Accuracy Targets when Forecasts Influence Outcomes

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Motivation - feedback effects from forecasts

Economic forecasts often influence the outcomes they are trying to predict, thus leading to limits on predictability whenever the feedback mechanism is not identified. Some examples in tech:

- **Intel chip shortage prediction**: publicly forecasted semiconductor shortages lead to stockpiling of chips and in turn reduce supply
- **Zillow home value forecasts**: positive forecasts spur demand in certain real estate markets and in turn lead to higher prices
- **Quotas for ad sales** (*our focus*): sales goals set based on revenue forecasts motivate sales teams to drive certain revenue outcomes

Tractable Example: trading off quota accuracy and sales rep excellence

- Sales Quotas define the minimum level of revenue a sales rep needs to collect from customers to meet expectations. Quotas are set in line with revenue forecasts to ensure they are feasible but not too easy
- Quotas very different than actuals is worrying: are sales reps unable or unmotivated to hit their target?
- But quotas equal to actuals is also worrying: shouldn’t we expect some sales reps to beat our expectations?
- **Our goal**: define the accuracy “sweet spot” (i.e., the forecast error variance which optimizes this tradeoff)

Why quotas ≠ actuals?

Total Forecast Error	=	**(1) Estimation Error** *Model is correct, but not enough data. Or true model is just noisy.*	+	**(2) Instability Error** *Model no longer captures the right dynamics after a change in economic or business conditions.*	+	**(3) Feedback Effects** *Model output changes the outcome it is predicting.*

Assumption: (1) & (2) can be reduced indefinitely to zero by investing in better data and better models with better models and data

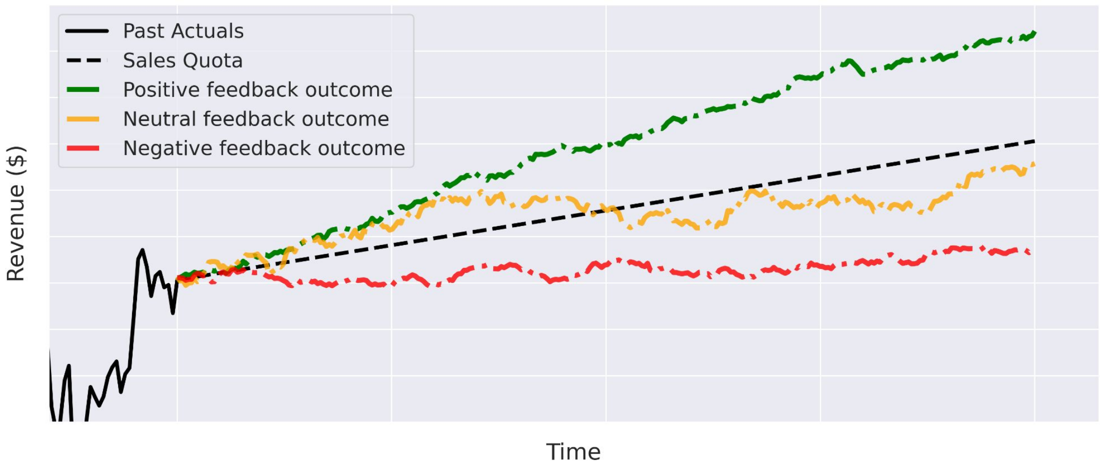
Proposition: we can lower bound (3) based on simple compensation and performance guidelines- this allows us to define “best-case accuracy”

Assumption 1: quotas work as intended

Positive Feedback (*assumed*): sales reps are motivated and able to deliver on quotas, and quotas are set based on fair and feasible stretch goals

Neutral Feedback: sales reps have limited influence on revenue, and quotas are set based on stable expectations of the future which are not very sensitive to sales effort

Negative Feedback: sales reps are unmotivated by compensation, and unambitious quotas continue to be driven lower by a lack of motivation



Assumptions 2-3: defining ideal performance

(2) **Normal Attainment**: attainment (actual / quota) across Sales Reps follows a bell-curve, meaning reps are sufficiently diversified across clients

