# A CAUSAL ANALYSIS OF SKILL AND LUCK IN AGENT OUTCOMES

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Abstract. The inability to rigorously separate skill from luck in human outcomes represents perhaps the most consequential unsolved problem in social science, underpinning every question of justice, merit, responsibility, and institutional design. Despite millennia of philosophical inquiry and centuries of statistical analysis, we have lacked the mathematical foundation to quantify what portion of observed inequality reflects genuine differences in ability versus the capricious distribution of fortune. This paper provides that foundation.

We develop the first complete mathematical framework for decomposing agent outcomes into skill and luck components by integrating probability theory, decision theory, and causal inference. Our formalization defines luck as value-weighted surprise of outcomes not explained by controllable factors, enabling principled measurement of both individual events and population-level distributions. This framework fundamentally transforms our ability to address questions that have remained intractable: How much of economic inequality is attributable to circumstances versus choices? What degree of outcome variation lies beyond individual control? How should institutions account for luck when evaluating performance and allocating resources?

The implications are profound and far-reaching. This framework provides the missing analytical foundation for understanding social stratification, meritocracy, and distributive justice. It enables evidence-based policy design by quantifying the extent to which outcomes reflect factors beyond individual agency. It offers a rigorous basis for moral philosophy's treatment of responsibility and desert. And it supplies the tools necessary for evaluating whether our institutions reward skill or merely reinforce the accidents of birth and circumstance. By making measurable what was previously only intuited, this work establishes the theoretical basis for a more scientifically grounded understanding of the human condition in modern society.

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## 1. Introduction

The attribution of outcomes to skill versus luck influences judgments across domains including moral philosophy, economic policy, educational assessment, and institutional design. Despite widespread intuition that both factors matter, formal methods for separating and quantifying these contributions remain underdeveloped. This gap impedes rigorous analysis of questions such as: To what extent do observed inequalities reflect differences in ability versus circumstance? How should institutions account for luck when evaluating performance? What policies are justified when outcomes depend substantially on factors beyond individual control?

Existing approaches often conflate luck with randomness or treat it as a residual category. We propose that luck can be formally defined and measured through a multi-component framework that integrates probability (rarity of events), utility (value to the agent), and control (degree of agency over outcomes). This formalization enables quantitative analysis while preserving philosophical distinctions between different forms of luck.

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The framework addresses three interconnected problems. First, it provides a method for rating individual events on a luck scale, accounting for context-dependent information and agent-specific values. Second, it enables decomposition of outcomes into skill and luck components through counterfactual reasoning and expected value calculations. Third, it supports societal-level analysis by aggregating individual luck scores and measuring distributional properties such as luck inequality and the correlation between circumstances and outcomes.

This paper proceeds as follows. Section **??** enumerates our major contributions. Section **??** discusses the conceptual foundations and motivation. Section **??** develops the mathematical theory, including axioms, probability models, and the core luck function. Section **??** presents practical methods for rating events and decomposing skill from luck. Section **??** extends the framework to societal modeling. Section **??** examines consequences for policy and institutions. Section **??** concludes.

## 2. Contributions

This paper makes the following major contributions:

- **First Complete Mathematical Framework:** We provide the first rigorous formalization integrating probability theory, decision theory, and causal inference to decompose outcomes into skill and luck components.
- **Axiomatic Foundation:** We establish axioms ensuring theoretical soundness, including scale invariance, additivity, and proper control attribution.
- **Unified Cross-Disciplinary Theory:** Our framework bridges moral philosophy, economics, statistics, and causal inference, resolving conceptual ambiguities across disciplines.
- **Practical Measurement Methodology:** We develop implementable methods for rating events and computing luck scores from observational or experimental data.
- **Societal-Level Analysis Framework:** We extend from individual events to population dynamics, enabling measurement of luck inequality and empirical evaluation of meritocracy.
- **Causal Model of Outcomes:** We formalize relationships between circumstances, choices, and shocks, enabling variance decomposition and policy analysis.
- **Evidence-Based Foundation for Policy:** By making luck measurable, we transform philosophical debates about responsibility and justice into empirically tractable questions.

These contributions establish the theoretical foundation for a scientific approach to merit, fairness, and responsibility.

## 3. Background and Motivation

3.1. **Conceptual Foundations.** The concept of luck appears in diverse contexts with varying definitions. In ordinary language, luck refers to outcomes influenced by chance. In moral philosophy, particularly the literature on moral luck, it denotes factors outside an agent's control that affect judgments of praise or blame. In statistical analysis, luck often represents deviations from expected performance or unexplained variance.

We propose a unifying definition: luck is the value-weighted surprise of an outcome that the agent did not significantly control, relative to the agent's prior information. This definition incorporates three essential components:

- **Probability:** Low-probability events contribute more to luck than expected occurrences.
- **Value:** Events must matter to the agent; neutral outcomes are not lucky.
- **Control:** Outcomes predominantly caused by the agent's choices reflect skill rather than luck.

These components distinguish luck from related concepts. Pure randomness becomes luck only when it affects valued outcomes. Skill represents the portion of outcomes explained by controllable actions. Circumstance refers to background conditions that shape probabilities and opportunities.

The distinction between luck and skill manifests through multiple related conceptual pairs. Table **??** summarizes common terminology across disciplines, with external factors (luck) on the left and internal factors (skill) on the right. These pairs reflect different emphases—philosophical (brute luck vs. earned skill), statistical (noise vs. signal), or causal (exogenous vs. endogenous)—but all capture the fundamental dichotomy between controllable and uncontrollable outcome determinants.

| **Luck / External Factors** | **Skill / Internal Factors** |
|---|---|
| Luck | Skill |
| Chance | Ability |
| Randomness | Competence |
| Variance | Consistency |
| Noise | Signal |
| Fortune | Merit |
| Happenstance | Expertise |
| Contingency | Mastery |
| Exogenous factors | Endogenous factors |
| Brute luck | Earned skill |
| Random shocks | Preparation |
| Timing | Judgment |
| Opportunity | Capability |

Table 1. Terminology for luck versus skill across disciplines. External factors (left column) represent uncontrollable influences on outcomes, while internal factors (right column) represent controllable determinants. Different terms emphasize different aspects: philosophical (brute luck vs. earned skill), statistical (noise vs. signal), causal (exogenous vs. endogenous), or temporal (timing vs. judgment).

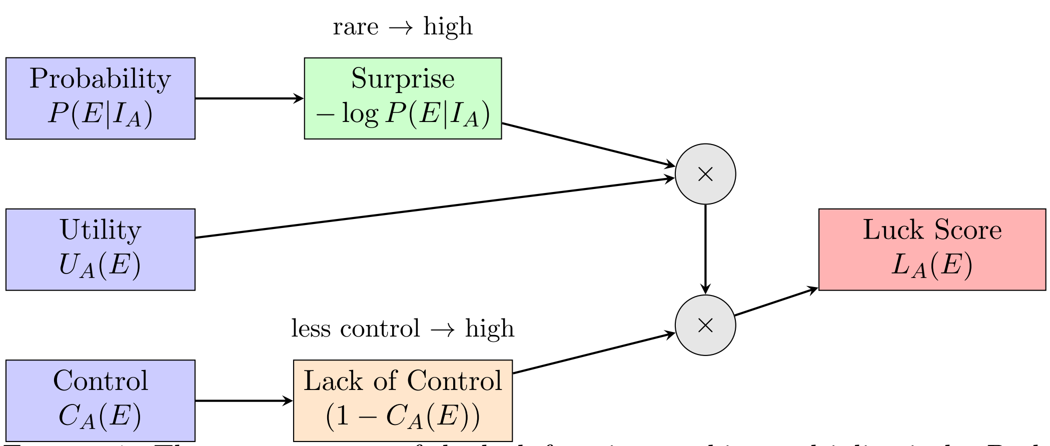



Figure 1. Three components of the luck function combine multiplicatively. Probability is transformed into surprise (rarer events score higher), control is inverted (less control increases luck), and utility provides value weighting.

3.2. **Motivation for Formalization.** Formalizing luck serves multiple purposes. In moral and political philosophy, it clarifies debates about desert and responsibility. If outcomes depend substantially on luck, claims that individuals deserve their positions become more difficult to sustain. In institutional design, understanding luck enables fairer evaluation systems that account for factors beyond individual control. In policy analysis, measuring the role of luck informs debates about taxation, social insurance, and equality of opportunity.

Empirical measurement requires precise definitions. Without formal structure, assertions about the importance of luck remain speculative. A mathematical framework enables testable predictions, quantitative comparisons across contexts, and evidence-based policy recommendations.

3.3. **Related Concepts.** Several mathematical and philosophical traditions inform this framework:

- **Probability Theory:** Provides the foundation for quantifying surprise and rare events through probability measures and information theory.
- **Decision Theory:** Supplies utility functions for valuing outcomes and expected utility calculations for separating realized outcomes from expectations.
- **Causal Inference:** Offers tools for identifying controllable versus uncontrollable factors through causal graphs and counterfactual reasoning.
- **Game Theory:** Distinguishes strategic skill from chance elements in mixed games of skill and luck.
- **Moral Philosophy:** Examines the normative implications of luck through analyses of moral luck and distributive justice.

## 4. Mathematical Framework

4.1. **Notation and Definitions.** Let $\Omega$ denote a sample space of possible events, $\mathcal{F}$ a $\sigma$-algebra on $\Omega$, and $P$ a probability measure. An agent $A$ at time $t$ possesses an information set $I_A(t) \subseteq \mathcal{F}$ representing their knowledge. An event $E \in \mathcal{F}$ occurs with conditional probability $P(E \mid I_A(t))$.

**Definition 4.1** (Agent Utility)**.** A utility function $U_A : \mathcal{F} \to \mathbb{R}$ assigns value to events from the perspective of agent $A$. Positive values represent favorable outcomes, negative values represent unfavorable outcomes, and zero represents neutral events.

**Definition 4.2** (Control)**.** The control function $C_A : \mathcal{F} \to [0, 1]$ measures the degree to which agent $A$ causally influences event $E$. $C_A(E) = 0$ indicates no control (pure chance), while $C_A(E) = 1$ indicates complete control (fully determined by agent's actions).

4.2. **Core Luck Function.** We define luck as a function of probability, utility, and control.

