Project Overview – Conceptual Brief (dra

Context and Motvaton

In Swiss table tennis, each competitive player is Elo
This ratng can be thought of as a point estimate of a player's co

- A player with more Elo points is considered stronger than a player with fewe
- The diference in Elo points between two players refects how l against the other.
- When a player wins or loses a match, their E

In this sense, the Elo ranking is a system where players are ordered by points evolve over tme as matches are played.

While the Elo update rule is deterministc once a uncertain. Players face diferent opponents, matc competton can lead to very diferent ranking traj

As a competitve player, I am not interested in pr Instead, I want to understand the range of plausible outcomes
How much could my Elo realistcally increase or d

Core Idea of the Project

The key idea of the project is to treat the month as a random experiment rather than a fxed trajectory.

Instead of asking:

"What will my Elo be next month?"

the project asks:

"If this month were replayed many tmes under rea would we observe?"

To answer this question, the project uses Monte Carlo simulation: the same month is s thousands of tmes, each tme with diferent random outcom of fnal Elo points, rather than a single predicted value.

What Is Being Simulated

The project simulates the evolution of Elo over one month of competition, treatng this month as a probabilistc expe of events.

At a high level, each simulated month follows th

1. A monthly competiton is defined, consistng of league
2. For each match, an opponent is chosen, according to instituton rosters or tournament pools).

3. A probability of winning is assigned to the match.
4. A win or loss outcome is randomly drawn based on this pro
5. Elo points are updated using the ofcial Swiss Elo upda
6. The entre month is repeated many times (Monte Carlo simulaton
   distributon of possible end-of-month Elo outcomes.

The goal is not to predict a single future Elo v
plausible realizatons of the same compettve mont

All detailed modeling assumptons (competton form
and parameter values) are explicitly described in Modeling Choices & Hypothes

Why Monte Carlo Simulaton Is Used

A single month of competton is subject to substa
opponents vary in strength, and small diferences

Monte Carlo simulaton addresses this uncertainty thousands of tim
each tme with diferent random outcomes. This produces a distributon of final
values, rather than a single point estmate.

This distributon-based perspectve allows us to quantfy:

- expected Elo change,
- downside and upside risk,
- and the overall variability of ranking outcor

Role of Win Probability Modeling

A key component of the simulaton is the assignme

The project deliberately distnguishes between:

- the simulaton of match outcomes,
- the update of Elo points, which always follows the ofcial S

Two alternatve models are used to generate match

1. Ofcial Elo-based probabilities, derived directly from the Swis
2. Machine-learning-based probabilities, learned empirically from hi
   involving many players.

Importantly, the two models only difer in how match outcomes are gener
All Elo point updates use the ofcial Swiss Elo update, ensuring that the
ranking evoluton remains realistc and comparable

What Is Compared Across Simulatons

The simulaton is run separately under each proba
constant.

The comparison focuses on:

- how the distribution of monthly Elo outcomes
- whether dispersion, skewness, or tail risk d
- and how sensitive ranking uncertainty is to p

The project does not aim to declare one probabil sense. Instead, it evaluates how different modeli profiles for ranking evolution.

Output of the Project

The final outputs of the simulation are:

- distribution of end-of-month Elo values,
- summary statistics (mean, quantiles),
- and visual comparisons between scenarios.

These outputs form the basis for interpretation,

Transition to Modeling Choices & Hypotheses

The remainder of the project formalizes the elem In particular, the Modeling Choices & Hypotheses section specifies:

- the exact structure of a competitive month,
- opponent sampling rules,
- win probability models,
- and the Elo update mechanism.

The code implementation is expected to follow the additional assumptions.

Research Question

How uncertain are the short-term Elo evolutions of a Swiss table tennis month of competition, and how sensitive is this uncertainty to mod (official Elo-based probabilities versus realistic alternative

Modeling Choices and Hypothes

Scope and Objective of the Model

The objective of the model is not to predict a distribution of short-term ranking outcomes for a Swiss table t The model therefore focuses on variability rather than point fore

The analysis is restricted to a time horizon of one month, which allows the model to remain interpretable while captur evolution.

