Probabilistic Market Budget Allocator

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Priors / Sampling Assumptions

CPM (lognormal).

$$\ln(\mathrm{CPM}_i) \sim \mathcal{N}(\mu_i^{\mathrm{cpm}},\ (\sigma_i^{\mathrm{cpm}})^2)$$

CTR and CVR (beta). Given mean $m \in (0,1)$ and std s, the beta parameters are $\mathrm{v} = \mathrm{s}^2, \qquad k = \frac{m(1-m)}{v} - 1,$
$\alpha = m\,k, \qquad \beta = (1-m)\,k,$
$X \sim \mathrm{Beta}(\alpha, \beta), \quad X \in \{\mathrm{CTR}_i, \mathrm{CVR}_i\}.$

Quality multiplier (lognormal).

$$\ln(q_i) \sim \mathcal{N}(\mu_i^q,\ (\sigma_i^q)^2), \quad with default \mu^q = 0,\ \sigma^q = 0.1.$$

Capacity θ (lognormal).

$$\ln(\theta_i) \sim \mathcal{N}(\mu_i^\theta,\ (\sigma_i^\theta)^2).$$

AOV per sale (lognormal).

$$\ln(AOV_i^{sale}) \sim \mathcal{N}(\mu_i^{aov},\ (\sigma_i^{aov})^2).$$

Distributions

CPM, AOV log normal distributions because positive and right skewed

CVR, CTR beta distribution because between 0-1

Fixed Quality multiplier from lognormal for to calculate effective values

Capacity theta as max cap from lognormal. Currently also same for all 4 channels

Marketing-to-Revenue Funnel

We model the ad spend to revenue process in four stages:

1. Spend → Impressions

Ads are purchased at a cost-per-thousand impressions (CPM).

$$Impressionsper\$ = \frac{1000}{\mathrm{CPM}_{\mathrm{eff}}}$$

where $\mathrm{CPM}_{\mathrm{eff}}$ is adjusted for channel quality.

2. Impressions → Clicks

A fraction of impressions convert to clicks at the click-through rate (CTR). The CTR is quality-adjusted and capped at 5% for realism:

$$Clicksper\$ = \frac{1000}{\mathrm{CPM_{eff}}} \cdot \mathrm{CTR_{eff}}$$

3. Clicks → Leads

A fraction of clicks convert to leads at the click-to-lead conversion rate (CVR), also quality-adjusted and capped at 5%:

$$Leadsper\$(base) = \frac{1000}{\mathrm{CPM_{eff}}} \cdot \mathrm{CTR_{eff}} \cdot \mathrm{CVR_{eff}}$$

This base rate defines the initial slope of the saturation curve.

4. Leads $\rightarrow$ SQL $\rightarrow$ Wins $\rightarrow$ Revenue

Leads pass through two sales funnel stages:

$$p_{\ell \to s} = 0.25, \quad p_{s \to w} = 0.15$$

where $p_{\ell \to s}$ is the probability of a lead becoming a sales qualified lead (SQL), and $p_{s \to w}$ is the probability of an SQL converting to a win.

Let $\mathrm{AOV}^{\mathrm{sale}}$ be the average contract value per sale. The effective average order value per lead is:

$$\mathrm{AOV}^{\mathrm{eff}} = \mathrm{AOV}^{\mathrm{sale}} \cdot p_{\ell \to s} \cdot p_{s \to w}$$

Response Curve (exponential saturation curve)