**Definition 4.3** (Luck)**.** The luck experienced by agent $A$ from event $E$ is:

$$L_A(E) = U_A(E) \cdot S(E \mid I_A) \cdot (1 - C_A(E)) \tag{1}$$

where $S(E \mid I_A)$ is the surprise function measuring the unexpectedness of $E$ given information $I_A$.

The surprise function $S$ quantifies rarity. A natural choice based on information theory is:

$$S(E \mid I_A) = -\log P(E \mid I_A) \tag{2}$$

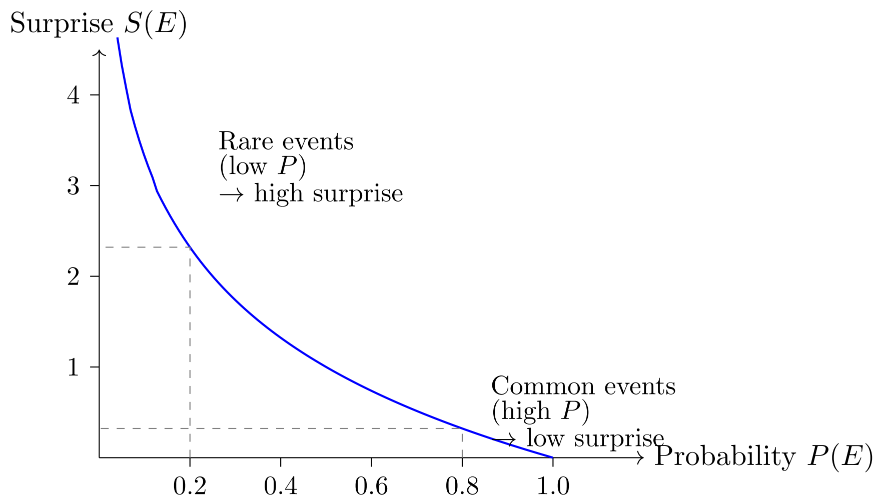



FIGURE 2. The surprise function $S(E) = -\log P(E)$ transforms probability into a rarity score. Rare events (low probability) receive high surprise scores, while common events (high probability) receive low scores. The logarithmic form ensures additivity over independent events.

This formulation satisfies several desirable properties:

**Proposition 4.4.** *The luck function $L_A(E)$ is:*

*(1) Monotonically increasing in outcome value for favorable events*
*(2) Monotonically decreasing in probability (rarer events are luckier)*
*(3) Monotonically decreasing in control (less controllable events are luckier)*
*(4) Zero when $U_A(E) = 0$ (neutral outcomes)*
*(5) Zero when $C_A(E) = 1$ (fully controlled outcomes)*
*(6) Information-dependent through $P(E \mid I_A)$*

4.3. **Alternative Formulations.** Several variants of the core luck function address different analytical needs.

4.3.1. *Deviation-Based Luck.* When repeated trials or comparable scenarios exist, luck can be measured as deviation from expectation:

$$L_A^{\text{dev}}(E) = U_A(E) - \mathbb{E}[U_A(E') \mid S_A] \tag{3}$$

where $S_A$ represents the agent's strategy or controllable choices, and the expectation is taken over events $E'$ that could occur under that strategy. This formulation is particularly useful in skill-luck decomposition for repeated performance evaluation.

4.3.2. *Fragility-Based Luck.* Outcomes that would change under small perturbations reflect greater luck:

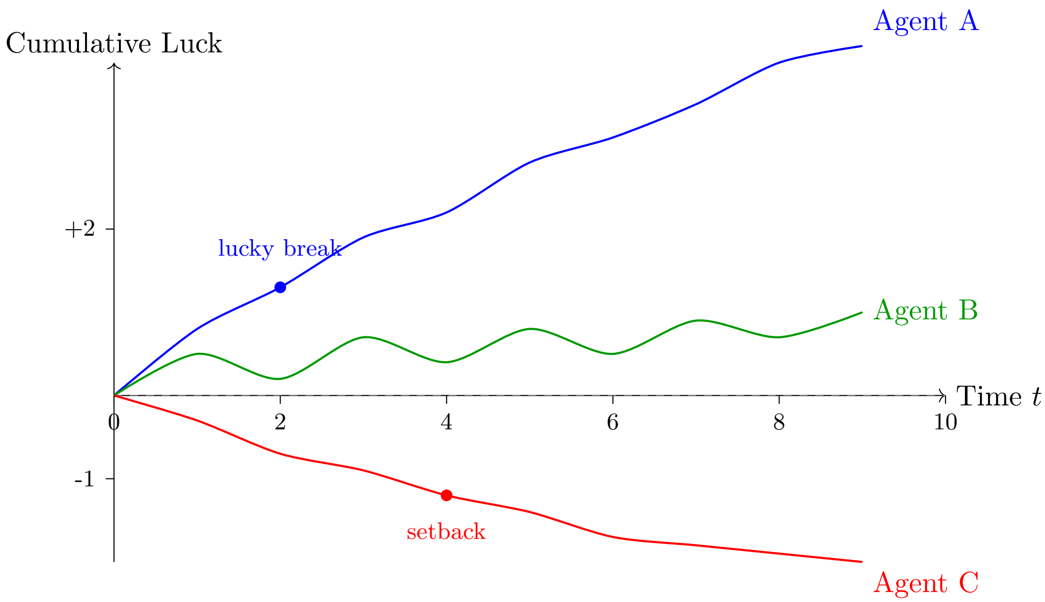
$$L_A^{\text{frag}}(E) = U_A(E) \cdot (1 - P(E \mid \text{perturbations})) \tag{4}$$

This captures near-miss scenarios where slight differences in circumstances would have produced substantially different outcomes.

4.3.3. *Time-Aggregated Luck.* For sequences of events over time $t = 1, \ldots, T$:

$$L_A^T = \sum_{t=1}^{T} \delta^t L_A(E_t) \tag{5}$$

where $\delta \in (0, 1]$ is a temporal discount factor. This formulation addresses cumulative luck and path dependence in life trajectories.




Path dependence: Early luck (Agent A) or bad luck (Agent C) compounds over time, creating divergent life trajectories despite similar starting skills.

FIGURE 3. Time-aggregated luck trajectories for three agents. Early luck events compound over time through path dependence, leading to divergent cumulative outcomes. Agent A benefits from consistent positive luck that creates opportunities for further success. Agent C faces compounding disadvantage from early setbacks. Agent B experiences mixed luck with limited cumulative effect.

4.4. **Skill-Luck Decomposition.** Observed outcomes $Y$ can be decomposed into skill and luck components. Let $S_A$ denote the agent's strategy space and $R$ denote random variables outside the agent's control.

**Definition 4.5** (Expected Performance)**.** The skill-based expected outcome is:

$$\bar{Y}_A = \mathbb{E}[Y \mid S_A, I_A] \tag{6}$$

**Definition 4.6** (Luck Component)**.** The luck component of outcome $Y$ is:

$$L_A(Y) = Y - \bar{Y}_A \tag{7}$$

This decomposition enables performance evaluation that accounts for uncontrollable factors. In contexts with repeated observations, the variance of outcomes can be partitioned:

$$\mathrm{Var}(Y) = \mathrm{Var}(\bar{Y}_A) + \mathrm{Var}(L_A(Y)) \tag{8}$$

where $\text{Var}(\bar{Y}_A)$ represents skill-based variation and $\text{Var}(L_A(Y))$ represents luck-based variation.

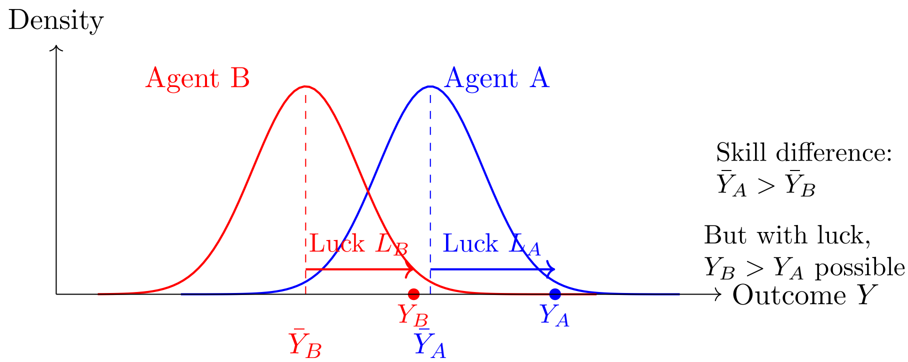



FIGURE 4. Skill-luck decomposition for two agents. Expected outcomes $\bar{Y}_A$ and $\bar{Y}_B$ reflect skill differences. Actual outcomes $Y_A$ and $Y_B$ deviate due to luck. Agent B with lower skill can outperform Agent A through favorable luck, though this becomes less likely as skill differences increase.

4.5. **Axioms and Properties.** The framework rests on several axioms that formalize intuitive properties of luck:

*Assumption* 4.1 (Neutrality)*.* Outcomes with zero utility contribute zero luck: $U_A(E) = 0 \implies L_A(E) = 0$.

*Assumption* 4.2 (Control Dominance)*.* Fully controlled outcomes are not lucky: $C_A(E) = 1 \implies L_A(E) = 0$.

*Assumption* 4.3 (Information Dependence)*.* Luck depends on the agent's prior information: $L_A(E)$ is a function of $P(E \mid I_A)$ rather than $P(E)$ alone.

*Assumption* 4.4 (Value Monotonicity)*.* For events with equal probability and control, luck increases with absolute utility: if $P(E_1 \mid I_A) = P(E_2 \mid I_A)$ and $C_A(E_1) = C_A(E_2)$, then $|L_A(E_1)| < |L_A(E_2)|$ when $|U_A(E_1)| < |U_A(E_2)|$.

