Luck, Talent and Effort in Business and Career Success

Combined report: research literature and simulation study · 13 November 2026

Sources combined: the literature review `research_report.pdf`, and the simulation study `results/simulation_results.md` with its data file `results/results.json` (model code in `simulation/model.py`).

1. Executive summary

The question. When some people or businesses do far better than others, how much is due to talent, skill and effort, and how much to luck?

How we answered it. We combined two pieces of work. The first is a review of published research, drawing on tax and social-security records, business registers, startup-investment data and psychology studies. The second is a computer simulation of working lives: 1,000 runs of 1,000 people for each scenario, with settings taken from that research wherever it had evidence.

Short answer. It depends on what you measure. Everyday outcomes, such as yearly pay or total lifetime earnings, are mostly shaped by lasting differences between people. Extreme outcomes, such as a huge startup sale or great wealth, are mostly shaped by luck. Talent and skill raise your odds; they do not decide your outcome. And many "personal" advantages (genes, family, the year you start work) were themselves luck.

#	Main finding	Confidence
1	The more extreme the outcome, the larger luck's role.	Literature: **High**. Simulation agrees: traits fixed at age 23 explain 62% of the variation in lifetime earnings, but only 31% of the variation in final wealth (in proportional terms).
2	For lifetime earnings, about 55–65% of the differences between people are already in place at age 23; the other 35–45% come from later events.	Literature: **Medium** (other models range up to 90/10). The simulation was built to match this, so it is not an independent check.
3	For any single startup, the founder's lasting qualities explain only a minority of its success; chance and timing dominate. One large venture-capital firm's own scores correlated only about 0.1 with results.	Literature: **Medium**. Simulation agrees: even perfect knowledge of talent correlates only 0.16 with a venture's payoff.
4	Skill is real, builds up over time and can partly be learned. It shifts the odds.	Literature: **High**. Simulation: talent helped in all 60 variants of the full model. The most talented tenth reach the top 1% 5.53% of the time (least talented tenth: 0.017%), yet 44.7% of the top 1% come from outside the most talented tenth.
5	If genes, family and birth timing count as luck, luck's share is larger than any figure above.	Literature: **Medium** (depends on definitions). Not tested by the simulation.
6	People credit themselves for success and blame circumstances for failure.	Literature: **High** (266 studies). Not tested by the simulation.
7	A steady income from work is the strongest equaliser: it reduces inequality and ties outcomes more closely to talent.	Simulation only: the direction held in all 33 of 33 paired tests; the size depends on assumptions. Fits the literature's finding that repeated, everyday outcomes are less luck-driven.
8	Two disagreements. (a) The literature suggests the very top performers are weaker evidence of skill than the next tier; the simulation never found this. (b) "Take more shots" raises the average and the chance of a big win, but lowers the typical outcome unless you can survive the losses.	Simulation results that depend on the model. They show the literature's points are not automatic, not that they are wrong.

Key caveats.

- Luck and skill cannot be observed directly. Every estimate comes from a model, and the answer depends on its assumptions and on what counts as "luck". No single "luck percentage" is reliable.
- The simulation was built from the literature, so where they agree this is partly by design. 34 of its 60 settings are assumptions. The two that matter most for inequality (how often people get risky opportunities, and how much they stake) have no direct evidence behind them.
- Most evidence is from the U.S., and some figures come from secondary sources. Minor inconsistencies in both source files are listed in Section 7.3 of the full report; none changes these conclusions.

2. Introduction and approach

2.1 The question and why it is hard

When some people or businesses do far better than others, how much is due to talent, skill and effort, and how much to luck? The answer matters for how individuals plan careers, how investors read track records and how governments think about insurance against bad luck.

The question is hard because neither luck nor skill can be seen directly. Researchers infer them from patterns in data, using models whose assumptions largely drive the answer. The answer also depends on definitions. This report uses the literature review's definitions:

- **Luck:** outcome-relevant factors outside a person's control at the relevant time.
- **Skill:** a persistent, person-specific capacity that raises expected outcomes.

On these definitions, being born talented or into a well-off family is luck, even though it later shows up as "ability" or "background" (Section 3.5).

2.2 The two sources

The literature review (`research_report.pdf`) gave priority to peer-reviewed papers and working papers that use administrative data or natural experiments: U.S. Social Security records, U.S. Census business registers, Swedish tax registers and venture-capital deal databases. It also drew on official business statistics (U.S. Bureau of Labor Statistics Business Employment Dynamics, reached through secondary tabulations), meta-analyses in psychology and agent-based simulation models. Popular books (Mauboussin's *The Success Equation*, Frank's *Success and Luck*) frame the debate but were not relied on for figures. The review describes four ways researchers separate luck from skill: **persistence tests** (if skill matters, past performance should predict future performance, while luck by definition does not repeat); **variance decomposition** (splitting the observed spread of outcomes into a part due to persistent factors and a part due to later shocks, using statistical or economic models); **natural experiments** (random events such as lottery wins, recessions at graduation or plant-closure layoffs show the causal effect of pure luck); and **simulation** (computer models show what spread of outcomes a given mix of talent and chance would produce: what is possible, not what is true).