Structural Assumptons on Competton Fo

A month of competton is modeled as a fxed and s to approximate a realistc compettve workload rat

The player is assumed to partcipate in:

- two league, each consisting of three individual matches
- one natonal. tournament

To ensure a consistent number of matches across a hypothetcal placement-based structure that guarantees a fxed work tournament is assumed to involve four group-stage ... placement, yielding a total of tournament matches

This structure does not refect the standard Swiss tournament s reduce the number of matches played to approximate the intensity of competton over a month while r Monte Carlo simulatons. The implicatons of this

Match Outcome Assumptons

Each match outcome is modeled as a binary variable (win or loss).

- Match scores, set diferences, and margin of v
- The efect of these omited variables is implic

Match outcomes are assumed to be conditionally independent, given the ... that any dependence between matches operates onl tme.

Opponent Sampling Assumptons

Opponents faced by the player during the month for the natonal tournament, refectng the institut

League opponents (club-based selection), roster

For league play, the opposing club's roster is assumed fxed at the beginning of the league. For each of faced by the player is modeled as a random draw from

To refect selecton paterns in team matches, the assumed to be proportional to observed participation (e.g., the number of matches played by that player divided by the tot

Tournament opponents (A/B pool with no rematches

For the natonal tournament, eligible opponents database, restricted to players in the A and B series. This restriction refec player partcipates only in tournaments whose re series, and it ensures that the analysis remai competitive level.

In the baseline model, opponents are sampled u

minimal tournament realism without

an opponent has been faced in the tournament,

tournament simulation. This approximation captures

repeated matchups, while remaining computationall

Win Probability Models

To simulate match outcomes within the Monte Carl

probability that the focal player wins a given m

probability models are considered: an Elo-based and a machine l

model. The purpose of this comparison is not to

but to assess how sensitive ranking uncertainty i

Elo-Based Probability Model

In the first approach, win probabilities are com

formulation. Under this model, the probability that the player wins is a function of the

difference between their Elo ratings and is given

$$(\text{wins against}) = \frac{1}{1+10^{\,/400}}$$

where and denote the Elo ratings of players and, respectively.

This formulation is directly embedded in the Swi

theoretical benchmark. It assumes that the Elo rating fully s

outcomes are probabilistically determined by ratn

Machine Learning Probability Model

The second approach replaces the fixed Elo-based probab

estimate learned from historical match data.

Rather than imposing a predefined functional re

probabilities, the machine learning model infer

matches. Conceptually, the model learns how Elo characteristics of

and uses this information to estimate the probabilit

To avoid player-specific overfitting and to ensure general a

is trained on a dataset comprising many historical Sw

than only matches played by the focal player. Th

player within the Monte Carlo simulation.

Minimal Feature Specification

In line with the objective of maintaining interpre

machine learning model uses a minimal feature set

- Elo rating of the focal player

- Elo ratng of the opponent

No additonal contextual variables (such as recen
included in the baseline specifcaton. This desi
remains directly comparable to the Elo-based model, as both rely on the same info

Model Choice and Interpretaton

A logistc regression model is used as the basel
deliberate trade-off between fexibility and transparency:

- Logistc regression outputs calibrated probabilites.
- Its structure closely mirrors the logistc for
  estmated from data rather than fxed a priori
- The resultng probability functon can be inter
  the Elo formula.

Importantly, the machine learning-based model is not b
constructon. It is empirically calibrated to match observed
frequencies in the data.

Role in the Monte Carlo Simulaton

Both probability models are embedded separately
structural assumptons, opponent sampling procedu
diferences observed in the resultng Elo ratngs distributon therefo
diferences in the underlying probability modeling rather than to

Interpretaton Scope

Diferences between the Elo-based and ML-based simulatons are interpre
uncertainty in probability estmaton, not as defnitve
comparison highlights how the tournament rankings uncertainty is to
in probability modeling.