Revenue from spend S: We model leads generated from spend S using an exponential saturation curve:

$$\text{Leads}(S) = \theta\left(1 - e^{-\beta S}\right)$$

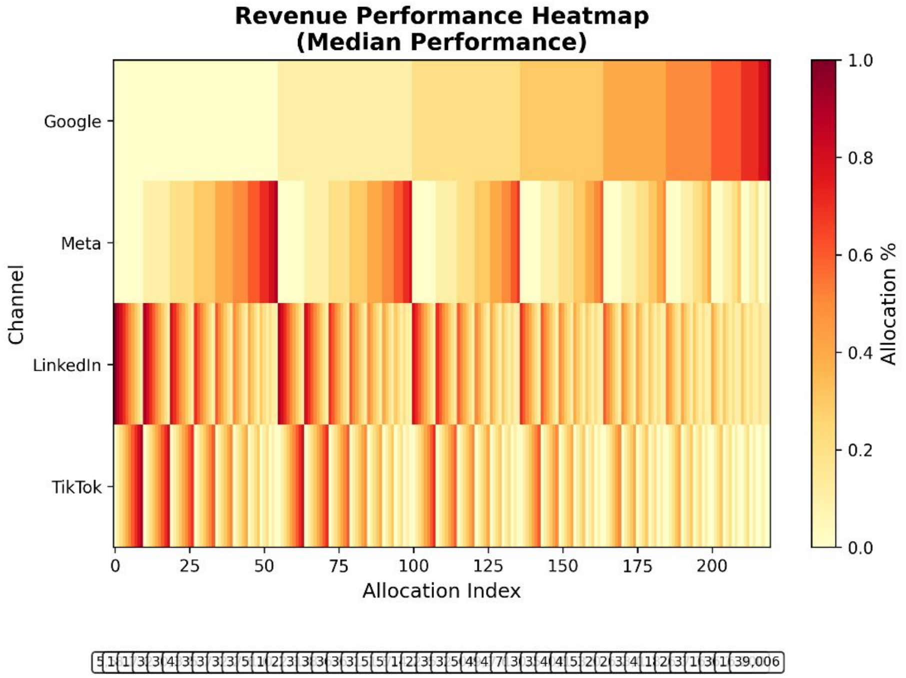
where θ is the maximum lead capacity and $\beta = \frac{base}{\theta}$ ensures the initial slope matches the base rate.

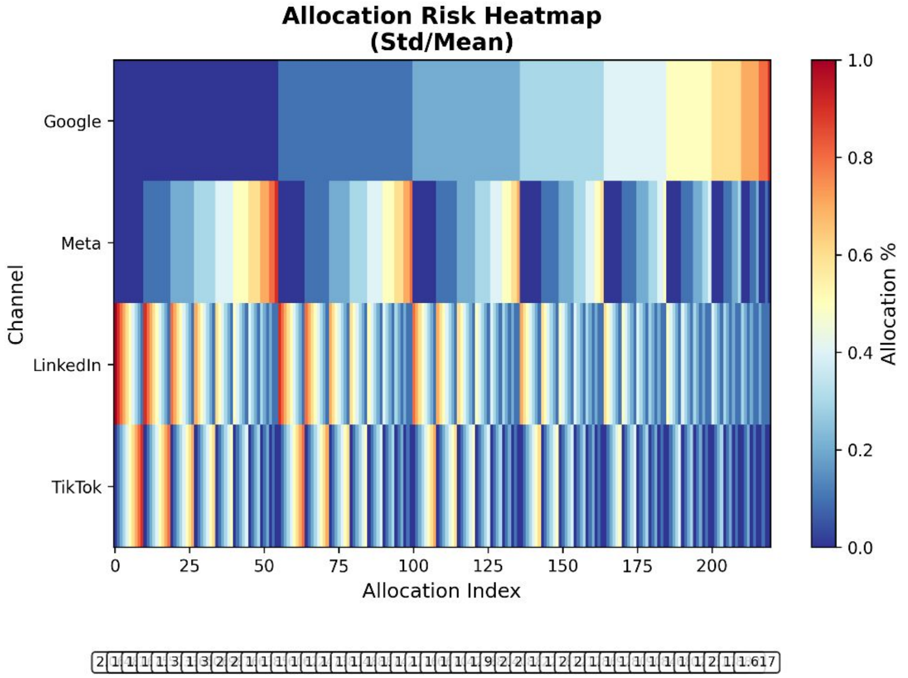
The revenue is then:

