# ZOMATO UNIT ECONOMICS & RISK SIMULATOR (FY24)

Monte Carlo Based Profitability Model

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# WHY MODEL UNIT ECONOMICS?

- Food delivery profitability is highly sensitive to small fluctuations in AOV, CAC, refunds, and rider payouts
- Static Excel models hide risk because they assume fixed averages
- Real-world costs behave like distributions, not constants
- Monte Carlo helps quantify risk of loss per order (vs. point estimates)
- Goal: simulate volatility, identify failure points, and test strategy levers

# FY24 OPERATING INPUTS USED IN THE SIMULATOR (ZOMATO ACTUALS + INDUSTRY RANGES)

- This simulator is built on Zomato's FY24 food-delivery metrics and realistic industry cost distributions. These assumptions form the baseline for the Monte Carlo model.
- These parameters define the statistical "shape" of unit economics and allow us to simulate 10,000 realistic profit outcomes instead of a single static estimate.

| Driver | Value Used | Source / Logic |
|---|---|---|
| **AOV (Mean)** | ₹428 | Zomato FY24 AOV |
| **AOV (Std Dev)** | ₹50 | Basket size volatility |
| **Commission Rate** | 22.5% | Typical take rate |
| **Delivery Fee** | ₹33 | FY24 average per order |
| **Rider Cost (Mean)** | ₹32 | Industry avg payout |
| **Rider Cost (Std Dev)** | ₹10 | Traffic/rain variability |
| **Packaging Cost** | ₹12 | Restaurant reimbursement |
| **CAC/Marketing Cost** | ₹20 (SD 10) | FY24 marketing allocation |
| **Refund Probability** | 2% | Cancellations/refunds |
| **Refund Loss Amount** | = AOV | Full order value lost |
| **Payment Gateway Fee** | 2.4% of AOV | Standard MDR |
| **Monthly Orders (FY24)** | ~66 million | GOV ÷ AOV |

# THE “GOLDEN EQUATION” OF PROFIT PER ORDER (UNIT ECONOMICS FRAMEWORK)

- Zomato’s profitability fundamentally depends on how revenue and variable costs behave at the order level.
- This equation defines how every assumption in the model flows into profit:

**Net Profit per Order = Revenue per Order - Cost per Order**

Revenue Components

- Revenue = (AOV × Commission Rate) + Delivery Fee
- Commission = Platform take rate from restaurant
- Delivery Fee = Paid by customer

Cost Components

- Costs = Rider Cost + Packaging Cost + CAC/Marketing + Payment Gateway Fee + Refund Loss
- Rider Cost: Payout to delivery partner (varies with traffic, rain → modeled as Normal dist.)
- Packaging Cost: Reimbursement/charge per order
- CAC / Marketing Cost: Spread across acquired users
- Gateway Fee: % of AOV (typically 2–3%)
- Refund Loss: = AOV × (refund probability)

**Example: FY24 Average Order (Illustration)**

- AOV = ₹428
- Commission (22.5%) = ₹96.3
- Delivery Fee = ₹33 → **Revenue ≈ ₹129.3**
- Rider Cost ≈ ₹32
- CAC ≈ ₹20
- Packaging ≈ ₹12
- Gateway Fee ≈ ₹10.3
- Refund Cost (2% × AOV) ≈ ₹8.5
  → **Total Cost ≈ ₹82.8**
- **Net Profit ≈ ₹46.5 per order**
- *(This matches the baseline simulation output)*

*This equation converts Zomato’s operating model into a simulation-ready financial structure, enabling risk and profitability modeling across thousands of scenarios.*

# MONTE CARLO SIMULATION: MEASURING PROFITABILITY & RISK UNDER REAL WORLD UNCERTAINTY

- Traditional unit economics assume fixed costs. But in reality, rider payouts, CAC, refunds, packaging, and AOV fluctuate daily.
- Monte Carlo simulation introduces *probability* into the equation — generating thousands of possible outcomes instead of just one number.
- This allows Zomato to measure profit volatility, downside risk, and sensitivity to operational changes.