The simulation study (`simulation/model.py`, results in `results/`) is an agent-based Monte Carlo model: a program that follows many simulated people ("agents") through randomly drawn life events, and repeats this many times. Each person works for 40 years from age 23. Their final wealth depends on talent, effort, unchosen background, a steady income from work, and random good and bad events. Each model version was run 1,000 times with 1,000 people per run (1,000,000 simulated lives per version), plus 93 sensitivity variants of 1,000 runs each. Of the model's 60 settings, 19 come directly from the literature review, 7 are calibrated (tuned so the model reproduces figures from the review or, in one case, a stated assumption) and 34 are assumptions, each labelled and justified in `results.json`.

2.3 How this report was put together

- **No new analysis or claims.** Everything here comes from the source files. Where the sources contradict each other or themselves, or an argument looks weak, this is flagged (marked **Flag**) rather than resolved. All flags are collected in Section 7.3.
- **Confidence ratings.** Ratings for literature findings (High, Medium, Low, and the evidence-quality ratings in Section 3.9) are the review's own. The simulation study does not assign confidence ratings. For its findings we report instead how many of its sensitivity tests a result survived, which is how the study itself judges robustness.
- **Numbers.** Literature figures are as stated in the review. Every simulation figure was read from `results/results.json` and is rounded only for display. Where the rounding in `simulation_results.md` differs from `results.json`, this report follows `results.json` and notes the difference in Section 7.3. Simulation figures are averages over 1,000 runs. Their 95% confidence intervals are very narrow (for example, the Gini coefficient of version A is 0.515, interval 0.513 to 0.518) and are mostly omitted. Figures that appear in the simulation write-up but are not stored in `results.json` are described without numbers.
- **Citations** are given as author and year. Full references, with the links used in the source files, are in Section 8.

2.4 Key terms

Term	Meaning in this report
Variation (variance)	How spread out an outcome is across people. "X explains 60% of the variation" means X accounts for 60% of that spread.

Term	Meaning in this report
Correlation	A number from −1 to 1 showing how closely two things move together (0 = no relation, 1 = perfect). *Pearson* correlation uses raw values and is pulled around by a few extreme values. *Spearman* (rank) correlation uses people's positions in a ranking.
Median, mean	The median is the middle value (half above, half below); the mean is the ordinary average. A few very rich people pull the mean well above the median.
Gini coefficient; top 1% share	Inequality measures. Gini: 0 means everyone has the same, 1 means one person has everything. Top 1% share: the share of all wealth held by the richest 1%.
Heavy-tailed, power law, Pareto, lognormal	Distributions in which a few values are enormous compared with typical ones. Power-law (Pareto) tails are heavier than lognormal ones.
Skewness, kurtosis	Skewness says whether a distribution's long tail points up (positive) or down (negative). Kurtosis says how heavy the tails are; a normal ("Gaussian", bell-curve) distribution has kurtosis 3.
Standard deviation (SD)	The typical distance from the average. "+1 SD of talent" means one standard deviation above average talent.
Heritability	The share of variation in a trait associated with genetic differences, in a given population.
Effect size *d*	The difference between two groups, measured in standard deviations.
Structural model	An economic model of people's decisions, fitted to data, that splits outcomes into parts due to starting conditions and later shocks.
Natural experiment	A real event that hits people essentially at random (a lottery, a recession at graduation), so its effect can be measured as cause and effect.
Calibration	Choosing a model's settings so that it reproduces known figures. A calibrated match is there by design and is not an independent test.
Sensitivity analysis	Re-running a model with one setting changed at a time to see which results hold up.
95% confidence interval	A range that, with 95% confidence, contains the true value being estimated (here, the model's long-run average).
Log scale, proportional terms	Comparing values by ratio ("twice as rich") rather than by difference.
pp	Percentage points: the difference between two percentages (30% against 20% is 10 pp).

3. What the research literature shows

This section summarises `research_report.pdf`. Where the review offers its own interpretation, this is labelled.

3.1 The review's headline

Luck is a large factor in business success, but not the only one. For extreme outcomes, such as which startup becomes a huge exit, chance and timing account for most of the observed variation. For steadier measures, such as lifetime earnings or whether a small business survives, persistent personal factors (skill, experience, starting endowments) account for roughly half to two-thirds of the variation. A large share of those "personal" factors were themselves unchosen luck: genes, family and the year you were born.

Overall confidence (review's rating): high on the direction, medium on magnitudes for earnings, and low on any precise "luck %" for entrepreneurship. The split depends heavily on how success is measured, on what counts as luck and on modelling assumptions, so any single headline percentage is unreliable.