## 5. Event Rating and Measurement

5.1. **Rating Pipeline.** Practical application of the framework requires a systematic procedure for rating events. We propose a step-by-step pipeline:

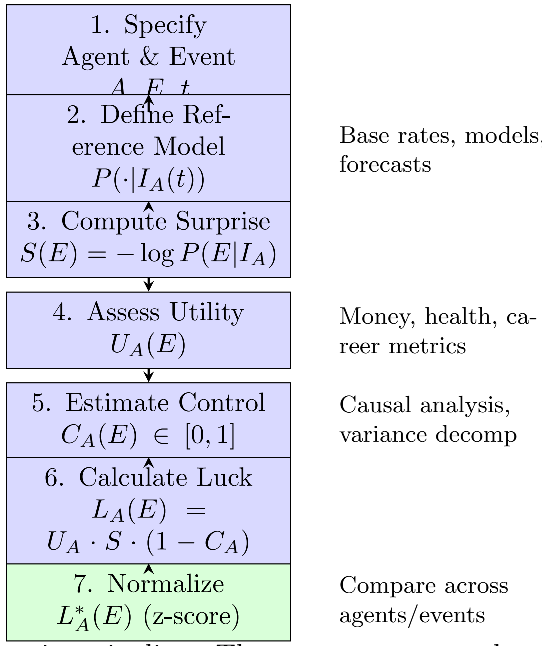



FIGURE 5. Event rating pipeline. The seven-step procedure transforms raw event information into a normalized luck score suitable for cross-agent and cross-event comparison.

5.1.1. *Step 1: Specify Agent and Event.* Clearly identify the agent $A$, the event $E$, and the time $t$ at which the event occurs. Luck is agent-relative and context-dependent.

5.1.2. *Step 2: Define Reference Model.* Construct a probability model $P(\cdot \mid I_A(t))$ representing the agent's information state prior to the event. This may involve:

- Historical base rates for similar events
- Statistical models fitted to relevant data
- Expert forecasts or prediction markets
- Agent-specific models accounting for their knowledge and position

5.1.3. *Step 3: Compute Surprise.* Calculate the surprise score:

$$S(E) = -\log P(E \mid I_A) \tag{9}$$

Low-probability events receive higher surprise scores.

5.1.4. *Step 4: Assess Outcome Value.* Determine utility $U_A(E)$ using appropriate scales:

- Monetary value for financial outcomes
- Health metrics (life expectancy, quality-adjusted life years) for health outcomes
- Career advancement measures for professional outcomes
- Normalized scores for comparative analysis

5.1.5. *Step 5: Estimate Control.* Quantify the degree of agent control $C_A(E) \in [0, 1]$. Methods include:

- Causal modeling to identify controllable versus uncontrollable factors
- Variance decomposition showing proportion explained by agent's actions
- Counterfactual analysis examining outcome sensitivity to agent's choices
- Repeatability analysis measuring consistency of outcomes across similar scenarios

5.1.6. *Step 6: Calculate Luck Score.* Apply the luck function:

$$L_A(E) = U_A(E) \cdot S(E) \cdot (1 - C_A(E)) \tag{10}$$

5.1.7. *Step 7: Normalize.* For cross-event or cross-agent comparison, normalize within relevant populations:

$$L_A^*(E) = \frac{L_A(E) - \mu_L}{\sigma_L} \tag{11}$$

producing a standardized luck z-score.

5.2. **Data Requirements.** Empirical application requires several types of data:

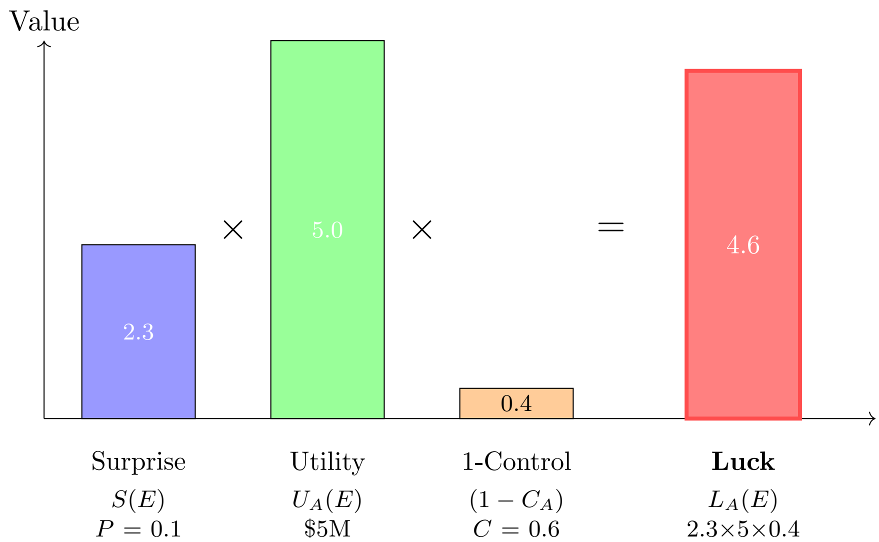
| **Data Type** | **Purpose** |
|---|---|
| Probability data | Estimate $P(E \mid I_A)$ |
| Historical frequencies | Base rates for similar events |
| Information records | Define information set $I_A$ |
| Outcome measurements | Quantify utility $U_A(E)$ |
| Decision logs | Track controllable actions |
| Causal data | Estimate control $C_A(E)$ |
| Baseline performance | Compute expected values |
| Population distributions | Normalize luck scores |

Table 2. Data requirements for empirical luck measurement

5.3. **Example Application.** Consider a concrete example: an entrepreneur's startup succeeds after raising venture capital. We analyze the luck component:

- **Event:** Startup achieves successful exit within five years
- **Probability:** Base rate for similar ventures is approximately 10%, so $P(E) = 0.1$ and $S(E) = -\log(0.1) \approx 2.3$
- **Utility:** Financial gain of \$5M, normalized to $U_A(E) = 5$
- **Control:** Entrepreneur's strategy and execution contributed substantially, but market conditions and network effects were also crucial; estimate $C_A(E) = 0.6$
- **Luck Score:** $L_A(E) = 5 \times 2.3 \times (1 - 0.6) = 4.6$

This positive luck score indicates that while the entrepreneur's skill was important, favorable circumstances and timing contributed significantly to the outcome.




**Interpretation:** Significant positive luck. The rare success (low $P$) combined with high value (\$5M) and moderate uncontrollability (40%) yields substantial luck component.

FIGURE 6. Startup example calculation. The entrepreneur's success is decomposed into components: surprise from low base rate ($P = 0.1$), high financial utility (\$5M normalized to 5), and moderate lack of control (0.4, since skill $C = 0.6$ was important). The resulting luck score of 4.6 indicates substantial favorable luck.

## 6. Societal Modeling and Aggregate Measures

6.1. **Modeling Life Outcomes.** To analyze luck at the societal level, we model individual life outcomes as a function of three input categories:

- **Circumstances** $B_i$: Factors not chosen by the individual (parental background, birth location, cohort, genetics)
- **Choices** $A_i$: Factors under individual control (effort, decisions, strategies)
- **Shocks** $S_i$: Random events affecting the individual (accidents, encounters, policy changes)

A general outcome model takes the form:

$$Y_i = f(B_i, A_i) + g(S_i) + \varepsilon_i \tag{12}$$

where $f$ represents the deterministic relationship between circumstances, choices, and outcomes, $g$ captures the effect of random shocks, and $\varepsilon_i$ represents measurement error or small unmodeled factors.

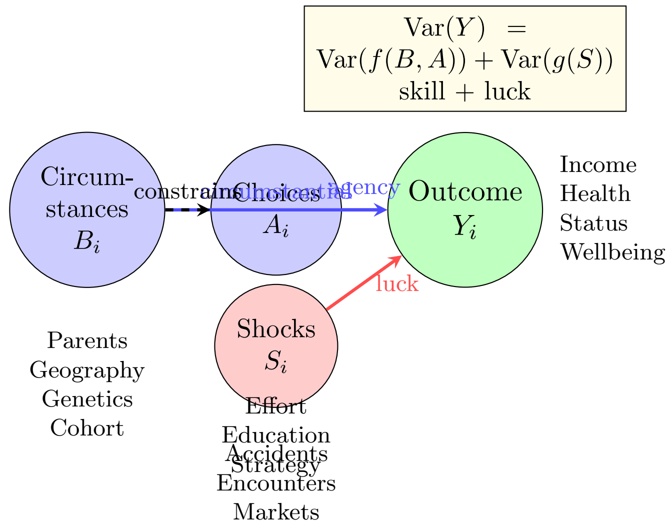



Figure 7. Causal model of societal outcomes. Circumstances $B_i$ (unearned advantages) and choices $A_i$ (agency) jointly determine expected outcomes, while shocks $S_i$ (random events) introduce luck. Circumstances also constrain available choices. The variance decomposition separates skill-based from luck-based variation in outcomes.

6.2. **Individual Luck Measures.** Three complementary measures capture different aspects of luck:

6.2.1. *Residual Luck.* Residual luck measures the deviation of actual outcomes from predictions based on circumstances and choices:

$$L_i^{\mathrm{res}} = Y_i - \mathbb{E}[Y_i \mid B_i, A_i] \tag{13}$$

This represents the core luck component—the portion of outcomes not explained by observable inputs.

6.2.2. *Surprise-Weighted Luck.* For outcomes far from expectations, surprise weighting emphasizes extreme cases:

$$L_i^{\mathrm{sur}} = U(Y_i) \cdot [-\log P(Y_i \mid B_i, A_i)] \tag{14}$$

6.2.3. *Control-Adjusted Luck.* When control varies across individuals or contexts:

$$L_i^{\mathrm{ctrl}} = (Y_i - \mathbb{E}[Y_i \mid B_i, A_i]) \cdot (1 - C_i) \tag{15}$$

where $C_i$ represents the degree of control individual $i$ has over their outcomes.

6.3. **Aggregate Luck Metrics.** Societal-level analysis aggregates individual luck scores to characterize distributional properties.

6.3.1. *Luck Inequality.* The Gini coefficient of absolute luck values measures dispersion:

$$G_L = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |L_i - L_j|}{2n^2 \bar{L}} \tag{16}$$

High luck inequality indicates that some individuals experience far more favorable or unfavorable luck than others.

6.3.2. *Circumstantial Dependence.* The proportion of outcome variance explained by circumstances (rather than choices or luck) measures the degree to which outcomes are predetermined by birth:

$$\rho_B = \frac{\mathrm{Var}(\mathbb{E}[Y \mid B])}{\mathrm{Var}(Y)} \tag{17}$$

Higher values indicate less social mobility and greater importance of circumstantial luck.