→ We also assume the mean is 100%, but this is not strictly required

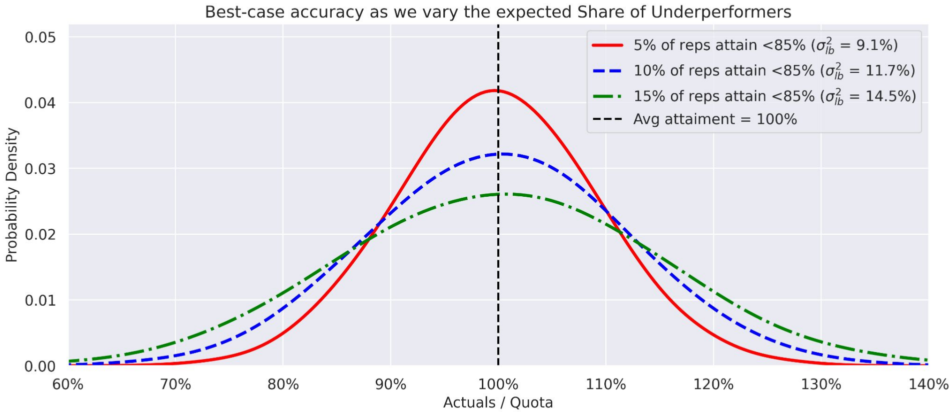
(3) **Bounds on Underperformance**: we define (i) a threshold of “good-enough” performance Y and (ii) a share of underperformers X such that:

→ We expect X% of Sales Reps to attain no more than Y% on quota

→ We let X vary between 5-15%, and Y vary between 80-90%

Simulating "best-case" forecast errors

Assumptions (1)-(3) define a lower bound on forecast error variance (σ_{lb}^2)



→ σ_{lb}^2 grows as we lower the threshold for "good enough" attainment

→ σ_{lb}^2 grows as we increase expected Share of Underperformers below threshold

Extending to higher levels of aggregation

- So far we have lower bounded the variance of percent errors ($\sigma_{lb}{}^2$) at the Sales Rep level ($var(e_i)$ where $e_i = (y_i - \hat{y}_i) / y_i$). Also define:
  - Total variance across N reps: $e_N = (\sum_i y_i - \sum_i \hat{y}_i) / \sum_i y_i)$
  - Correlation across reps $\rho = corr(e_i, e_j), i \neq j$
  - Revenue share $w_i = y_i / \sum_i y_i$
- Then:

$$\mathrm{var}(e_N) = \mathrm{var}\left[\left(\sum_{i=1}^{N} y_i - \sum_{i=1}^{N} \hat{y}_i\right) / \sum_{i=1}^{N} y_i\right] = \underbrace{\rho}_{\text{correlation}} \cdot \sigma_{lb}^2 + (1-\rho) \cdot \sigma_{lb}^2 \cdot \underbrace{\sum_{i=1}^{N} w_i^2}_{\text{concentration}}$$

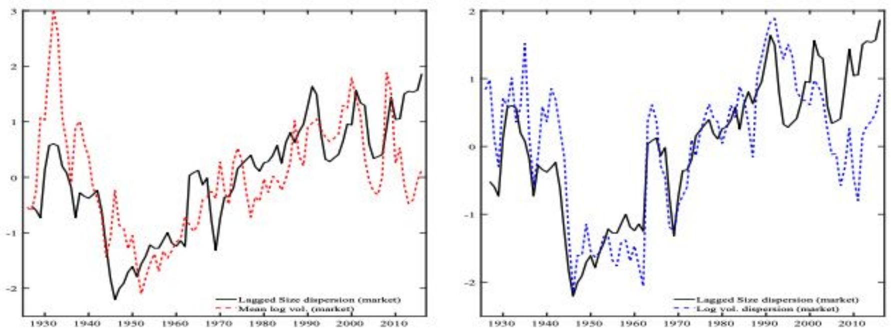
- **UB**: $var(e_N) \leq \sigma_{lb}{}^2$ with equality when $w_i = 1$ and $w_j = 0$ for all $i \neq j$
- **LB**: $var(e_N) \geq \sigma_{lb}{}^2 / N$ with equality when $w_i = 1/N$ for all i and $\rho = 0$

Determinants of revenue volatility - customer concentration

Aggregate forecast error variance is higher the more concentrated revenue is across individual Sales Reps

Consistent with economic literature (e.g., Gabaix. (2011), Herskovic et al. (2020))