3.2 How small differences in luck become large differences in outcomes

The "Talent vs Luck" (TvL) model. Pluchino, Biondo & Rapisarda (2018) simulate 1,000 agents over 40 years in six-month steps. Talent is normally distributed. In each step, an agent hit by a lucky event doubles its capital with probability equal to its talent, and an agent hit by an unlucky event halves its capital. Capital ends up heavy-tailed (Pareto-like), and the richest agents are usually of near-average talent but unusually lucky. The authors conclude that talent is "necessary but not sufficient". The model has been influential, including winning an Ig Nobel prize. The review reports these critiques:

- **Sensitivity.** Elvidge (2020) finds the model "very sensitive to both random sampling and the choice of value for the input parameters". Repeated runs with identical inputs give "a range of output values of over 50% of the mean value", and the probability of a lucky event affects maximum capital "almost three times more than any other individual parameter".
- **Talent is weak by construction.** An informal, non-peer-reviewed reimplementation by J.B. Whitmore calculates that a 95th-percentile agent's per-step advantage over a 5th-percentile agent is only about 2.6%.
- **Unverified AI replication.** An AI-generated "living paper" on GitHub reports that the released code does not truncate talent as the paper describes, and that the paper's "3%" figure for highly talented winners comes out at about 8% in the paper's own engine. The review says it is unverified and should be treated with caution.

- **Follow-up work.** Hamada (2023) shows analytically that a simplified version produces a lognormal rather than power-law capital distribution, even with normally distributed talent. Challet, Pluchino, Biondo & Rapisarda (2020), the original authors, confirm that a model with only lucky events reproduces the inequality; this is not an independent check.

The review's interpretation: the model is a valid existence proof (multiplicative dynamics plus random events *can* turn modest talent differences into extreme, mostly luck-driven outcome differences), but not an estimate of the real-world luck share, because its parameters were not calibrated to data.

Top performers. Denrell & Liu (2012) show the conditions under which the top performer is not the most skilled. When performance is noisy and subject to rich-get-richer feedback, "whether higher performance indicates higher ability depends on whether extreme performance could be achieved by skill or requires luck". In luck-heavy domains, the second-best is a better guide to skill. The review calls this a model result with empirical support in work by the same research programme. **Flag:** no specific empirical study is cited for that support; the linked sources are a press release and a summary website.

Field experiments. van de Rijt and colleagues (2014) randomly gave early success to some recipients in real funding, endorsement, status and reputation systems. The random early boosts led to more later success: causal evidence that arbitrary early luck can compound.

3.3 Persistence: evidence that skill exists

- **Serial entrepreneurs.** Gompers, Kovner, Lerner & Scharfstein study venture-backed founders. In the working-paper version (NBER WP 12592, 2006), previously successful entrepreneurs "have a 30% chance of succeeding in their next venture", against 18% for first-timers and 20% for those who previously failed. The published version (*Journal of Financial Economics*, 2010) reports 21% for first-timers and 22% for prior failures. The persistence shows up as skill at choosing industry and timing, but the authors stress that part of it may be *perceived* skill: suppliers and customers commit resources to founders with a track record, so "success breeds success". *The review's interpretation:* treating each venture as a coin flip with a base rate of about 20%, a 30% versus 18% pattern implies a correlation of only about 0.1–0.15 between a founder's consecutive outcomes, so venture-specific chance dominates.
- **Age and experience.** Azoulay, Jones, Kim & Miranda (2020), using U.S. Census data, find that the mean founder age for the 1-in-1,000 fastest-growing new ventures is 45.0, and that "prior experience in the specific industry predicts much greater rates of entrepreneurial success".
- **Traits and earnings.** Levine & Rubinstein (2017) find that people who become incorporated business owners had, as teenagers, higher learning-aptitude scores, higher self-esteem and more illicit or risk-taking behaviour. The incorporated self-employed earn more per hour than comparable salaried workers (residual hourly earnings about 18% higher after incorporating, in the working-paper version); the unincorporated self-employed earn much less.
- **Venture-capital funds.** Kaplan & Schoar (2005) found strong persistence across successive funds of the same firm. Harris, Jenkinson, Kaplan & Stucke (2020/2023) find that for buyout funds, persistence measured with the information available at fundraising is modest and driven by the bottom quartile, while "persistence for VC funds persists even when using information available at the time of fundraising". VC skill and networks appear real, though access to top deals (a self-reinforcing advantage) is part of the mechanism.
- **Limits of prediction.** Kerr, Nanda & Rhodes-Kropf (2014), using one large VC firm's internal data, find that the firm's scores at the time of investment had a raw correlation of 0.1 with eventual return multiples, and that the scores of big winners and failures were statistically indistinguishable. Even expert screeners explain only about 1% of the variance in outcomes in advance.