Elo Update Mechanism

Afer each simulated match, the player's Elo ratn
Elo update rule. For a given match, the Elo chan

$$\Delta Elo = K \times (result - E), \quad result \in \{1, 0\},$$

where:

- $K = 15$ is the Elo adjustment factor,
- $result$ equals 1 in case of a win and 0 in case of
- E is the Elo-based win probability implied by the official Swiss ranking

The win probability is computed using the fxed Elo ratngs o

$$= \frac{1}{1 + 10^{\frac{opp - player}{200}}}.$$

Importantly, within a given month, all matches use the same player's Elo ratng at the beginning of the month

If the player participates in matches in the month, the total by the sum of individual match updates:

$$\Delta Elo_{month} = \sum_{=1} \Delta Elo$$

The player's Elo ratng at the end of the month i

$$Elo_{end} = Elo_{start} + \Delta Elo_{month}$$

where Elo_{start} denotes the Elo ratng at the beginning of

In the Monte Carlo simulaton, match-based outcomes are model or the ranking-based probability model described e always follow Swiss, ensuring that simulated ra consistent with the real-world ranking system.

Monte Carlo Assumptons

Uncertainty in rankings over Monte Carlo is modeled using

- The same month of competton is simulated repe
- Each simulaton uses independent random draws
- The collecton of fnal Elo ratngs across simul outcomes.

The number of simulatons is chosen sufciently l propertes such as quantles and variance.

Simplifcatons and Excluded Factors

Several real-world factors are intentonally excluded fro

- Physical conditon, fatgue, and injuries
- Psychological efects
- Strategic behavior and learning during tourna
- Long-term form dynamics

These exclusions are motvated by data limitatons and interpretable. Their potental impact is disc

Interpretaton Framework

The resultng Elo distribution is analogous to return ... fnancial modeling.

Diferences between distributons obtained under model uncertainty rather than purely random noise.

Methodology (Conceptual Algor

This secton describes the simulaton procedure for one-month Elo ... ratngs.
The methodology translates the modeling choices without introducing additonal specifc assumptons or impl

Step 1 – Initalizaton

At the beginning of each simulaton run:

- A focal player is defned with an inital Elo
- This Elo ratng remains fxed throughout the reference ratng for all probability and Elo u
- All model parameters (competton structure, o fxed and identcal across simulaton runs.

As a result, all variability in simulated outcor and match outcomes.

Step 2 – Defniton of the Competve Month

Each simulaton run represents one stylized month

The compettve month consists of a fxed sequence

- two league encounters, each composed of three
- one natonal tournament with a fxed total numb

The tournament structure is designed to guaran includes insttutonal constraints such as the abs

The player is assumed to partcipate in all sched

Step 3 – Opponent Selecton

For each match in the simulated month, an oppone

- League opponents: are drawn from the rosters selecton probabilites refectng observed part
- Tournament opponents: are sampled from a ranked player subject to a no-rematch constraint within the tourname

Opponent Elo ratngs are treated as known and fxe

Step 4 – Win Probability Assignment

Once an opponent is selected, a probability of w

Two alternatve probability models are considered

- Elo-based probabilites computed using the ofcial Swiss E ratng.
- Machine-learning-based probabilites estimated from historical ma the same Elo inputs.

In both cases, win probabilites depend on the fx Elo ratng.

Step 5 – Match Outcome Simulaton

Given the assigned win probability:

- The match outcome is simulated as a binary ra
- Outcomes are generated using independent ranc assigned probabilites.

This step captures the intrinsic randomness of c

Step 6 – Elo Update Calculaton

Afer each simulated match:

- An Elo change is computed using the ofcial Sv
- The expected score used in the update formula ratng and the opponent's Elo ratng.

Although Elo changes are calculated at match level, they do not affect subsequent probabilites within the same month.