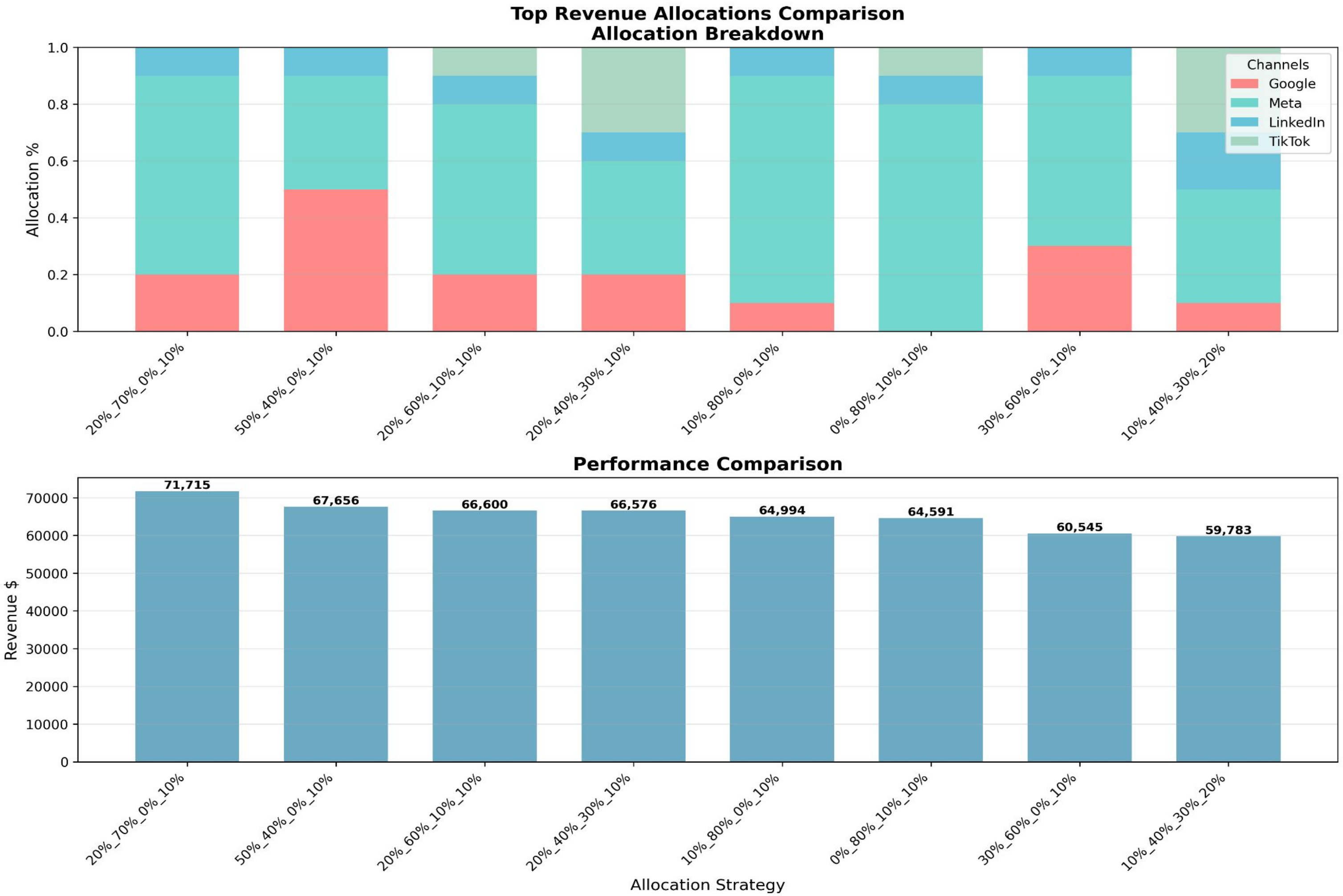
$$R(S) = \text{Leads}(S) \cdot \text{AOV}^{\text{eff}}$$