3.4 Why the measure of success changes the answer

- **Business survival** (BLS Business Employment Dynamics, via secondary tabulations). Of U.S. private establishments born in the year to March 2015, 79.6% survived 1 year, 50.2% survived 5 years and 34.7% survived 10 years. One third-party tabulation gives 50.6% at 5 years, so the review advises checking BLS Table 7 before use. Five-year survival has stayed between about 45% and 52% for every cohort since 1994, and was about 61.7% in retail against 46.8% in information. The aggregate rate barely moves with the business cycle, which suggests most failures are idiosyncratic. That fits a large role for venture-specific chance, but is equally consistent with persistent differences in founder quality.
- **Venture-backed founders.** Hall & Woodward (2010), covering 22,004 venture-backed companies, find that the average founder received $5.8 million in exit cash, yet "almost three-quarters of entrepreneurs receive nothing at exit and a few receive over a billion dollars". Judged by the average, entrepreneurship looks attractive; judged by the median, it looks like a losing bet.
- **VC portfolio returns.** Kerr et al. (2014) report that about 55% of VC-backed startups from 1985–2009 were terminated at a loss and only about 6% returned more than five times the investment; those few supplied roughly half of gross returns. Their example VC firm had 62% of investments at a loss.

- **Self-employment earnings.** Hamilton (2000) finds that most entrepreneurs have lower initial earnings and lower earnings growth than in paid work. The median earnings gap is 35% after 10 years in business, while "a handful of entrepreneurs earn substantial returns". This contrasts with Levine & Rubinstein's finding for the incorporated; the answer differs by definition (incorporated versus all self-employed) and by statistic (median versus mean).
- **Wage earnings.** Guvenen, Karahan, Ozkan & Song (2021), using Social Security records, find that year-to-year earnings changes are strongly negatively skewed, with kurtosis "as high as 30 compared with 3 for a Gaussian distribution". In a given year most people experience very small changes and a few experience very large ones. Positive shocks to high earners are transitory while negative ones persist; the reverse holds for low earners.

The review's interpretation, which it calls the most robust pattern in the evidence: the luck share is smallest for averaged, repeated, bounded outcomes (annual wages, survival) and largest for one-shot, multiplicative, unbounded outcomes (exit value, extreme wealth).

3.5 Starting conditions versus later shocks

- **Huggett, Ventura & Yaron (2011)** estimate a model with human-capital shocks and differences in learning ability, initial human capital and initial wealth. Conditions at age 23 account for 61.5% of the variation in lifetime earnings and 64.0% in lifetime utility (well-being). With initial wealth added, the figures are 61.2% (earnings), 62.4% (wealth) and 66.0% (utility), leaving roughly 34–39% to shocks during working life. Alternative data targets give 53.8% (earnings) and 57.3% (utility). Initial human capital matters most: one standard deviation more raises expected lifetime wealth by about 47%, against about 8% for learning ability. The authors note that the paper "is silent on the prior forces which shape the individual differences" at age 23.
- **Keane & Wolpin (1997)**, as summarised by Todd & Zhang (2020): "90% of the total variance in expected lifetime utility is explained by unobserved skill endowments at age 16" (white men in the NLSY79 survey). Todd & Zhang add that family background accounts for less than 10% of the variation in lifetime utility, and that adding cognitive ability raises the explained share only to 14%. Shocks account for about 10%. Storesletten, Telmer & Yaron (2004) find slightly under half from age 22 in their model. The review treats the spread across models (roughly 50–90%) as itself a measure of uncertainty.
- **Heritability.** Nicolaou, Shane, Cherkas, Hunkin & Spector (2008) study 870 identical and 857 fraternal UK twin pairs and estimate that 37–42% of the variation in becoming an entrepreneur is associated with genes, with little effect of shared family environment. Critics note that similar heritability appears for many occupations.

Key interpretive point (review): "initial conditions" are not the same as merit. Genes, parental resources and the skills formed in childhood are not chosen. On a strict definition of luck (anything outside one's control), most of the 60–90% initial-conditions share is also luck. On a looser definition (luck = only shocks after starting work), luck is about 35–40% of the variation in lifetime earnings. Which definition is right is a philosophical choice, not an empirical one.

3.6 Natural experiments: the effect of pure luck

Shock	Finding	Source
Job loss in a mass layoff (U.S. men, Social Security records 1974–2008)	Present-value loss of 1.4 years of prior earnings when national unemployment is below 6%, and "a staggering 2.8 years" when it is above 8% (20-year horizon, 5% discount rate)	Davis & von Wachter 2011
Graduating in a recession (Canada)	"Unlucky graduates suffer persistent earnings declines lasting ten years"; losses are larger and longer for less advantaged graduates, so luck interacts with starting endowments	Oreopoulos, von Wachter & Heisz 2012
Hospital admission (insured adults aged 50–59)	Employment falls 11 percentage points; annual earnings fall by $8,753 on average over three years (about 20% of earlier earnings), persistently	Dobkin, Finkelstein, Kluender & Notowidigdo 2018
Lottery win (Swedish players)	Labour earnings fall by about 1% of the prize per year, immediately and persistently	Cesarini, Lindqvist, Notowidigdo & Östling 2017
Regional lottery windfall (Spanish Christmas Lottery: about 75% of Spaniards play; about 0.3% of GDP at stake)	More firm creation, startup job creation and self-employment, especially where finance is hard to get; firms created in winning provinces are larger, more profitable and survive longer	Bermejo, Ferreira, Wolfenzon & Zambrana 2022

Together these show that unchosen events have large and lasting effects, and that who becomes an entrepreneur, and how well their firm does, depends partly on random access to capital.