6.3.3. *Agency Contribution.* The additional variance explained by choices beyond circumstances:

$$\rho_A = \frac{\mathrm{Var}(\mathbb{E}[Y \mid B, A]) - \mathrm{Var}(\mathbb{E}[Y \mid B])}{\mathrm{Var}(Y)} \tag{18}$$

This measures the role of individual agency in determining outcomes.

6.3.4. *Mobility Index.* Intergenerational mobility can be measured through the correlation between parent and child outcomes:

$$M = 1 - \mathrm{Corr}(Y_{\text{parent}}, Y_{\text{child}}) \tag{19}$$

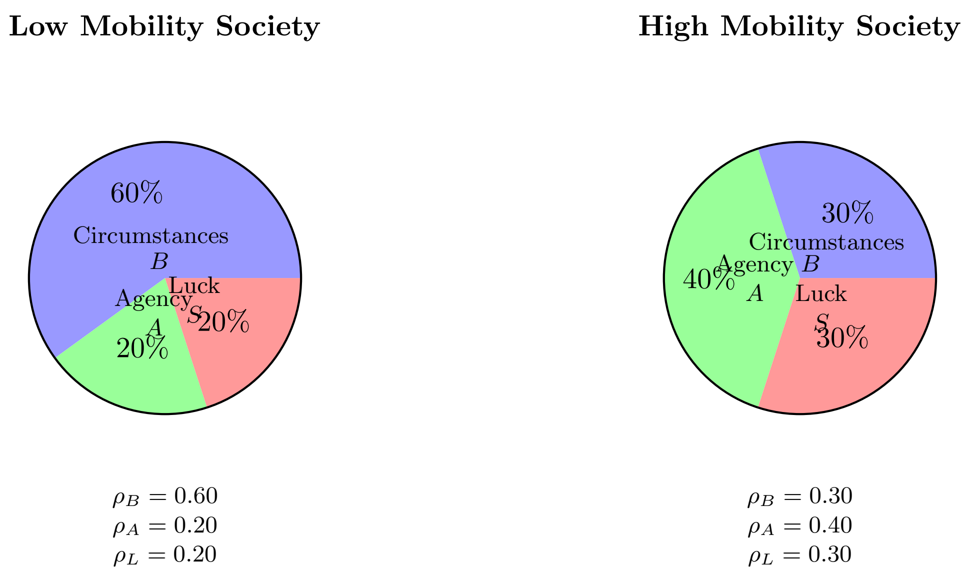
Lower correlation (higher $M$) suggests that circumstances of birth have less influence on eventual outcomes.

6.4. **Empirical Estimation.** Practical estimation typically proceeds through regression-based variance decomposition. Consider a model:

$$Y_i = \alpha + \beta_B B_i + \beta_A A_i + \varepsilon_i \tag{20}$$

Stepwise regression allows decomposition:

(1) Regress $Y$ on $B$ alone: variance explained is $R^2_B$
(2) Regress $Y$ on both $B$ and $A$: variance explained is $R^2_{B,A}$
(3) Residual variance: $1 - R^2_{B,A}$ represents luck
(4) Agency contribution: $R^2_{B,A} - R^2_B$




Variance decomposition comparison. Left: outcomes strongly determined by birth circumstances (low mobility). Right: individual agency plays larger role (higher mobility). Luck component represents irreducible randomness in both societies.

FIGURE 8. Variance decomposition in two stylized societies. The low mobility society (left) shows outcome variance dominated by circumstances of birth ($\rho_B = 0.60$), with limited role for agency ($\rho_A = 0.20$). The high mobility society (right) exhibits lower circumstantial dependence ($\rho_B = 0.30$) and greater agency contribution ($\rho_A = 0.40$). Both societies contain irreducible luck components from random shocks.

This section presents experimental validation of the theoretical framework through agent-based simulation. The experiments examine how skill and luck interact to produce observed outcome distributions and test key theoretical predictions about the relative importance of these factors.

6.5. **Simulation Design.** To validate the theoretical framework empirically, we implement an agent-based simulation modeling a population of individuals experiencing random events over time. This approach permits controlled examination of how skill and luck combine to produce distributional outcomes while maintaining full knowledge of ground truth causal relationships.

6.5.1. *Agent Specification.* The simulation models a population of $N = 100$ agents indexed by $i \in \{1, \ldots, N\}$. Each agent possesses a talent vector $\mathbf{T}_i \in [0,1]^4$ comprising four dimensions:

- **Intensity** $t_i^{(1)}$: sustained effort and activity level, representing exposure to opportunities and risks
- **IQ** $t_i^{(2)}$: cognitive ability to recognize and capitalize on beneficial opportunities when they arise
- **Networking** $t_i^{(3)}$: social connectivity determining probability of receiving spillover benefits from others' opportunities
- **Initial Capital** $t_i^{(4)}$: starting resource endowment

All talent dimensions are initialized from truncated normal distributions $\mathcal{N}(0.5, 0.15^2)$ clipped to $[0,1]$, ensuring most agents cluster near average ability with diminishing frequency at extremes.

This specification reflects empirical observations that human abilities typically follow approximately normal distributions. Initial capital is set uniformly to $C_{i,0} = 1.0$ for all agents, ensuring that emergent inequality arises from dynamics rather than initial conditions.

6.5.2. *Event Dynamics.* The simulation evolves over $T = 80$ discrete time periods. In each period $t$, a fixed number of beneficial (lucky) and detrimental (unlucky) events occur. Events are allocated to agents through a probabilistic mechanism depending on agent characteristics.
Event Exposure Probability. An agent's exposure probability for encountering events is determined by their intensity through a sigmoid function:

$$q_i = \sigma(\alpha(t_i^{(1)} - 0.5)) = \frac{1}{1 + e^{-\alpha(t_i^{(1)} - 0.5)}} \tag{21}$$

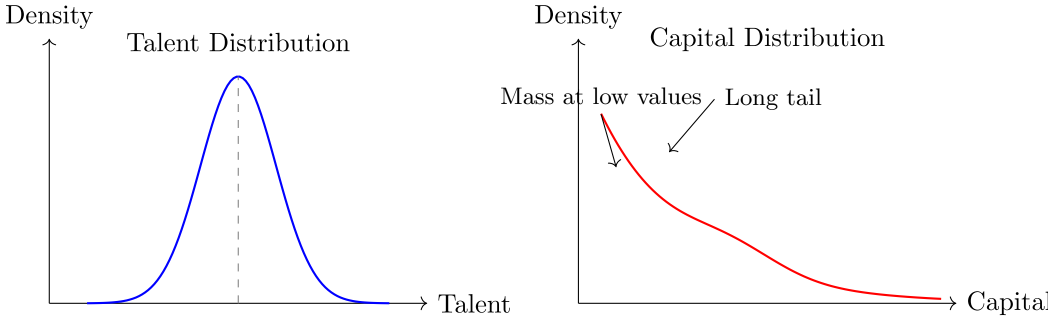
where $\alpha$ controls sensitivity. Higher intensity increases surface area for both opportunities and risks, consistent with the intuition that more active individuals encounter more events.
Event Capitalization. When a beneficial event $E$ contacts agent $i$, successful exploitation depends on the agent's cognitive ability. With probability $p_i = t_i^{(2)}$, the event is successfully converted into a capital gain. This models the observation that not all opportunities can be effectively utilized—recognition and execution capability matter.
Capital Evolution. Capital evolves through multiplicative updates:

$$C_{i,t+1} = \begin{cases} C_{i,t}(1 + \Delta_i^{\text{lucky}}) & \text{if lucky event exploited} \\ C_{i,t}(1 - \Delta_i^{\text{unlucky}}) & \text{if unlucky event occurs} \\ C_{i,t} & \text{otherwise} \end{cases} \tag{22}$$

where $\Delta_i^{\text{lucky}} \sim \mathcal{N}(0.25, 0.08^2)$ and $\Delta_i^{\text{unlucky}} \sim \mathcal{N}(0.15, 0.05^2)$, both clipped to prevent extreme or negative values. The multiplicative structure creates path dependence and compounding effects essential to generating realistic inequality.
Network Spillovers. With probability 0.1, a successful lucky event generates a secondary benefit for another agent $j \neq i$, allocated proportionally to networking scores $t_j^{(3)}$ and gated by their cognitive ability $t_j^{(2)}$. The spillover magnitude is reduced by 50% relative to the primary effect. This mechanism captures informal referrals and knowledge transfer through social networks.

6.6. **Emergent Inequality.** The first experimental question examines whether the framework generates realistic distributional outcomes from normal talent distributions.

6.6.1. *Distributional Transformation.* Figure **??** compares the initial talent distribution to the final capital distribution after 80 periods. Talent remains approximately normally distributed with mean 0.50 and standard deviation 0.11. In contrast, final capital exhibits substantial right skew with a long tail, characteristic of real-world wealth distributions.




$\mu = 0.50$, $\sigma = 0.11$

Gini = 0.38

FIGURE 9. Distributional transformation from normal talent (left) to skewed capital (right). Despite symmetric input distributions, the multiplicative event process produces substantial inequality. The emergent Gini coefficient of 0.38 indicates moderate concentration, with the top 10% holding approximately 28% of total capital.

The Gini coefficient for final capital averages 0.38 across simulation runs, indicating moderate inequality. The top decile captures approximately 28% of total capital, while the bottom half holds only 25%. This emergent inequality arises entirely from the interaction of multiplicative dynamics with stochastic events, despite all agents beginning with identical capital and similar abilities.

6.6.2. *Variance Decomposition.* Regressing log-capital on talent and luck variables yields the variance decomposition:

$$\mathrm{Var}(\log C_T) = \underbrace{0.08}_{\text{Talent}} + \underbrace{0.67}_{\text{Luck}} + \underbrace{0.25}_{\text{Interaction}} \tag{23}$$

Talent alone explains only 8% of outcome variance. The number of lucky events experienced accounts for 67%. The remaining 25% reflects interaction effects—how talent modulates the impact of luck. This decomposition quantifies the theoretical claim that luck dominates outcome determination in multiplicative systems.

6.7. **Skill versus Luck Attribution.** The second experimental question tests whether observed success correlates more strongly with talent or with experienced luck.