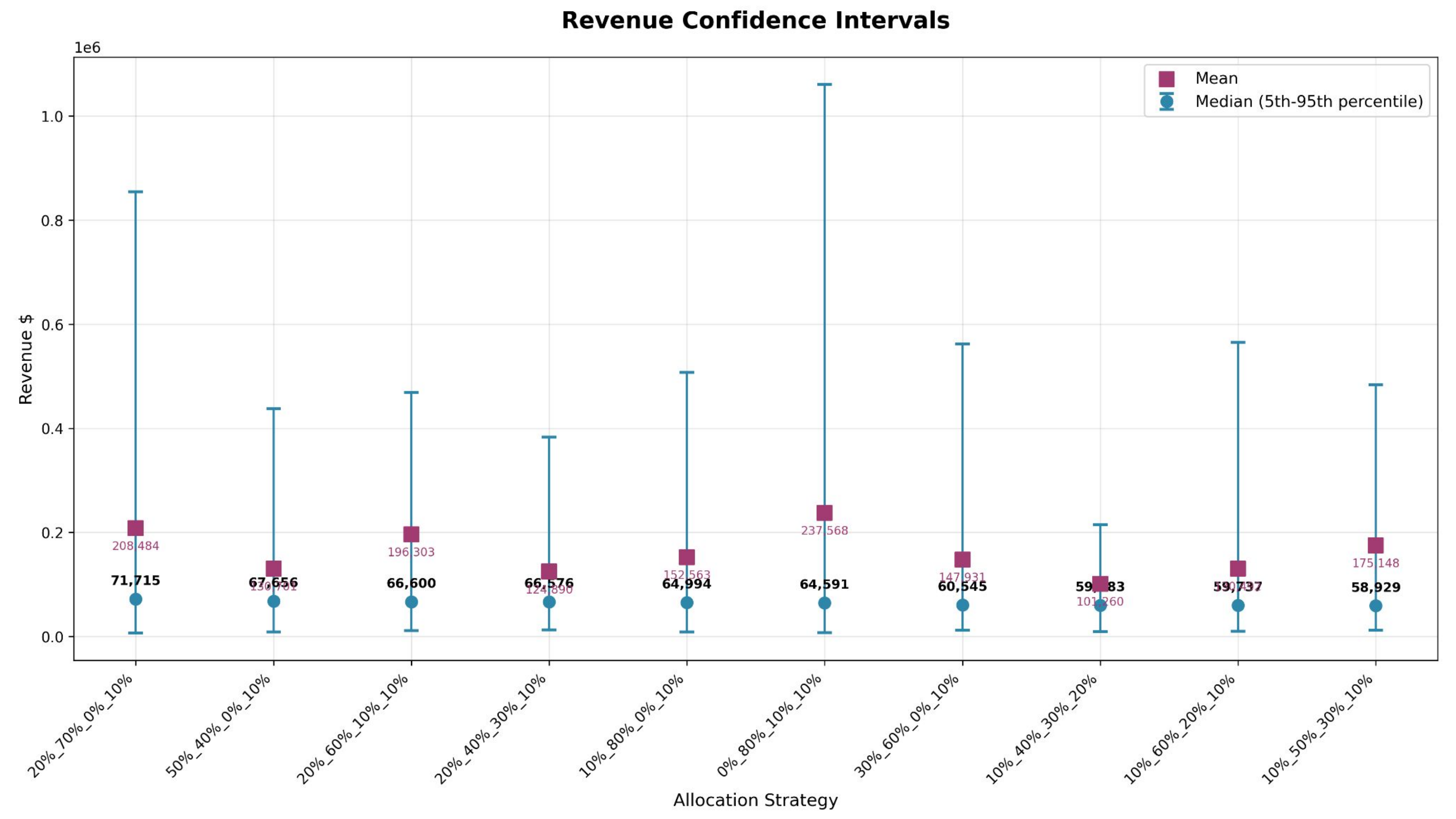
Monte Carlo Simulation + Grid Exploration as shown in demo