Figure 1: Market-based Dispersion in Firm Size and Firm Variance



(a) Panel A: Average Log Variance (b) Panel B: Dispersion in Log Variance

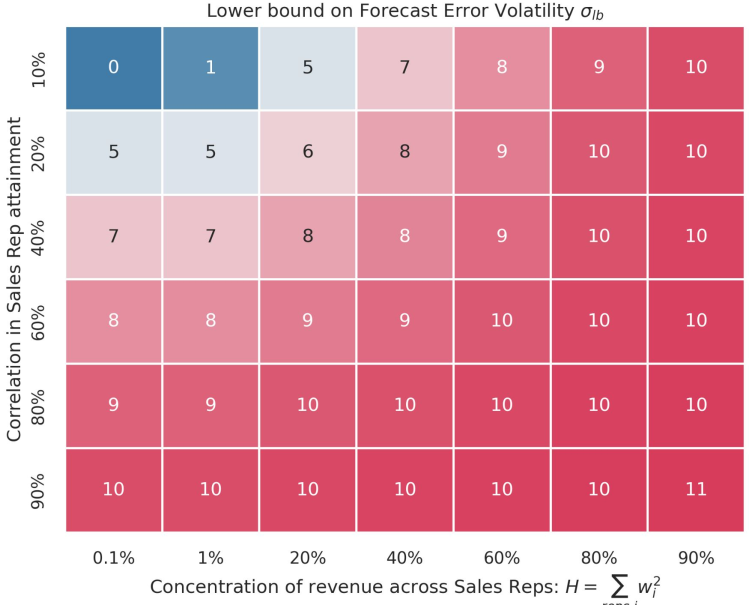
*Source: Herskovic, Kelly, Lustig, Van Nieuwerburgh (2020)

→ Intuitively, companies can **make revenue more predictable by increasing diversification** across individual Sales Reps

Determinants of revenue volatility - correlated performance

Aggregate forecast error variance is higher the more correlated performance is across individual Sales Reps

Companies can **make revenue more predictable by reducing correlated (systematic) risk exposure** across individual reps



→ Likely impossible to reduce correlation in performance to zero

Trading off profitability and predictability

- Companies must navigate the tradeoff between optimizing for revenue predictability vs. optimizing for expected revenue.
- Driven by a fat tail in the customer size distribution (i.e., revenue disproportionately concentrated in a few large customers)
- Taking on very large customers increases expected revenue but also inhibits diversification and makes revenue harder to project forward

Conclusion & Key Takeaways

- When there are feedback effects, we must incorporate the feedback mechanism in expectations about predictability
- We derive a lower bound on forecast error variance based on a statistical model of the ideal feedback mechanism for Sales Quotas
- We show that revenue volatility is a function of concentration and correlation across performance in different customer segments
  - Companies face a tradeoff between profitability and predictability
  - Consistent with economic literature on firm volatility, idiosyncratic risk, and production networks

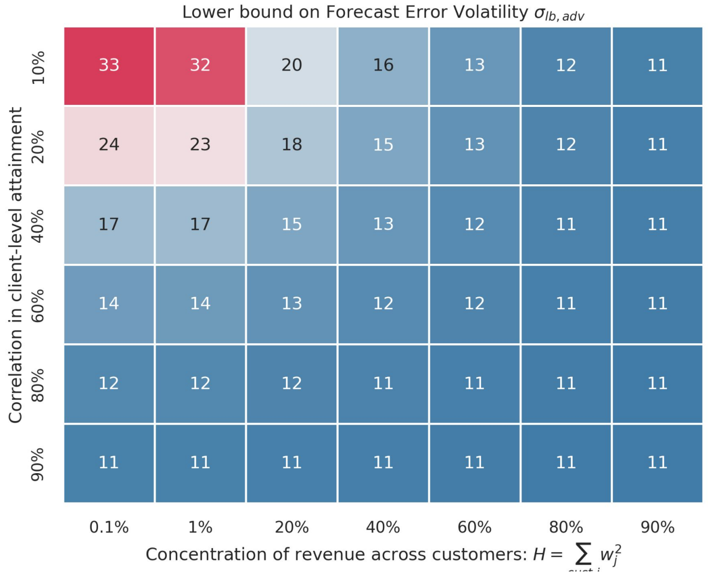
Appendix

Extending to the individual customer level

Normally distributed forecast errors likely do not exist at granular levels (i.e., tail risk in individual client performance)

Does not threaten identification at higher levels as long as forecast errors are sub-exponentially distributed

Much weaker ability to reduce instability and estimation error at this level (individual client behavior is just noisy)



→ Companies can **make revenue more predictable by increasing correlation in customers managed by the same individual rep**

Sensitivity Analysis