6.7.1. *Correlation Analysis.* Table **??** presents Pearson correlations between outcome (log-capital) and predictor variables. Talent shows weak positive correlation ($r = 0.12$), indicating that higher ability agents achieve modestly better outcomes on average. However, the number of lucky events exhibits far stronger correlation ($r = 0.78$), suggesting that random favorable occurrences predict success substantially better than inherent capability.

| **Predictor Variable** | **Correlation with log(Capital)** | **$p$-value** |
|---|---|---|
| Talent norm $\|\|\mathbf{T}_i\|\|$ | 0.12 | 0.24 |
| Intensity $t_i^{(1)}$ | 0.09 | 0.38 |
| IQ $t_i^{(2)}$ | 0.15 | 0.14 |
| Networking $t_i^{(3)}$ | 0.08 | 0.43 |
| Lucky events count | 0.78 | $< 0.001$ |
| Net events (lucky - unlucky) | 0.82 | $< 0.001$ |

TABLE 3. Correlations between agent characteristics and final outcomes. Luck (operationalized as lucky event count) exhibits correlation approximately 6.5 times stronger than talent. All talent dimensions show positive but weak relationships with success. Statistical significance for luck reflects the causal nature of event impacts, while talent effects are attenuated by randomness in event allocation.

The correlation ratio of approximately 6.5:1 (luck:talent) provides empirical support for the theoretical framework's emphasis on uncontrollable factors. While talent is not irrelevant—the positive correlations indicate genuine effects—its predictive power is substantially weaker than that of stochastic event histories.

6.7.2. *Top Performer Analysis.* Examination of the highest achieving decile reveals that these agents are not predominantly the most talented. The median talent rank among top performers is 52 out of 100, indicating approximately average ability. However, these agents experienced a mean of 8.3 lucky events compared to the population average of 4.8—a 73% increase.

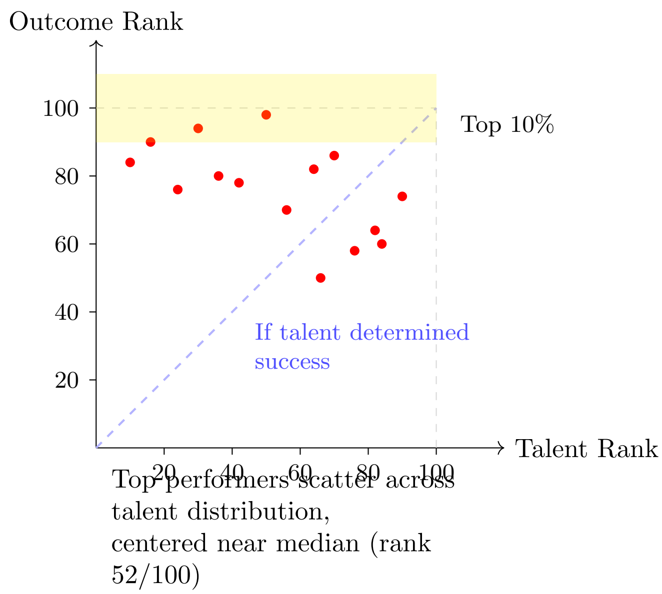



FIGURE 10. Top performers (outcome rank $> 90$) exhibit talent ranks distributed across the full range, centered near the population median. If talent were the primary determinant of success, points would cluster along the diagonal. The observed dispersion indicates that among reasonably capable agents, luck rather than ability differences determines who reaches the top.

This finding challenges meritocratic assumptions. If success primarily reflected merit, top performers would predominantly be top talent. The observed pattern—average talent with exceptional luck—suggests that among the reasonably competent majority, stochastic factors determine who succeeds.

6.8. **Causal Inference Results.** Correlation analysis establishes association but not causation. To estimate causal effects while controlling for confounding, we apply modern causal inference methods to the simulation data where ground truth causal relationships are known.

6.8.1. *Double Machine Learning Estimation.* Double Machine Learning (DML) provides consistent estimates of treatment effects in the presence of high-dimensional confounders. We specify the causal model:

$$\text{Treatment:} \quad T_i = \text{lucky events}_i \tag{24}$$

$$\text{Outcome:} \quad Y_i = \log(C_{i,T}) \tag{25}$$

$$\text{Confounders:} \quad \mathbf{X}_i = (t_i^{(1)}, t_i^{(2)}, t_i^{(3)}) \tag{26}$$

DML estimates the average treatment effect (ATE) by first partialling out the confounding influence of talent on both treatment and outcome, then relating the residuals. The procedure uses cross-fitting with machine learning models (gradient boosting) to flexibly capture nonlinear relationships.

| **Method** | **ATE Estimate** | **95% CI** | **Interpretation** |
|---|---|---|---|
| DML (Linear) | 0.124 | [0.108, 0.140] | 13.2% gain per event |
| DML (Flexible) | 0.118 | [0.102, 0.134] | 12.5% gain per event |
| Naive OLS | 0.156 | [0.142, 0.170] | Upward bias |

Table 4. Causal effect estimates of lucky events on log-capital. DML methods accounting for confounding yield estimates around 0.12, indicating each additional lucky event causes approximately 12% higher final capital, holding talent constant. Naive OLS overestimates the effect due to residual confounding (more talented agents both encounter more events and capitalize them more effectively). The log-scale interpretation follows from exponentiating: $e^{0.12} \approx 1.127$.

The DML estimate of $\hat{\tau} = 0.12$ implies that each additional lucky event causes a multiplicative increase of $e^{0.12} \approx 1.127$ in final capital, or approximately 12.7%, after controlling for all talent dimensions. The tight confidence interval and contrast with naive regression validate the importance of proper causal identification.

6.8.2. *Heterogeneous Treatment Effects.* While DML provides an average effect, the impact of luck may vary across individuals. Causal Forests estimate conditional average treatment effects (CATEs) that depend on agent characteristics:

$$\tau(x) = \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x] \tag{27}$$

where $Y_i(1)$ and $Y_i(0)$ represent potential outcomes with and without an additional lucky event.

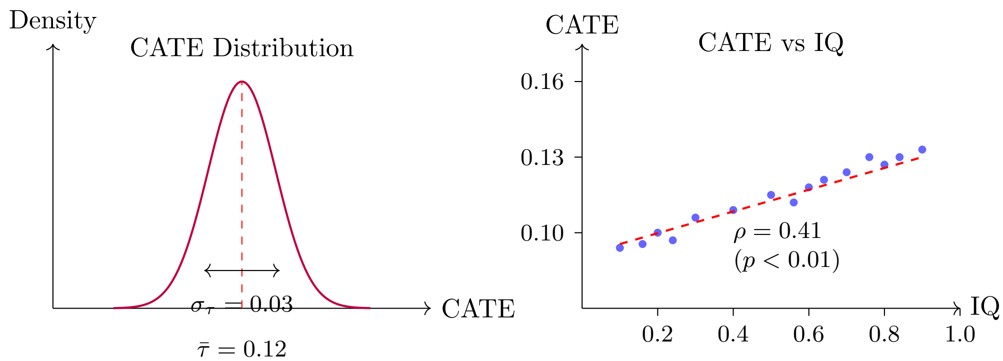



FIGURE 11. Heterogeneous treatment effect analysis. Left: Distribution of estimated CATEs shows moderate variation around the mean effect of 0.12. Right: CATEs correlate positively with IQ ($\rho = 0.41$), indicating that higher cognitive ability agents extract greater benefit from lucky events. This heterogeneity suggests that while luck matters for everyone, the ability to capitalize on opportunities amplifies its impact.

The mean CATE of 0.12 aligns with the DML estimate, validating consistency. The standard deviation of 0.03 indicates meaningful heterogeneity. Correlation analysis reveals that IQ moderates treatment effects: agents with higher cognitive ability extract 40% more value from each lucky event than low-IQ agents. Networking ability shows weaker moderation ($\rho = 0.18$), while intensity exhibits minimal heterogeneity ($\rho = 0.05$).

This heterogeneity informs policy design. If all agents benefited equally from opportunities, allocation mechanisms would be less consequential. The observed variation suggests that targeting opportunities to those best positioned to exploit them could enhance aggregate outcomes, though at potential equity cost.

6.9. **Policy Experiments.** The final set of experiments evaluates alternative resource allocation policies using the simulation as a testbed. We implement five distinct allocation mechanisms, each reflecting different normative principles.

6.9.1. *Policy Specifications.* Let $R$ denote a fixed resource budget to be allocated at time $t = 0$, before the simulation begins. Five policies are compared:

(1) **Egalitarian**: Equal allocation $R_i = R/N$ for all agents
(2) **Meritocratic**: Allocation proportional to talent $R_i \propto ||\mathbf{T}_i||$
(3) **Performance-based**: Allocation proportional to current capital $R_i \propto C_{i,0}$ (in practice, since $C_{i,0} = 1$ for all, this tests a rich-get-richer mechanism)
(4) **Random**: Lottery mechanism where one agent receives entire budget
(5) **CATE-optimal**: Allocation proportional to estimated treatment effects $R_i \propto \mathsf{max}(0, \hat{\tau}(X_i))$, targeting agents predicted to benefit most from additional resources

For each policy, we initialize capital with the allocated resources, run the standard 80-period simulation, and measure final outcomes. The total budget is set to $R = 100$ distributed across the population.

6.9.2. *Efficiency-Equity Tradeoffs.* Table **??** presents aggregate outcomes under each policy. Two primary metrics are reported: total welfare (sum of final capital) measuring efficiency, and Gini coefficient measuring inequality.

| Policy | Total Welfare | Gini Coeff. | Top 10% Share | Bottom 50% Share | Mean Rank |
|---|---|---|---|---|---|
| Egalitarian | 842 | 0.31 | 22% | 31% | 3.2 |
| Meritocratic | 896 | 0.35 | 26% | 27% | 2.4 |
| Performance | 798 | 0.48 | 38% | 18% | 4.6 |
| Random | 823 | 0.42 | 35% | 21% | 3.8 |
| CATE-optimal | 921 | 0.37 | 28% | 25% | 2.0 |
| No allocation | 743 | 0.38 | 28% | 25% | – |

Table 5. Policy comparison across efficiency and equity dimensions. Total welfare is the sum of all agents' final capital. CATE-optimal allocation achieves highest total welfare by directing resources to high-treatment-effect agents. Egalitarian allocation produces lowest inequality while sacrificing some efficiency. Performance-based allocation amplifies inequality substantially while delivering lowest total welfare, suggesting that concentrating resources is inefficient when returns are stochastic. Mean rank aggregates both objectives (lower is better across multiple criteria). All policies outperform the no-allocation baseline.