Allocation Heatmap






Top Revenue Allocations Comparison
Allocation Breakdown
Allocation %
1.0
0.8
0.6
0.4
0.2
0.0
Channels
Google
Meta
LinkedIn
TikTok
20%_70%_0%_10%
50%_40%_0%_10%
20%_60%_10%_10%
20%_40%_30%_10%
10%_80%_0%_10%
0%_80%_10%_10%
30%_60%_0%_10%
10%_40%_30%_20%
Performance Comparison
Revenue $
70000
60000
50000
40000
30000
20000
10000
0
71,715
67,656
66,600
66,576
64,994
64,591
60,545
59,783
20%_70%_0%_10%
50%_40%_0%_10%
20%_60%_10%_10%
20%_40%_30%_10%
10%_80%_0%_10%
0%_80%_10%_10%
30%_60%_0%_10%
10%_40%_30%_20%
Allocation Strategy



Revenue Confidence Intervals
1e6
Revenue $
Allocation Strategy
Mean
Median (5th-95th percentile)
0.0
0.2
0.4
0.6
0.8
1.0
208,484
71,715
67,656
196,303
66,600
66,576
152,563
64,994
237,568
64,591
147,931
60,545
101,260
175,148
58,929
20%_70%_0%_10%
50%_40%_0%_10%
20%_60%_10%_10%
20%_40%_30%_10%
10%_80%_0%_10%
0%_80%_10%_10%
30%_60%_0%_10%
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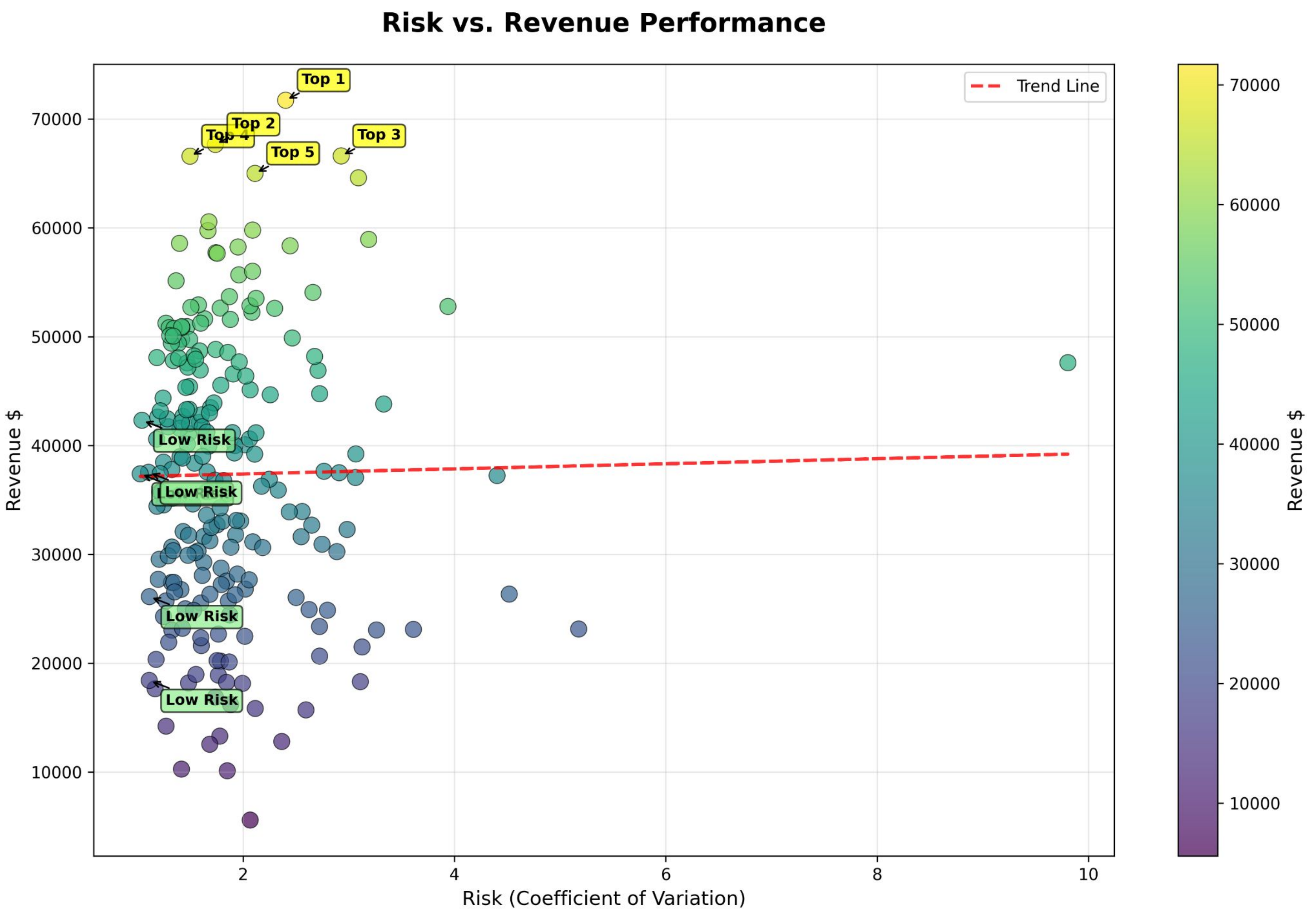
10%_50%_30%_10%



