shown by Cohen's d.

Recommendation:
The campaign should not be dismissed, but it should also not be assumed to be a high-impact revenue driver on its own.

4.2 Strategic Scaling with Caution

Given the small effect size:

- Full-scale rollout should be approached cautiously
- Cost-benefit analysis is essential

If campaign costs are low relative to the average revenue increase of approximately **1,189 per store**, scaling may still be profitable. If costs are high, the campaign may need optimization before expansion.

4.3 Optimization Opportunities

Rather than applying the campaign uniformly, the business should:

- Identify segments or store types where the effect is stronger
- Test variations of the campaign to increase impact
- Combine the campaign with complementary strategies (pricing, promotions, store layout)

This approach increases the likelihood of turning a small statistical effect into a meaningful commercial outcome.

4.4 Data and Sampling Improvements

If the data primarily represents **urban stores**, results should not be generalized to rural or semi-urban markets. Future analyses should incorporate:

- Stratified sampling across regions
- Separate effect size estimates by location
- Continuous monitoring over time

This will improve decision quality and reduce the risk of biased conclusions.

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5. Conclusion

The analysis provides strong statistical evidence that the sales campaign increases revenue, with campaign stores earning an average of **8,590.06** compared to **7,401.28** for non-campaign stores. While the effect is statistically significant, the practical impact is **small**, emphasizing the importance of evaluating effect size alongside p-values.