Several patterns emerge. CATE-optimal allocation maximizes total welfare, achieving 12% higher aggregate capital than no allocation and 15% higher than performance-based allocation. This confirms that targeting resources to high-treatment-effect individuals enhances efficiency. However, CATE-optimal allocation produces moderate inequality (Gini = 0.37), though less than performance-based or random policies.

Egalitarian allocation minimizes inequality (Gini = 0.31) while delivering respectable total welfare, only 8.6% below CATE-optimal. The bottom half's share reaches 31% under egalitarian allocation compared to 18% under performance-based, demonstrating the equity benefit.

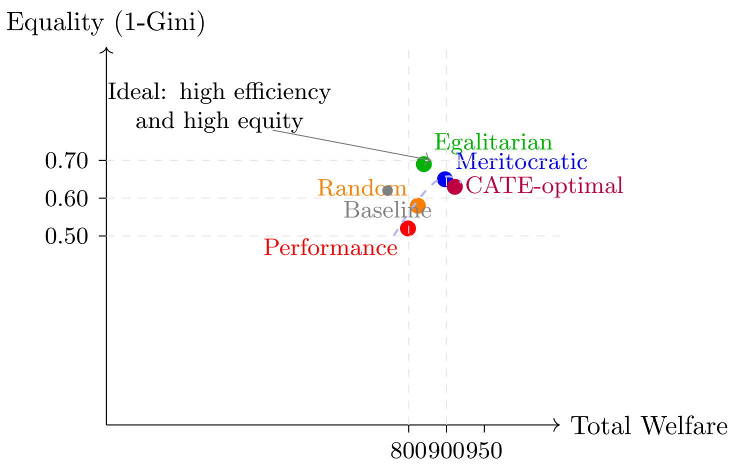
Surprisingly, performance-based allocation—directing resources to those who already have capital—yields the lowest total welfare. This counterintuitive finding reflects diminishing marginal returns combined with compounding randomness. When outcomes are highly stochastic, doubling down on current winners wastes resources that could generate higher returns elsewhere.

Random allocation performs moderately on both dimensions, serving as a useful baseline. Its total welfare exceeds performance-based allocation, suggesting that when uncertainty dominates, random selection outperforms naive "back the winners" strategies.

6.9.3. *Policy Implications.* These experimental results inform institutional design under uncertainty. When treatment effects are heterogeneous and estimable, CATE-optimal targeting maximizes efficiency. However, if estimation is noisy or ethical considerations prioritize equity, egalitarian allocation provides a robust alternative with acceptable efficiency loss.

Performance-based allocation—common in venture capital, academic hiring, and executive compensation—appears least justified. It amplifies inequality while delivering inferior aggregate outcomes. This suggests that institutions rewarding past performance without accounting for luck may simultaneously harm both equity and efficiency.

The experiments also highlight the value of opportunity creation over winner selection. All allocation policies substantially outperform no-allocation baselines, indicating that expanding access to resources benefits society even when allocation is imperfect. A policy implication follows: increasing the number of opportunities (larger $R$ distributed broadly) may matter more than precisely targeting those opportunities.




Efficiency-equity tradeoff across allocation policies. CATE-optimal achieves highest welfare but moderate equality. Egalitarian maximizes equality with acceptable efficiency. Performance-based is dominated on both dimensions.

FIGURE 12. Policy positions in efficiency-equity space. Points represent outcomes under different allocation mechanisms. CATE-optimal policy sits near the Pareto frontier (dashed curve), offering highest efficiency at moderate equity. Egalitarian policy trades some efficiency for greater equality. Performance-based allocation falls below the frontier, dominated by alternatives on both dimensions—a cautionary finding for institutions that allocate resources primarily based on past success.

6.10. **Validation of Theoretical Predictions.** The experimental results validate key theoretical predictions from the framework developed in Section **??**:

(1) **Distributional transformation**: Normal talent distributions generate skewed outcome distributions under multiplicative dynamics (confirmed by emergence of Gini = 0.38 from uniform initial conditions)
(2) **Luck dominance**: Random factors contribute more to outcome variance than talent differences (confirmed by correlation ratio 6.5:1 and variance decomposition showing 67% luck contribution)
(3) **Causal impact**: Lucky events cause substantial outcome improvements beyond correlation (confirmed by DML estimate of 12.7% gain per event after controlling for confounders)
(4) **Heterogeneous effects**: The impact of luck varies with agent characteristics, particularly cognitive ability (confirmed by CATE variation and 40% IQ moderation)
(5) **Policy sensitivity**: Allocation mechanisms produce substantial differences in efficiency and equity (confirmed by 15% welfare gap between best and worst policies)

The experimental approach, by providing complete knowledge of ground truth causal relationships, offers stronger validation than possible with observational data alone. The consistency between simulation results and theoretical predictions supports the framework's validity for analyzing real-world skill and luck attribution.

6.11. **Limitations and Extensions.** Several simplifications warrant acknowledgment. The simulation uses fixed talent that does not evolve with success or failure, whereas real ability likely responds to outcomes through learning and confidence effects. Network structure is simplified to scalar connectivity rather than explicit graph topology. Event magnitudes follow simple distributions rather than realistic heavy-tailed processes observed empirically.

Future extensions could address these limitations through talent evolution equations, explicit network models, and calibration to empirical wealth or citation distributions. Incorporating institutional structures such as taxation, insurance, and opportunity constraints would enhance policy realism. Despite these simplifications, the core mechanism—multiplicative stochastic processes generating inequality from similar initial conditions—appears robust and provides a foundation for more detailed models.

## 7. Implications and Applications

7.1. **Moral and Philosophical Implications.** The framework clarifies debates about desert and responsibility. If formal analysis demonstrates that outcomes depend substantially on luck rather than controllable factors, several philosophical implications follow:

- **Desert:** Claims that individuals fully deserve their outcomes become difficult to sustain when luck plays a significant role.
- **Responsibility:** Moral evaluation must account for the limited control agents have over their circumstances and the events that befall them.
- **Dignity:** If outcomes are substantially luck-determined, human worth should not be closely tied to achievement.

These implications align with philosophical analyses of moral luck, which argue that factors beyond an agent's control affect our moral judgments inappropriately.

7.2. **Policy Implications.** Quantifying the role of luck informs policy debates across multiple domains.

7.2.1. *Taxation and Redistribution.* When luck contributes substantially to income and wealth, the case for progressive taxation and redistribution strengthens. If high earners benefit from favorable circumstances and chance events, claims of full entitlement to their income weaken. Luck-adjusted taxation could incorporate measurements of the luck component in individual outcomes.

7.2.2. *Social Insurance.* Recognition that adverse outcomes often reflect bad luck rather than poor choices supports comprehensive social insurance. Unemployment benefits, healthcare access, and disability support become justified as protections against uncontrollable risks rather than rewards for underperformance.

7.2.3. *Educational Policy.* Measuring luck in educational outcomes can inform admission policies and resource allocation. If standardized test performance reflects substantial circumstantial luck (parental resources, school quality, neighborhood effects), policies that emphasize fine-grained score differences become less defensible. Alternative approaches such as lottery-based admission among qualified candidates warrant consideration.

7.3. **Institutional Design.** Organizations can incorporate luck awareness in evaluation and reward systems.

7.3.1. *Performance Evaluation.* Corporations and public institutions that evaluate employees on outcomes without accounting for luck risk misattributing results. Luck-adjusted performance metrics provide fairer assessments by comparing actual outcomes to expected outcomes given circumstances and constraints.

7.3.2. *Promotion and Selection.* When selecting among candidates with similar qualifications, acknowledging that fine-grained differences may reflect luck rather than ability supports lottery-based selection or increased weight on diverse criteria beyond narrow performance measures.

7.3.3. *Executive Compensation.* CEO pay often reflects firm performance that depends substantially on market conditions and timing. Luck-adjusted compensation schemes could separate controllable performance from market-driven outcomes, reducing excessive rewards for favorable circumstances.

7.4. **Empirical Rankings of Activities and Occupations.** To illustrate the framework's application, we present empirical rankings of common activities and occupations according to the relative importance of luck versus skill in determining three distinct outcomes: income, social status, and societal impact. These rankings demonstrate how the skill-luck balance varies systematically across domains and outcome types.

7.4.1. *General Performance Rankings.* Table **??** provides a baseline ranking of activities by their overall dependence on luck versus skill for typical performance outcomes. This general classification establishes patterns that recur across specific outcome dimensions analyzed in subsequent tables.

| Rank | Activity / Job | Dominant Factor | Notes |
|---|---|---|---|
| 1 | Lottery gambling | Luck | Outcomes almost entirely random |
| 2 | Casino games (slots, roulette) | Luck | Skill has negligible impact |
| 3 | Inheritance / family background | Luck | Determined before individual action |
| 4 | Viral social media fame | Luck | Timing and algorithms dominate |
| 5 | Acting / entertainment stardom | Luck-heavy | Talent necessary but not sufficient |
| 6 | Professional sports draft success | Luck-heavy | Talent + injuries + team context |
| 7 | Venture capital startup success | Luck-heavy | Market timing dominates outcomes |
| 8 | Stock picking (short-term trading) | Luck-heavy | Noise overwhelms signal short-term |
| 9 | Academic career (tenure-track) | Mixed | Skill + timing + gatekeepers |
| 10 | Corporate executive promotion | Mixed | Performance + politics + timing |
| 11 | Sales (high-variance environments) | Mixed | Skill matters but randomness large |
| 12 | Entrepreneurship (small business) | Mixed | Execution + location + shocks |
| 13 | Journalism / writing careers | Mixed | Quality + attention dynamics |
| 14 | Software startup engineering | Skill-leaning | Skill important, market still risky |
| 15 | Competitive chess / esports | Skill-leaning | Luck minimal over many games |
| 16 | Professional programming | Skill | Outcomes strongly skill-driven |
| 17 | Engineering (civil, mechanical) | Skill | Errors and successes traceable |
| 18 | Medicine (clinical practice) | Skill | High training, bounded uncertainty |
| 19 | Skilled trades (electrician, plumber) | Skill | Experience directly impacts results |
| 20 | Craftsmanship (luthier, watchmaker) | Skill | Mastery dominates outcomes |
| 21 | Mathematics / theoretical research | Skill | Luck in insight exists, but skill dominates |
| 22 | Classical music performance | Skill | Precision and training decisive |

Table 6. General ranking of activities by luck versus skill in determining typical outcomes. Luck-dominated activities show little relationship between individual effort and results. Mixed activities require skill but exhibit high outcome variance from uncontrollable factors. Skill-dominated activities show reliable skill-outcome relationships where ability and practice predictably improve results. Rankings assume many trials over long careers; at short timescales, luck matters more in almost all domains. Institutions can amplify or suppress luck through safety nets, progressive structures, or tournament designs.