3.7 Perception and bias

- **Self-serving attribution.** Mezulis, Abramson, Hyde & Hankin (2004) meta-analyse 266 studies (503 effect sizes) and find an average effect size of $d = 0.96$, which the review calls very large: people attribute successes to themselves and failures to circumstances. The bias is smaller in Asian samples ($d = 0.30$) than in U.S. (1.05) or Western (0.70) samples, and smallest in samples with depression (0.21).
- **Survivorship and selection bias.** Studying only surviving or successful firms hides the many who did the same things and failed. With about 50% of new establishments gone within five years and about 75% of venture-backed founders getting nothing at exit, success-only samples are badly unrepresentative. Denrell & Kovács (2008) formalise this problem.
- **Reverse bias.** The perception of skill can itself create persistence (Gompers et al. 2010), so persistence overstates "pure" skill.

3.8 The strongest arguments on each side

For a large role of luck	For a large role of skill and effort
Outcome distributions are extremely skewed.	Measurable persistence exists among serial founders and VC funds.
Experts cannot predict winners (correlation about 0.1).	Experience and age predict high growth.
Persistence is modest.	Specific traits predict both who enters and who earns more.
Random early advantages compound (field experiments).	Initial human capital, which is partly built through effort, dominates lifetime-earnings variation in structural models.
Natural experiments show large, lasting effects of unchosen shocks.	Under the multiplicative logic of the luck models, a small skill edge applied over many trials and decades compounds into large expected differences, even if any single outcome is noisy.
Much of "talent" comes from genes, family and birth timing.	

The review concludes that both sides are right about different measures; the disagreement is mainly about definitions and about which outcome is studied.

3.9 The review's conclusions and confidence ratings

#	Conclusion	Confidence	Basis given by the review
L1	Luck's share rises with the extremity and path-dependence of the outcome.	**High**	Consistent across distributional data, persistence studies, field experiments and theory.
L2	For lifetime earnings, about 55–65% of variation reflects pre-career differences and about 35–45% reflects later shocks.	**Medium**	Structural models with contestable assumptions; alternative models range up to 90/10.
L3	For any single venture, persistent founder factors explain only a minority of success; venture-specific chance and timing dominate.	**Medium**	Inferred from modest persistence (30% vs 18–21%) and low expert predictability ($r \approx 0.1$); the exact share is not directly estimated in the literature reviewed.
L4	Skill is real, cumulative and partly learnable (industry experience, age, track record).	**High**	No separate basis stated (see Section 3.3).
L5	The strict-sense luck share (counting genes, family and birth timing as luck) is larger than any of these figures.	**Medium**	Heritability and initial-condition estimates support it, but the boundary is definitional.
L6	People over-attribute success to themselves.	**High**	Large meta-analysis.

The review also turned its evidence into ranges for simulation work, each with an evidence-quality rating. The simulation study took its evidence-based settings from this table (Section 4).

Quantity	Evidence-based range	Source	Evidence quality
Lifetime-earnings variance due to conditions at career start	54–66% (shocks 34–46%)	Huggett, Ventura & Yaron 2011	Medium (model-dependent)
Same, measured at age 16, lifetime utility	About 90% (shocks about 10%)	Keane & Wolpin 1997, as summarised by Todd & Zhang 2020	Medium-low
Annual earnings changes	Strongly negatively skewed; kurtosis about 10–30 (Gaussian = 3); mostly near-zero, rare large jumps	Guvenen et al. 2021	High
Persistence of positive vs negative shocks	High earners: positive shocks transitory, negative persistent; reverse for low earners	Guvenen et al. 2021	High
Mass-layoff job loss	1.4 (unemployment below 6%) to 2.8 (above 8%) years of prior earnings, present value	Davis & von Wachter 2011	High