**How the Simulator Runs (Step-by-Step):**

- **Randomly generates 10,000 "virtual orders"**
  Each order has:
  - AOV drawn from a Normal distribution
  - Rider cost drawn from a Normal distribution
  - CAC drawn from a Normal distribution
  - Refund occurrence drawn from a Bernoulli distribution (0 or 1)
- **Applies the Golden Equation** to every order
  Net Profit = Revenue – Costs
  (using that order's random variables)
- **Creates a Profit Distribution**
  Instead of one number, you get a curve of outcomes (your bell-shaped graph).
- **Calculates Key Risk Metrics:**
  - Average profit per order
  - Probability of loss (profit < 0)
  - Range of best-case and worst-case outcomes
- **Scales this to Monthly Profit** using FY24 volumes (~66M orders per month)

**Why Monte Carlo Is Valuable for Food Delivery:**

- **Captures real operational uncertainty**
  Rider with rain, traffic, peak costs vary ours.
- **Models edge cases**
  High refund days, spikes in CAC, festival demand.
- **Shows the downside risk of decisions**
  Example: Increasing delivery fee lowers loss risk but reduces order volume.
- **Helps design pricing, commissions, and incentives**
  By seeing which variables matter most.
- **Transforms unit economics from static to probabilistic**

*Monte Carlo simulation converts Zomato's unit economics into a predictive risk engine — enabling smarter decisions on pricing, incentives, and profitability levers.*

# BASELINE SIMULATION RESULTS (10,000 ORDERS)

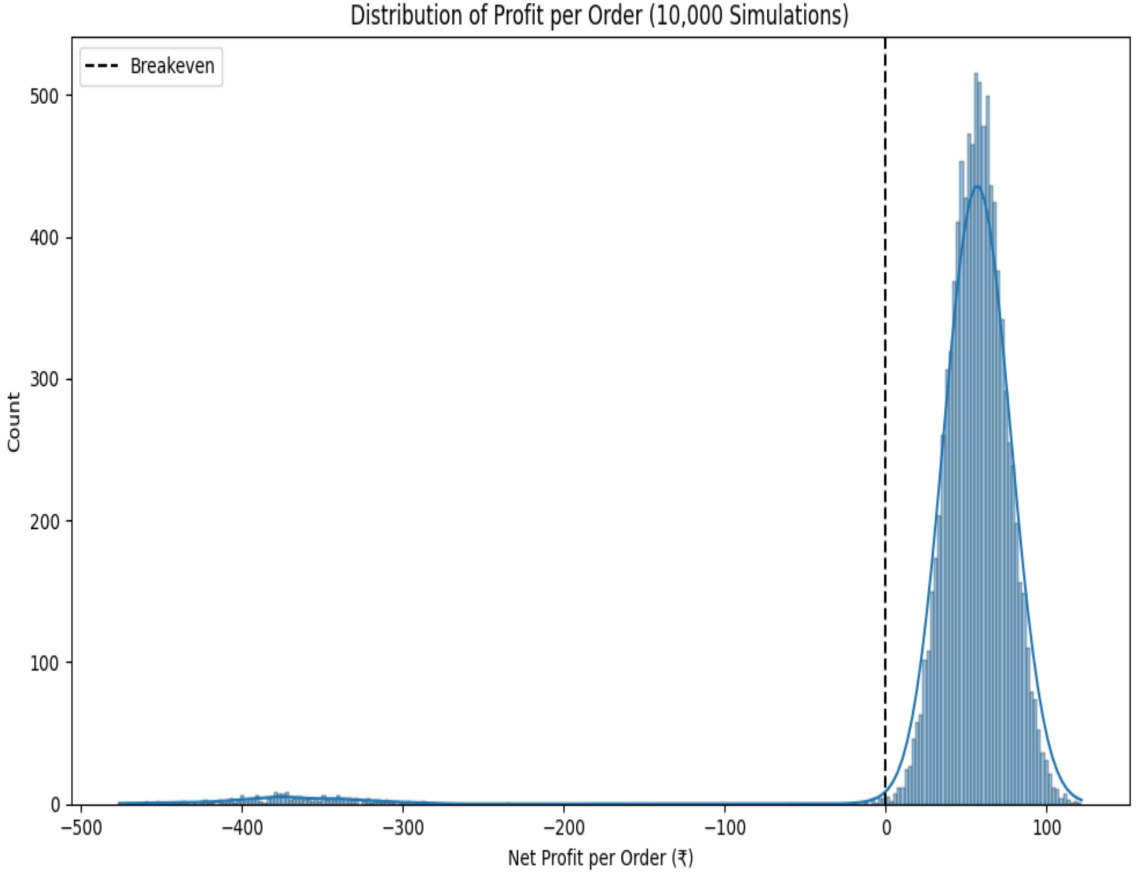
**Baseline (FY24 Inputs):**

- Avg Profit/order: **₹48.26**
- Loss Risk: **2.20%**
- 5th–95th Percentile Range: **₹10** → **₹100**
- Monthly Orders: **~66M**
- Monthly Profit: **₹318.5 Cr**

**Interpretation:**

- Unit economics are **solidly profitable**.
- Loss-making orders are **rare (~2%)**.
- Profit distribution is **stable + predictable**.