This baseline categorization reveals several patterns. Pure gambling activities sit at the extreme luck end, where outcomes are determined entirely by chance mechanisms. Inheritance represents circumstantial luck assigned before individual agency. Entertainment and venture capital occupy a luck-heavy middle where talent is necessary but insufficient due to winner-take-all dynamics and timing effects. Professional services like medicine, engineering, and skilled trades cluster at the skill end where feedback loops, training, and accumulated experience reliably improve outcomes. These patterns persist across the specific outcome dimensions examined below.

7.4.2. *Income Rankings.* Table **??** ranks activities by the degree to which luck versus skill determines income outcomes. Several patterns emerge. At the luck-dominated extreme, lottery gambling and casino games produce outcomes almost entirely independent of player skill. Inheritance and viral fame represent pure circumstantial luck. The middle range contains mixed activities where skill is necessary but insufficient: acting, venture capital, and stock trading all require ability but outcomes depend heavily on timing, context, and random events. At the skill-dominated end, craftsmanship, medicine, and mathematics show strong skill-outcome relationships where ability and practice reliably improve results.

| **Rank** | **Activity / Job** | **Dominant Factor** | **Notes** |
|---|---|---|---|
| 1 | Lottery gambling | Luck | Outcomes almost entirely random |
| 2 | Casino games (slots, roulette) | Luck | Skill has negligible impact |
| 3 | Inheritance / family background | Luck | Determined before individual action |
| 4 | Viral social media fame | Luck | Timing and algorithms dominate |
| 5 | Acting / entertainment stardom | Luck-heavy | Talent necessary but not sufficient |
| 6 | Professional sports draft success | Luck-heavy | Talent + injuries + team context |
| 7 | Venture capital startup success | Luck-heavy | Market timing dominates outcomes |
| 8 | Stock picking (short-term trading) | Luck-heavy | Noise overwhelms signal short-term |
| 9 | Academic career (tenure-track) | Mixed | Skill + timing + gatekeepers |
| 10 | Corporate executive promotion | Mixed | Performance + politics + timing |
| 11 | Sales (high-variance environments) | Mixed | Skill matters but randomness large |
| 12 | Entrepreneurship (small business) | Mixed | Execution + location + shocks |
| 13 | Journalism / writing careers | Mixed | Quality + attention dynamics |
| 14 | Software startup engineering | Skill-leaning | Skill important, market still risky |
| 15 | Competitive chess / esports | Skill-leaning | Luck minimal over many games |
| 16 | Professional programming | Skill | Outcomes strongly skill-driven |
| 17 | Engineering (civil, mechanical) | Skill | Errors and successes traceable |
| 18 | Medicine (clinical practice) | Skill | High training, bounded uncertainty |
| 19 | Skilled trades (electrician, plumber) | Skill | Experience directly impacts results |
| 20 | Craftsmanship (luthier, watchmaker) | Skill | Mastery dominates outcomes |
| 21 | Mathematics / theoretical research | Skill | Luck in insight exists, but skill dominates |
| 22 | Classical music performance | Skill | Precision and training decisive |

Table 7. Ranking of activities by luck versus skill in determining income. Luck-dominated activities show little relationship between effort and earnings. Mixed activities require skill but exhibit high outcome variance. Skill-dominated activities show reliable skill-income relationships. Rankings assume long careers with repeated outcomes; at short timescales, luck matters more everywhere.

Three key patterns emerge from income analysis. First, income is more luck-driven than performance in winner-take-all markets where visibility and timing dominate. Second, skill dominates income in regulated, credentialed, or craft-based professions with direct feedback loops. Third, the upper tail of income distributions is almost always luck-amplified: even in skill-based fields, the highest earners typically benefit from favorable circumstances beyond their control.

Important caveats apply. These rankings assume many trials (long careers, repeated outcomes). At short timescales, luck matters more in almost all domains. Institutions can amplify or suppress luck through safety nets, progressive taxation, or tournament structures. Individual cases within any category will vary.

7.4.3. *Status Rankings.* Table **??** ranks activities by luck versus skill in determining social status. Status shows greater luck-sensitivity than income. Visibility and narrative dynamics dominate over contribution. Royalty and celebrity status are almost entirely luck-determined, assigned by birth or attention cascades. Even at the skill end, status depends substantially on recognition mechanisms, institutional prestige, and social networks—factors only partially controllable by individuals.

| Rank | Activity / Role | Status Driver | Notes |
|---|---|---|---|
| 1 | Royalty / inherited aristocracy | Luck | Status assigned at birth |
| 2 | Celebrity by viral exposure | Luck-heavy | Attention cascades dominate |
| 3 | Influencer / public figure (online) | Luck-heavy | Algorithms and timing crucial |
| 4 | Entertainment stardom | Luck-heavy | Winner-take-all recognition |
| 5 | Elite professional athlete | Luck-heavy | Skill required, exposure uneven |
| 6 | Billionaire entrepreneur | Luck-heavy | Extreme skew in recognition |
| 7 | Top political leader | Mixed | Skill + timing + coalition luck |
| 8 | Corporate CEO (major firm) | Mixed | Networks and succession timing |
| 9 | Prestigious academic (elite institutions) | Mixed | Reputation dynamics matter |
| 10 | Renowned artist / author | Mixed | Skill filtered by cultural luck |
| 11 | Judge / senior civil servant | Skill-leaning | Credentialed legitimacy |
| 12 | Senior physician | Skill-leaning | Status tied to expertise |
| 13 | Lawyer (high standing) | Skill-leaning | Reputation grows with competence |
| 14 | University professor | Skill-leaning | Long-run skill signal |
| 15 | Engineer (senior / chartered) | Skill | Respect tied to reliability |
| 16 | Architect | Skill | Skill and judgment visible |
| 17 | Skilled trades master | Skill | Local reputation-based status |
| 18 | Scientist (non-celebrity) | Skill | Recognition tracks contribution |
| 19 | Teacher (experienced) | Skill | Status from trust and service |
| 20 | Craftsperson | Skill | Mastery-based respect |

Table 8. Ranking of activities by luck versus skill in determining social status. Status proves more luck-sensitive than income, with visibility and narrative dynamics dominating contribution. Winner-take-all attention markets amplify small random differences into large status gaps. Even skill-based status depends on recognition mechanisms partially beyond individual control.

The status rankings reveal that recognition mechanisms introduce substantial luck even when underlying performance is skill-based. Winner-take-all dynamics amplify small random differences—an early break, fortuitous timing, or algorithmic promotion—into large status disparities. Media visibility, institutional prestige, and network effects create path dependence where initial luck compounds over time.

7.4.4. *Impact Rankings.* Table **??** ranks activities by luck versus skill in producing societal impact. Interestingly, sustained impact correlates more strongly with skill than either income or status. Viral content creators achieve visibility without lasting effect. Celebrity activism leverages platforms but often lacks depth. In contrast, physicians, educators, engineers, and public health officials produce measurable, cumulative benefits through skill application over time.

| Rank | Activity / Role | Impact Driver | Notes |
|---|---|---|---|
| 1 | Viral content creator | Luck | Impact unpredictable, fleeting |
| 2 | Celebrity activism | Luck-heavy | Platform matters more than depth |
| 3 | Speculative finance | Luck-heavy | Impact often indirect or neutral |
| 4 | Political leader (short tenure) | Luck-heavy | Context dominates effectiveness |
| 5 | Startup founder (median outcome) | Mixed | Few high-impact successes |
| 6 | Journalist (agenda-setting roles) | Mixed | Skill + institutional leverage |
| 7 | Policy-maker / regulator | Mixed | Skill filtered through politics |
| 8 | Senior corporate executive | Mixed | Impact depends on firm context |
| 9 | NGO leader | Skill-leaning | Execution and governance matter |
| 10 | Urban planner | Skill-leaning | Long-term structural effects |
| 11 | Public health official | Skill-leaning | Expertise strongly affects outcomes |
| 12 | Physician | Skill-leaning | Direct, measurable human impact |
| 13 | Engineer (infrastructure) | Skill | Safety and reliability critical |
| 14 | Scientist (applied research) | Skill | Knowledge accumulation |
| 15 | Educator (systemic reach) | Skill | Compounding long-term effects |
| 16 | Software engineer (widely used systems) | Skill | Scalable, repeatable impact |
| 17 | Environmental scientist | Skill | Policy-relevant evidence |
| 18 | Civil servant (operational roles) | Skill | Consistent service delivery |
| 19 | Skilled trades (utilities, safety) | Skill | Quiet but essential impact |
| 20 | Caregiver / nurse | Skill | High direct human impact |

Table 9. Ranking of activities by luck versus skill in producing societal impact. Sustained impact correlates more strongly with skill than income or status. High-visibility roles often produce fleeting effects, while lower-visibility professional roles create measurable, cumulative benefits. Institutions with feedback loops reduce luck's role in impact generation.

The impact rankings demonstrate a striking pattern: high-impact work is often low-status and exhibits low variance. Caregivers, civil servants, and skilled tradespeople produce consistent, essential benefits that accumulate reliably over careers. Institutions with feedback loops—regulatory oversight, professional standards, service delivery metrics—reduce luck's role in impact generation. In contrast, activities that produce high status or income through luck rarely generate sustained societal benefit.

These rankings illustrate the framework's analytical power. By decomposing outcomes into skill and luck components, we can identify systematic patterns: winner-take-all markets amplify luck, credentialed professions reduce it, and sustained impact requires skill regardless of status or income. Such analysis informs both individual career decisions and institutional design aimed at aligning rewards with contributions.