Risk vs. Revenue Performance
Top 1
Top 2
Top 3
Top 4
Top 5
Low Risk
Low Risk
Low Risk
Low Risk
Trend Line
Revenue $
Risk (Coefficient of Variation)
70000
60000
50000
40000
30000
20000
10000
2
4
6
8
10
Revenue $

Assumptions & Trade offs

Assumptions

- **Channel Independence:** Each channel's performance is modeled independently; no cross-channel cannibalization or halo effects.
- **Fixed Funnel Rates:** Lead→SQL and SQL→Win rates are constant; in reality, these may vary with spend, seasonality, or targeting.
- **Capped CTR/CVR:** Click-through and conversion rates are capped at 5% to avoid unrealistic upside scenarios, especially for B2B contexts.
- **Coarse Grid Resolution:** Budget allocations are explored in 10% increments, trading off precision for computational simplicity.

Trade-offs

- **Grid Exploration Scalability:** The combinatorial space grows quickly with finer steps, making grid search computationally expensive for higher resolution or more channels.
- **Priors Dominating:** With no observed data, priors largely determine results. This is reasonable for early modeling but limits data-specific insights.
- **High Uncertainty:** Variance in results is expected due to limited empirical constraints; uncertainty reflects lack of real-world calibration.
- **Small Simulation Size:** Current simulation count (n=220) is low; this limits accuracy in estimating metrics like the risk–revenue curve. Higher n (≥10,000) would yield more stable estimates.

Next Steps

1. **Increase Simulation Runs** — Move from n=220 to n=10,000+ to stabilize risk/revenue estimates and percentiles.
2. **Refine Priors with Data** — Replace generic benchmarks with channel-specific historical data to shift from prior-dominated to posterior-informed results.
3. **Experiment with Optimization Methods** — Replace coarse grid search with more efficient algorithms (e.g., genetic algorithms, Bayesian optimization, NSGA-II) for finer allocation precision without excessive computation.(if required)
4. **Incorporate Spend–Rate Interactions** — Allow CTR/CVR/funnel rates to vary with spend to capture diminishing marginal quality.
5. **Model Cross-Channel Effects** — Introduce interaction terms or constraints to capture halo/cannibalization between channels.
6. **Sensitivity Analysis** — Quantify how changes in priors or funnel assumptions impact optimal allocations to identify the most influential variables.