**Baseline Profit Curve (10,000 Orders)**




**What the Curve Shows:**

- Most orders cluster at **₹45– ₹60 profit**.
- Upside driven by efficient delivery days.

**Implications:**

- Strong baseline before optimization.
- **Rider volatility**, **refunds**, and **CAC** are the **biggest levers**.

*Baseline FY24 economics show strong profitability with limited downside risk.*

# SCENARIO TESTING: EVALUATING PROFIT & RISK IMPACT ACROSS FIVE STRATEGIC LEVERS

Using Monte Carlo, we test how changes to pricing, refunds, rider costs, CAC, and commissions shift profitability and downside risk.

**Lever A — Delivery Fee (+₹5)**
**Goal:** Increase per-order revenue
**Risk:** Slight customer churn

**Lever B — Refund Probability (2% → 1%)**
**Goal:** Reduce refund-related losses
**Risk:** Lower new-user trust if refund policies tighten

**Lever C — Rider Cost Variance (SD 10 → 6)**
**Goal:** Stabilize delivery payouts
**Risk:** Potential rider dissatisfaction / slower supply response

**Lever D — Reduce CAC (₹20 → ₹10)**
**Goal:** Lower marketing spend per order
**Risk:** Slower user growth

**Lever E — Increase Commission (22.5% → 25%)**
**Goal:** Increase take rate from restaurants
**Risk:** Possible restaurant churn to competitors

**Why These 5?**
These five variables create 90% of Zomato's profit volatility:

- Delivery fee → revenue driver
- Refunds → pure downside loss
- Rider variance → operational unpredictability
- CAC → marketing efficiency
- Commission → platform monetization

**Together, they represent the core levers Zomato can realistically adjust.**

*These scenarios quantify how operational changes translate into profit shifts and risk reductions.*

# SCENARIO RESULTS: PROFITABILITY & RISK COMPARISON

| Scenario | Avg Profit / Order (₹) | Loss Risk (%) | Monthly Profit (₹ Cr) |
|---|---|---|---|
| **Baseline (FY24)** | **48.26** | **2.20%** | **318.5** |
| **A. +₹5 Delivery Fee** | 51.31 | 1.82% | 328.5 |
| **B. Refund ↓ (2% → 1%)** | 52.70 | **1.02%** | 337.4 |
| **C. Rider Cost Variance ↓** | 47.49 | 2.24% | 310.3 |
| **D. CAC ↓ (₹20 → ₹10)** | **59.27** | 1.82% | **371.6** |
| **E. Commission ↑ (22.5% → 25%)** | 58.24 | 2.20% | 376.7 |

*(All scenarios simulated using 10,000 Monte Carlo runs and scaled to FY24 monthly volumes)*

**Key Takeaways**

- **Biggest profit upside:** Reducing CAC and increasing commission
- **Lowest downside risk:** Reducing refund probability
- **Most stable economics:** Lower rider cost variance
- **Trade-offs exist:** Higher profits often come with churn or growth risk

*Not all profit levers are equal — CAC efficiency and refunds deliver the best risk-adjusted gains.*

# KEY INSIGHTS & STRATEGIC RECOMMENDATIONS

**KEY INSIGHTS**

- **Zomato's FY24 unit economics are structurally profitable**
  Baseline profit of ~₹48/order with low downside risk (~2%).
- **Not all levers deliver equal risk-adjusted returns**
  Some increase profit but introduce churn or growth risk.
- **Refund probability is the most effective risk reducer**
  Cutting refunds from 2% → 1% halves loss risk with minimal volume impact.
- **CAC efficiency unlocks the largest profit upside**
  Reducing CAC delivers the highest improvement in monthly profit.
- **Commission increases boost profit but carry ecosystem risk**
  Higher take rates risk restaurant churn over time.

**STRATEGIC RECOMMENDATIONS**

**1. Prioritize Refund Reduction (Low Risk, High Stability)**

- Improve order accuracy, packaging standards, and customer communication.
- Delivers the **lowest loss risk (≈1%)** with limited demand impact.

**2. Focus on CAC Efficiency, Not Absolute Cuts**

- Shift from blanket discounts to targeted, cohort-based incentives.
- Preserves growth while capturing **₹50+ Cr monthly upside**.

**3. Use Delivery Fee Increases Selectively**

- Apply dynamic pricing during peak demand and high congestion periods.
- Increases profitability without broad-based churn.

**4. Treat Commission Increases as a Secondary Lever**

- Pair higher commissions with restaurant value-adds (ads, analytics).
- Avoid long-term platform disintermediation risk.