The total Elo change over the month is obtained

Step 7 – End-of-Month Elo Recording

At the end of the simulated month:

- The player's fnal Elo ratng is computed as th
- This fnal Elo value represents one possible r model.

Step 8 – Monte Carlo Repetton

Steps 1–7 are repeated a large number of tmes.

Each repetton represents an alternatve but plau difering only through random opponent selecton a

This procedure generates an empirical distributon of month-end Elo ratings.

Step 9 – Aggregaton and Analysis

From the simulated distributon:

- summary statstcs (mean, variance, quantles) a
- distributonal propertes such as dispersion ar
- results are compared across probability mode

No individual simulaton run is interpreted as a
used for interpretaton.

Methodological Clarifcaton

The simulaton does nroets ualaitdsd.r teols tsperse dtihcet ffoultluorweing
queston:

Given a fxed compettve month and fxed -oEfnlo on trhe fere
Elo outcomes arises purely from randomness and p

Why This Methodology Is Consistent

- It respects the insttutonal rule that Elo ra
- It ensures full comparability across probabi
- It provides a clean additve structure for in

Expected Results and Interpre

This secton outlines the qualitatve paterns and
from the Monte pCrairolro tsoimoublsætrovnisn,g Talmeys enuemxepreictaalt
derived directly from the structure of the mod
assumptons described in the previous sectons.

The purpose of this secton is not to antcipate s
through which uncertainty arises and to defne in
results.

Expected Shape of the Elo Distributon

Given that the monthly Elo change is m-bodeveeleld a
updates, the -odifnsotnrtihbuEtlon raftnegnsd is expected to be

- approximately unimodal,
- centered around a mean close to the expected
- with dispersion increasing as the number of m

However, because individual match outcomes are b
probabilites difer from 50%, the resultng distri
mild skewness may arise lwlhyenf atvhoer epdl aoyre runifsavsoyrse
opponents.

Expected Role of Match Volume and Comp

The simulated month includes a relatvely large n a tournament.

As a result:

- the variance of the monthly Elo change is exp of a single match outcome,
- extreme positve or negatve outcomes become p moderate.

The tournament component, which introduces a b expected to contribute disproportonately to the downside risk relatve to league play alone.

Expected Impact of Fixed Elo Within th

Because the Elo ratng is held fxed throughout th

- win probabilites do not adapt to interim suc
- early wins do not mechanically increase the p

This absence of feedback implies that the total E independent realizatons. Consequently, the dis uncertainty rather than dynamic momentum efects.

This design choice is expected to yield cleaner ignoring short-term form or psycho-logical dynamics.

Expected Comparison Between Probabilit

When comparing simulations based on probability from the Elo model and a machine-learning-based probability model, several qualitatve dife

If both models produce similar average win proba change is expected to be comparable. However, higher-order distrib propertes:

- dispersion may difer if one model assigns mo
- tail risk may increase if the machine learnin present in the Elo formula,
- skewness may difer if one model systematically chances against specifc opponent segments.

Importantly, any such differences reflect model uncertainty in parameter estmaton, not as defnitve evidence of predictve sup

Expected Sensitvity to Opponent Sampl

Because opponents are sampled probabilistcally
outcomes is expected to be sensitve to the reali

Simulatons in which the player faces an unusual
populate the lower or upper tails of the distr
ranking uncertainty arises stnaolsoonlfyomfrothematoch
competton exposure.

Interpretaton Framework

The simulated Elo disrtirsikbuptroanfsalcargeouisn tteor prrettuerdn
fnancial contexts.

In this interpretaton:

- the mean Elo change represents expected perfo
- the dispersion captures ranking volatlity,
- the lower tail refects downside risk,
- the upper tail refects upside potental.

The comparison across iprnfobramboswilusisteynsimtovdeelpserntcheirvefd
to modeling assumptons, rather than providing a

Role of This Secton

This sectoncleastrabkxipsehcetsatoinswhich the empirical s
evaluated. Deviatons between observed results
informatve signals about the interacton between
stocchavsatriability.