Quantity	Evidence-based range	Source	Evidence quality
Entering the labour market in a recession	Persistent losses fading over about 8–10 years; larger for less advantaged	Oreopoulos et al. 2012	High
Health shock (hospitalisation, age 50–59, insured)	−11 pp employment; about −20% annual earnings, persistent	Dobkin et al. 2018	High
Frequency of major negative events per career	No good direct estimate gathered	—	Gap
Frequency of major positive career events	No good direct evidence; heavy right tail implies rare large positive jumps	Guvenen et al. 2021 (indirect)	Gap
New-business survival	1 yr about 80%; 5 yr about 50% (45–52% across cohorts since 1994); 10 yr about 35%	BLS BED (secondary tabulations)	High (verify against BLS tables)
Industry spread in 5-year survival	About 47% (information) to about 62% (retail)	BLS (via secondary tabulation)	Medium
VC-backed founder exit payoff	About 73–75% receive zero; mean about $5.8M; heavy right tail to over $1B	Hall & Woodward 2010	High
VC investment outcomes	About 55% terminated at a loss; about 6% return over 5x and supply roughly half of returns	Kerr, Nanda & Rhodes-Kropf 2014	High
Skill effect on venture success (track record)	30% (prior success) vs 18% (first-time) in NBER WP 12592; 21% first-time, 22% prior failure in JFE	Gompers et al. 2006/2010	Medium-high
Experts' advance prediction of venture returns	Correlation about 0.1	Kerr, Nanda & Rhodes-Kropf 2014	Medium (one firm)
Self-employment earnings vs paid work	Median −35% after 10 years (all self-employed); incorporated about +18% residual hourly	Hamilton 2000; Levine & Rubinstein 2017	Medium (definitions differ)
Talent converting luck (TvL rule)	Model assumption only (probability = talent); outputs vary over 50% across identical runs	Pluchino et al. 2018; Elvidge 2020	Low (uncalibrated)
Effect of a windfall on labour earnings	About −1% of the prize per year, persistent	Cesarini et al. 2017	High
Heritability of entering entrepreneurship	37–42%	Nicolaou et al. 2008	Medium

The review's guidance for simulations: model annual wages as a persistent personal component plus non-normal shocks (mostly small changes, rare large ones; a "normal mixture" fits this); model entrepreneurial payoffs as a separate heavy-tailed lottery in which about 75% get nothing (for VC-backed ventures); let skill shift the probability of success modestly (by a factor of about 1.5–1.7 for strong versus average) rather than determine it; and calibrate so that persistent factors explain about 55–65% of lifetime-earnings variance.

Flag: the review gives the lifetime-earnings share in four slightly different ways: 61.5% (headline), 60–66% (summary, covering earnings, wealth and well-being), 54–66% (table) and 55–65% (conclusions and simulation guidance). The underlying estimates run from 53.8% to 66.0%. The differences are small and change no conclusion.

4. What the simulation shows

This section summarises `results/simulation_results.md`. Every number is taken from `results/results.json`.

4.1 What was simulated

Each simulated person starts work at 23 and is followed for 40 yearly steps. Three traits are fixed at the start, each drawn from a bell curve (standard normal distribution) and unrelated to each other at baseline:

- **talent** (innate and unchosen) raises earnings, earnings growth and the success odds of ventures;
- **effort** raises earnings and the number of risky opportunities a person takes on;
- **background** (unchosen family, schooling and network advantages) raises earnings.

Every year brings earnings (a lasting personal level, an age profile, fat-tailed shocks, job loss, health shocks, and lasting damage from starting work in a recession) and a 3% return on wealth. It may also bring an **opportunity** (staking 25% of wealth on a venture-like bet that usually fails but occasionally pays off hugely), a **windfall** (pure luck) or a **wealth loss** (pure luck: 50% of wealth is lost). Ventures succeed 20% of the time on average, and 1.6 times as often for someone one standard deviation above average talent. An average-effort person meets an opportunity with probability 10% a year.

Version	What it contains
A: with work income	Everything above; 10% of each year's earnings is saved.
B: no work income	The same people and the same random events as A, but no earnings enter wealth.
C: Talent-vs-Luck reference	The rules of the Pluchino et al. (2018) model: talent drawn from a normal distribution with mean 0.6 and SD 0.1; in each of 80 half-year steps, a lucky event (probability 0.05) doubles capital with probability equal to talent, and an unlucky event (probability 0.05) halves it.

Units. Wealth is measured in years of median entry-level earnings. Everyone in A and B starts with 1.0; TvL agents start with 10.

Design. Versions A and B use the same people and the same random events ("common random numbers"), so their differences are measured on paired lives and are very precise. Traits and luck come from separate random streams, so the same people can be re-run with entirely new luck ("twin lives"). Every result is computed within each run of 1,000 people and then averaged over runs; the spread across runs (2.5th to 97.5th percentile) shows how much a single population can vary by chance.

4.2 Calibration and validation against the literature

The model was built to reproduce the review's figures wherever the review had them. "Calibrated" matches are there by design; "emerges" means the figure was not targeted, so the match is a partial test.