**5. Improve Rider Cost Predictability, Not Suppression**

- Use surge pricing and routing optimization instead of hard cost caps.
- Stabilizes operations without triggering supply shocks.

*The optimal strategy combines refund reduction and CAC efficiency first, with pricing and commission levers used selectively.*

# SENSITIVITY ANALYSIS: MONTHLY PROFIT IMPACT OF PRICING LEVERS

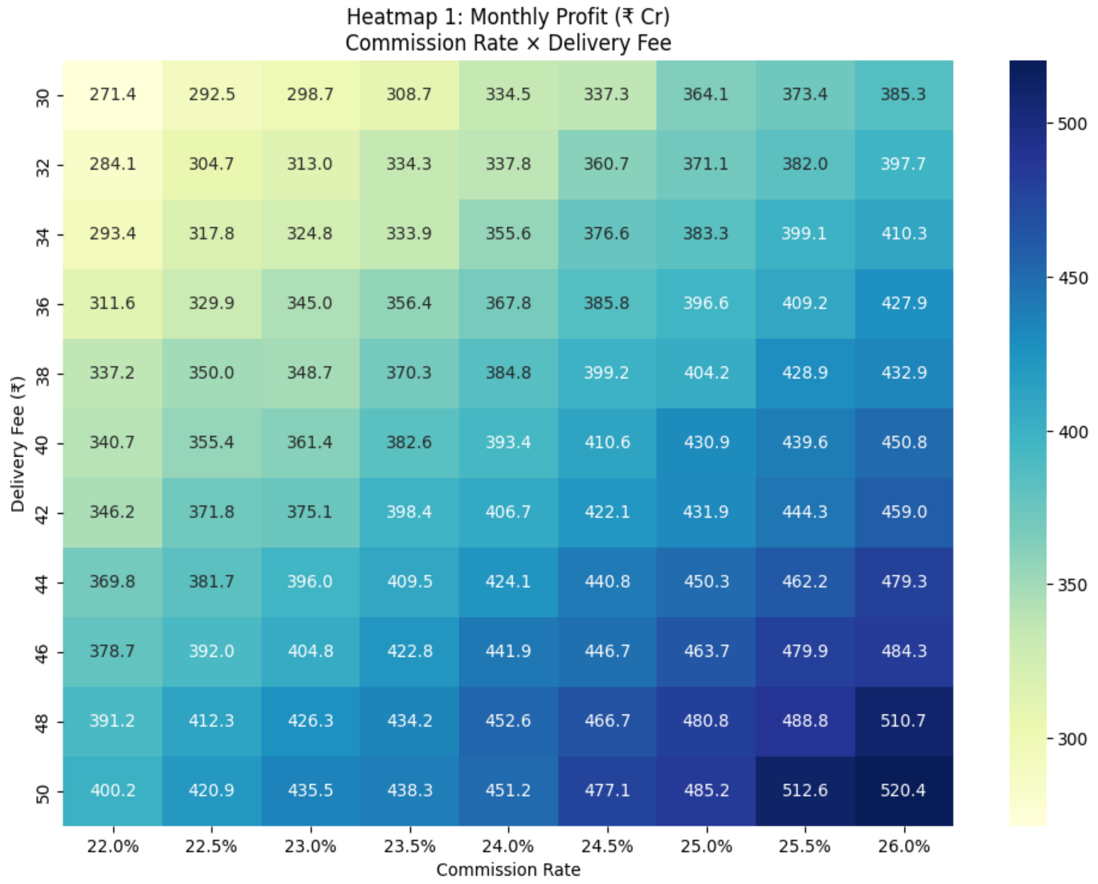
❖ **Monthly Profit Sensitivity (₹ Cr)**
**Commission Rate × Delivery Fee**

**What this shows:**

- Profit increases **monotonically** with higher commission and delivery fees
- **Delivery fee** increases have a **linear impact**
- **Commission** increases have a **compounding impact at scale**

**Insight:**

- Pricing levers are powerful
- Should be applied **selectively** to avoid customer or restaurant churn




*Pricing decisions materially impact profitability, but scale effects amplify commission changes.*