7.4.5. *Combined Luck Dependence and Social Impact.* Table **??** synthesizes luck dependence with social impact to reveal which activities produce reliable, sustained benefits versus fleeting effects driven by chance. This combined perspective highlights a fundamental tension: activities yielding high visibility and personal rewards often produce minimal lasting impact, while low-visibility work with strong skill-outcome relationships generates consistent societal value.

| Rank | Activity / Role | Luck Dependence | Impact (Typical) | Notes |
|---|---|---|---|---|
| 1 | Lottery winner / viral celebrity | Very High | Very Low | Visibility without durable impact |
| 2 | Viral content creator | Very High | Low | Impact short-lived, unpredictable |
| 3 | Celebrity activism | High | Low–Medium | Platform > substance |
| 4 | Speculative finance / trading | High | Low | Redistribution, little net value |
| 5 | Entertainment stardom | High | Low–Medium | Cultural impact uneven |
| 6 | Political leader (short tenure) | High | Medium | Context dominates outcomes |
| 7 | Venture-backed startup founder (median) | High | Medium | Few outsized successes |
| 8 | Influencer entrepreneur | High | Medium | Impact depends on audience luck |
| 9 | Journalist (agenda-setting roles) | Medium | Medium | Skill + institutional leverage |
| 10 | Corporate executive (large firm) | Medium | Medium | Impact constrained by system |
| 11 | NGO leader | Medium | Medium–High | Execution skill matters |
| 12 | Policymaker / regulator | Medium | Medium–High | Skill filtered through politics |
| 13 | Urban planner | Low–Medium | High | Long-term structural effects |
| 14 | Public health official | Low–Medium | High | Evidence-driven outcomes |
| 15 | Educator (system-level reach) | Low–Medium | High | Compounding long-term impact |
| 16 | Scientist (applied research) | Low | High | Knowledge accumulation |
| 17 | Software engineer (widely used systems) | Low | High | Scalable, repeatable impact |
| 18 | Engineer (infrastructure, safety) | Low | Very High | Failure intolerant |
| 19 | Civil servant (operations) | Low | Very High | Reliability over visibility |
| 20 | Nurse / caregiver | Very Low | Very High | Direct human impact |
| 21 | Skilled trades (utilities, safety) | Very Low | Very High | Quiet, essential services |
| 22 | Physician | Very Low | Very High | Skill tightly linked to outcomes |

Table 10. Combined ranking by luck dependence and typical social impact. Ordered from high luck / low reliable impact to low luck / high reliable impact. **Luck Dependence**: extent to which outcomes vary due to randomness, timing, or attention rather than skill. **Social Impact**: durability, scale, and reliability of positive effects on others. High-luck roles can achieve huge impact, but only rarely and unpredictably. Low-luck roles deliver consistent, compounding impact across time. The inverse relationship suggests that activities with greatest reliable social impact are typically those where luck matters least and feedback, standards, and accountability are strongest.

The combined rankings reveal a striking inverse relationship. At ranks 1–8, high luck dependence correlates with low or fleeting impact. Viral celebrities and content creators achieve visibility through algorithmic chance but produce minimal lasting value. Entertainment stardom and speculative finance offer high personal rewards but uncertain societal benefits. The middle ranks (9–15) show mixed patterns where institutional context mediates between skill and impact. Journalists, policymakers, and NGO leaders operate in environments where execution skill matters but political and organizational luck filters effectiveness.

At ranks 16–22, low luck dependence correlates strongly with high sustained impact. Physicians, nurses, engineers, and skilled tradespeople work in domains with tight feedback loops, professional standards, and accountability mechanisms. Their skills translate reliably into measurable benefits: infrastructure safety, healthcare outcomes, essential services. This work often receives low public visibility and modest status relative to its impact, yet produces the consistent, compounding benefits that constitute societal welfare.

This pattern suggests a fundamental misalignment between recognition systems and value creation. Winner-take-all attention markets reward luck-driven outcomes with disproportionate status and income, while skill-intensive work producing reliable impact receives limited recognition. Understanding this misalignment informs institutional design: societies might benefit from mechanisms that reduce luck amplification in reward structures and better recognize sustained, skill-driven contributions to collective welfare.

7.5. **Cultural and Psychological Effects.** Wider recognition of luck's role may produce several cultural shifts:

- **Increased Humility:** Successful individuals may develop greater appreciation for favorable circumstances rather than attributing outcomes entirely to personal merit.
- **Reduced Stigma:** Failure may be viewed with less moral judgment when understood as partially reflecting bad luck.
- **Systems Thinking:** Cultural narratives may shift from individual hero stories toward recognition of structural conditions and systemic factors.
- **Risk of Fatalism:** Overemphasis on luck without careful communication could reduce motivation and effort, particularly in educational contexts.

7.6. **Limitations and Caveats.** Several limitations warrant acknowledgment. First, quantifying control remains challenging and often requires judgment calls. Second, the framework assumes agents have definable utility functions, which may not capture all relevant dimensions of value. Third, practical application requires substantial data that may not always be available. Fourth, emphasizing luck could produce unintended psychological effects if not communicated carefully.

Despite these limitations, the framework provides a structured approach to a question that otherwise remains informal and speculative.

## 8. Related Work

Recent research has advanced the formal quantification and empirical analysis of skill and luck across multiple domains. This work complements and extends our theoretical framework by providing domain-specific applications and empirical validation.

**Game-Theoretic Foundations.** Silver [**?**] introduces a formal index to disentangle skill and luck in stochastic games by decomposing outcomes into "skill leverage" and "luck leverage." This framework provides algorithms to compute these components from game trees and maps games on a spectrum from pure chance to pure skill. The approach generalizes beyond games to any decision process under uncertainty, with applications in game design, AI performance evaluation, and risk management.

Jerdee and Newman [**?**] extend classical ranking models by adding a "luck" parameter capturing random upsets and a "depth of competition" metric. Fitting this model to sports, games, and social hierarchies, they find that human social hierarchies tend to be deep with significant luck factors, while sports and games show shallow competition with minimal luck-driven upsets. This quantification demonstrates different luck-skill balances across domains.

**Normative and Philosophical Analysis.** Liu and Tsay [**?**] build on prior chance models to formalize when high performance misleadingly signals merit versus luck. They define four versions of a normative luck framework integrating psychological insights with decision models, predicting conditions under which extreme success may indicate greater luck and even lower expected skill. They illustrate how highly cited publications can sometimes reflect lower true research quality through chance success, and discuss strategies to correct biases that lead people to mistake luck for skill.

Lefranc and Trannoy [**?**] situate the skill-luck distinction in inequality and social justice contexts. They refine equal opportunity definitions by distinguishing how luck enters before or after effort.

Their analysis highlights that the timing of luck relative to decision-making critically affects how policy should compensate for or nullify luck's effects.

**Agent-Based and Simulation Models.** Pluchino, Biondo, and Rapisarda [?] use agent-based modeling to explore how random events combined with talent distributions produce outcome distributions. They show that multiplicative effects of random lucky events can yield extremely skewed success outcomes even with normally distributed talent. Greatest successes often require being fortunate multiple times rather than being most talented, providing quantitative basis for the meritocracy-versus-luck debate.

**Empirical Studies in Education and Labor Markets.** Landaud et al. [?] exploit a natural experiment in Norwegian high school exams to measure luck. Students randomly assigned exam subjects experience "lucky" outcomes when tested in their strongest subjects. This exam luck significantly boosts grades, graduation probability, and leads to substantial lasting wage differences comparable to effects of parental education or teacher quality, underlining luck's role in educational and labor outcomes.

**Applications in Sports.** Holzmeister and Johannesson [?] quantify skill versus luck in professional soccer using seven European leagues. They decompose team performance relative to expected goals into skill and luck components, estimating that approximately 40% of over-or-under-performance variation is skill while 60% is luck. Simulations show luck changes the champion in 34% of seasons and decides relegations in 76% of cases, demonstrating that chance significantly sways season outcomes alongside skill.

**Corporate Governance and Executive Compensation.** Al-Sabah [?] examines whether CEOs accumulate influence through skill or fortunate outcomes. Findings show that good luck significantly increases CEO power within firms, while measurable skill has smaller effects. Boards often inadvertently reward CEOs for lucky outcomes, expanding authority beyond what skill alone would merit.

Bertrand and Mullainathan [?] define luck as observable shocks to firm performance outside CEO control and test whether such luck affects compensation. CEO pay increases due to lucky outcomes as much as for skill-driven performance. However, firms with strong governance better filter out luck, granting smaller raises for luck-driven gains. This evidence of "pay-for-luck" sparked debates on fair compensation and incentive contract design.

**Financial Markets.** Fama and French [?] address whether outperforming investment fund managers are skillful or lucky. Using bootstrap simulation on decades of U.S. mutual fund data, they show very few funds earn returns beyond chance expectations after fees. Most apparent outperformance can be explained by luck, reinforcing caution in attributing short-term success to manager skill.

Each of these works either builds upon similar luck-skill decomposition themes or applies them across domains including games, sports, education, finance, and corporate governance. Together, they advance theoretical foundations and provide empirical demonstrations, expanding our ability to quantify and act upon the interplay of skill and luck in real-world outcomes.

## 9. Conclusion

This paper develops a formal framework for quantifying skill and luck in agent outcomes. By integrating concepts from probability theory, decision theory, and causal inference, the approach provides mathematically precise definitions and measurement procedures. The framework distinguishes three essential components—probability, utility, and control—and combines them in a multiplicative luck function that satisfies intuitive axioms.

Applications span individual event rating, performance evaluation, and societal-level analysis. At the individual level, the framework enables luck-adjusted assessment of outcomes. At the aggregate level, it supports measurement of luck inequality, circumstantial dependence, and social mobility. These measurements inform debates about fairness, desert, and policy design.

Several directions for future work appear promising. Empirical applications to specific domains such as labor markets, financial markets, or educational outcomes could validate the framework and refine estimation methods. Extensions incorporating dynamic considerations such as path dependence and cumulative advantage would enhance understanding of lifetime trajectories. Integration with behavioral economics and psychology could address perception biases and motivation effects. Normative analysis of optimal policy under measured luck distributions could translate descriptive findings into prescriptive recommendations.

The framework suggests that outcomes depend more substantially on luck than commonly acknowledged. This recognition has implications for how societies structure incentives, allocate resources, and make judgments about individual responsibility. By providing formal tools for measurement and analysis, the framework enables more rigorous and evidence-based engagement with these questions.

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