Literature figure (source)	Literature value	Model value	How
Lifetime-earnings variance fixed at age 23 (Huggett et al. 2011)	61.5% (range 53.8–66%)	62.0% (twin lives); 61.5% (regression)	calibrated
Kurtosis of annual earnings changes (Guvenen et al. 2021)	about 10–30	15.7	calibrated
Skewness of annual earnings changes	strongly negative	−0.97	calibrated
"Most individuals experience very small earnings shocks"	qualitative	30.8% of yearly changes within ±5%; 5.5% beyond ±50%	emerges
Venture success rate, first-time founders (Gompers et al.)	18% / 21%	20%	evidence
Ventures returning more than 5x (Kerr et al. 2014)	about 6%	6.07%	calibrated
Share of all venture returns from those ventures	about 50%	50.1%	calibrated
Founders receiving nothing at exit (Hall & Woodward 2010)	about 73–75%	79.8% of ventures	emerges
Correlation of an advance assessment with venture return (Kerr et al. 2014)	about 0.1 (VC scores)	0.16 (with *perfect* knowledge of talent)	emerges
Success after a previous success (Gompers et al.)	30%	24.5%	emerges
Success after a previous failure (Gompers et al.)	20–22%	18.9%	emerges
Job-loss present-value loss (Davis & von Wachter 2011)	1.4 / 2.8 years	matched (initial earnings loss 20.2% / 38.6%, then fading)	calibrated
Hospital admission (Dobkin et al. 2018)	−20% earnings, persistent	−20%, no recovery	evidence
TvL output variability (Elvidge 2020)	range of outputs over 50% of the mean	richest agent's run-to-run range = 356% of its mean	emerges

In plain language: simulated earnings behave like the real earnings data the review describes (most years bring small changes, a few bring very large ones, mostly losses), and simulated venture payoffs look like the venture-capital statistics. Knowing someone's talent perfectly predicts their venture payoff about as poorly as venture capitalists predict theirs.

Flag: the model's share of ventures that pay nothing (79.8%) lies above the review's 73–75% range; the simulation write-up lists it without comment. The two are not measured identically (ventures in the model, founders in Hall & Woodward). The two persistence figures do not match the literature either; Section 5.2 explains why.

4.3 Headline results

Result (mean over 1,000 runs)	A: with work income	B: no work income	C: TvL reference
Median final wealth	10.4	1.70	3.085 (start = 10)
Mean final wealth	17.7	3.72	15.1 (start = 10)
Mean ÷ median	1.7	2.2	4.9
Share of wealth held by the top 1%	16.0%	20.5%	27.9%
Share held by the top 10%	43.1%	52.0%	67.4%

Result (mean over 1,000 runs)	A: with work income	B: no work income	C: TvL reference
Share held by the top 20%	57.3%	66.8%	81.2%
Share held by the bottom 50%	18.1%	11.4%	4.2%
Gini coefficient	0.515	0.631	0.776
Share ending below starting wealth	0.05%	31.2%	67.0%
Spearman (rank) correlation, talent and wealth	0.490	0.266	0.149
Pearson correlation, talent and wealth	0.288	0.183	0.101
Pearson correlation, talent and log wealth	0.501	0.281	0.157
Spearman correlation, effort and wealth	0.106	−0.093	–
Spearman correlation, background and wealth	0.180	−0.001	–
Talent percentile of the richest person (average)	90th	84th	71st
Share of the top 1% who are in the top 10% of talent	55.3%	41.75%	23.71%

A single population of 1,000 people varies a lot by chance. Across runs of version A, the top 1% share ranged from 9.2% to 33.9%, the Gini from 0.46 to 0.62 and the richest person's wealth from 227 to 4,394. In version C the richest agent's capital ranged from 320 to 5,120.

In plain language: with a steady income almost everyone ends several times richer than they started (the typical person about 10 times), with a long tail of very rich people on top. Without income the typical person ends only 1.70 times richer, and 31.2% end poorer than they started. Under the TvL rules most people end poorer (the median person keeps 0.25 of their starting capital) while a few become extremely rich. Luck plus compounding creates a lot of inequality even when everyone starts equal, works and saves the same share; a steady income compresses it considerably.

Version A leaves out debt, differences in saving behaviour and inheritance, all of which would widen inequality; when higher earners save a larger share of their earnings (a sensitivity variant), A's Gini rises to 0.65. **Flag:** the simulation write-up also compares A with real U.S. wealth, labelled "general knowledge, not from the report"; that comparison has no source in either file, so its figures are not repeated here.

4.4 Talent and outcomes

Talent tenth (decile)	1 (lowest)	5	9	10 (highest)
A: median final wealth	5.9	9.8	16.1	23.1
A: chance of ending in the top 1%	0.017%	0.238%	1.84%	5.53%
B: median final wealth	1.13	1.58	2.38	3.24
B: chance of ending in the top 1%	0.128%	0.452%	1.812%	4.175%
B: share ending below starting wealth	44.5%	32.8%	21.3%	15.0%
C: chance of ending in the top 1%	0.418%	1.405%	2.831%	3.875%
C: share ending below starting capital	78.0%	67.8%	60.4%	56.0%

In version A, the most talented tenth end with 3.9 times the median wealth of the least talented tenth and are about 325 times as likely to reach the top 1%. Even so, only 5.53% of them get there, and 44.7% of the top 1% come from outside the most talented tenth. In version A almost nobody ends poorer than they started, whatever their talent; without income (B), talent reduces that risk but does not remove it.