# SENSITIVITY ANALYSIS: LOSS RISK RESPONSE TO REFUND PROBABILITY

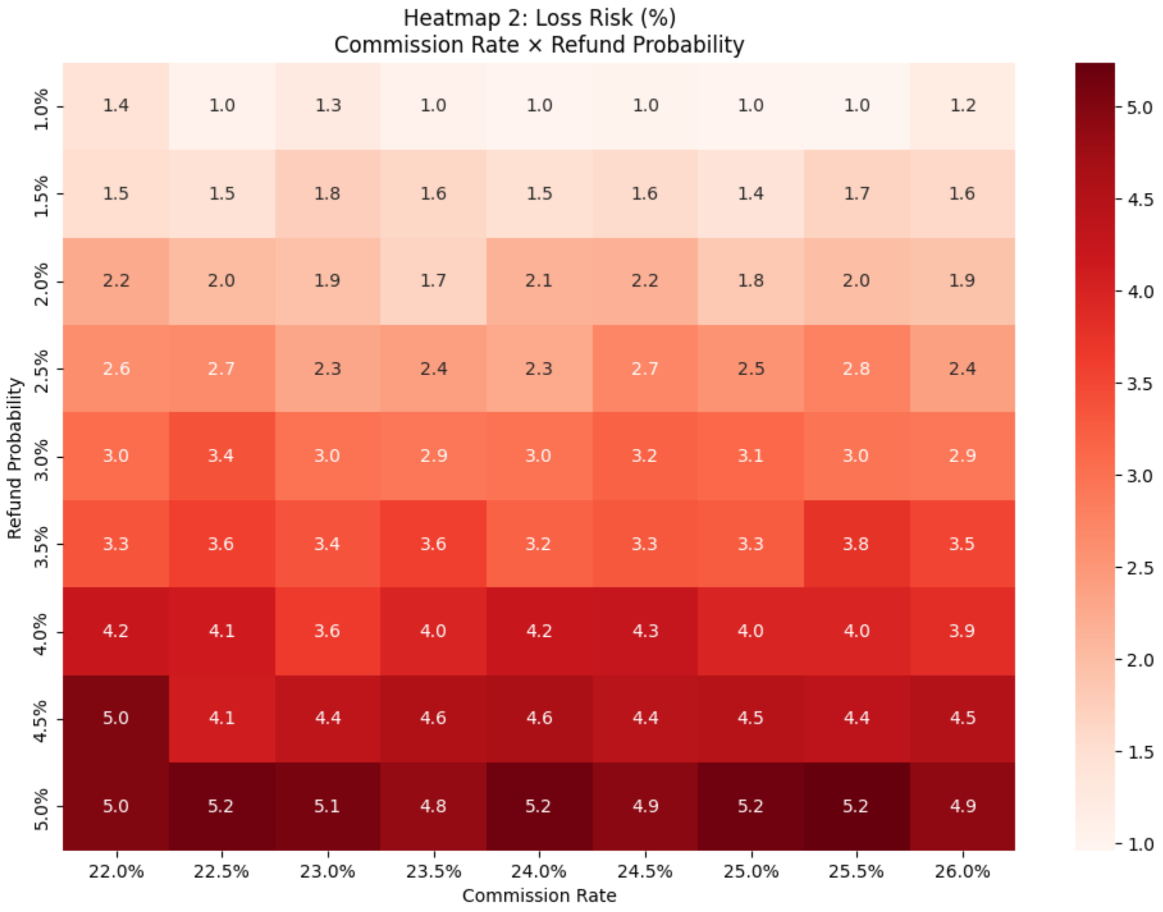
**Loss Risk Sensitivity (%)**
**Commission Rate × Refund Probability**

**What this shows:**

- **Refund probability is the dominant driver of downside risk**
- Higher commission **cannot offset high refund rates**
- Loss risk rises sharply beyond **~3–4% refund probability**

**Insight:**

- Operational quality and order accuracy matter more than monetization for risk control




*Refund control is the single most effective lever for reducing loss-making orders.*

# LIMITATIONS, ASSUMPTIONS & NEXT STEPS

**KEY ASSUMPTIONS**

- FY24 averages used for AOV, commissions, and order volumes
- Cost drivers modeled as independent probability distributions
- Order volume elasticity applied conservatively at scenario level
- Competitive landscape assumed stable in the short term

**LIMITATIONS**

- Does not model **long-term customer or restaurant churn dynamics**
- Cross-effects between levers (e.g., higher fees → refunds) not fully captured
- City-level, time-of-day, and cohort-level variations not modeled
- Results indicate **directional strategy impact**, not exact forecasts

**NEXT STEPS**

- Add **cohort-based demand and churn modeling**
- Extend simulator to **city-level and peak/off-peak analysis**
- Integrate **real-time operational data** for live decision support
- Use simulator as a **pricing & policy experimentation tool**

Code & Simulation Notebooks:
*https://github.com/Kushagra-1210/Zomato-Unit-Economics-Simulator.git*

*This simulator is a strategic decision-support tool — not a static forecasting model.*