Which correlation is quoted matters. In version A, Pearson correlation on raw wealth (0.29) is dragged down by a few enormous fortunes, while Spearman (0.49) and Pearson on log wealth (0.50) agree. A rank correlation of 0.49 means talent accounts for roughly a quarter of the variation in people's wealth rank. The simulation write-up notes that a headline correlation in this field can differ by almost a factor of two depending on the statistic chosen.

Who ends up at the very top? Average talent, in standard deviations from the mean:

Version	Richest person	Top 1%	Top 2–10%	Poorest 1%	Richest person in top 5% of talent	… in top 10%	… below median talent
A	+1.69	+1.38	+0.90	−1.07	52.4% of runs	69.1%	2.7%
B	+1.38	+1.06	+0.54	−0.53	40.1%	54.0%	8.4%
C	+0.76	+0.61	+0.32	−0.25	16.8%	28.7%	19.8%

In every version, people higher up the wealth ladder are more talented on average, and the single richest person is the most talented position of all. Talent is also no more variable within the top 1% than in the next tier (SD 0.85 against 0.88 in A), so the very top is not a *less* reliable signal of talent here. The top is still far from a pure meritocracy: under the TvL rules the richest person is on average only at the 71st talent percentile, and in every version the richest person is sometimes of

below-median talent. In version A the richest person's average talent position (the 89.8th percentile) sits just below the top-tenth cut-off; `results.json` records that it is below that cut-off in 42 of 60 variants of A.

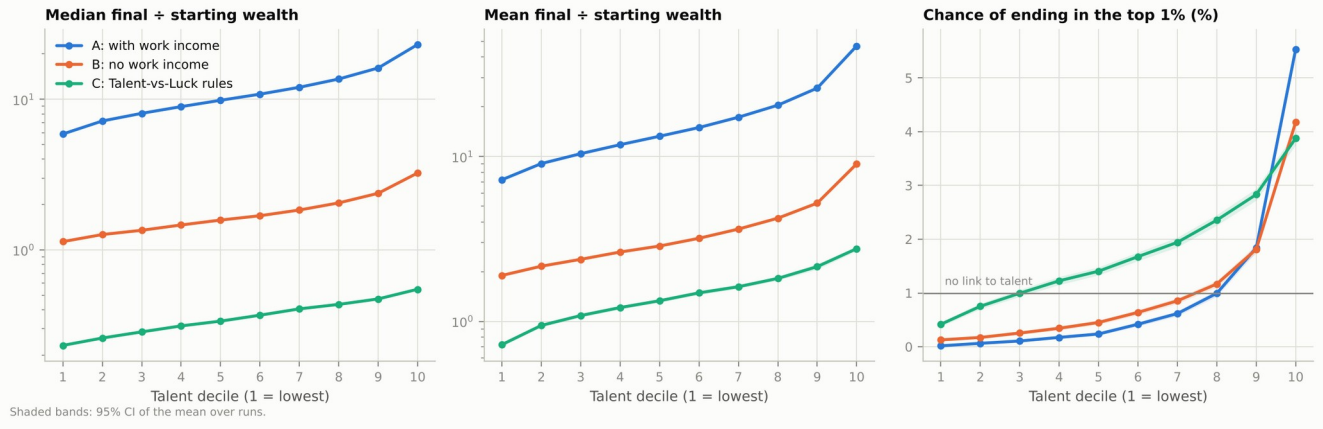


Figure 1. Median and mean final wealth (relative to the start) and chance of reaching the top 1%, by talent decile. Source: `results/charts/wealth_by_talent_decile.png`.

4.5 Effort and background

Effort works through two channels in the model: it raises earnings, which helps everyone, and it brings more risky opportunities, which helps on average but hurts the typical person, because most bets fail. With income (A), the net effect is positive but small (Spearman 0.11): the highest-effort tenth have a median wealth of 12.1 against 9.1 for the lowest, and a 2.74% chance of reaching the top 1% against 0.228%. Without income (B), high-effort people are more likely both to strike it rich and to end up poorer: from the lowest to the highest effort tenth, the chance of reaching the top 1% rises from 0.56% to 1.783% (about 3.2 times), the median falls from 1.98 to 1.32, and the share ending below their starting wealth rises from 23.3% to 41.6%. Background, which works only through earnings, matters more than effort in A (Spearman 0.18) and not at all in B (−0.001).

4.6 Twin lives: how much of the outcome is luck?

The same people (same talent, effort and background) were simulated a second time with completely new luck.

	A: with work income	B: no work income
Share of variation in log final wealth fixed by traits	31.2%	9.9%
Share of variation in final wealth (not logged) fixed by traits	5.4%	1.4%
Share of variation in log lifetime earnings fixed by traits	62.0%	same people; earnings do not enter wealth in B
Rank correlation of final wealth between the two lives	0.30	0.09
Chance of being in the top 1% again, if in the top 1% in the other life (pure chance: 1%)	7.75%	3.14%
Chance of being in the top 10% again (pure chance: 10%)	25.7%	14.6%
Chance of ending below the median, if in the top 1% in the other life	18.2%	37.7%
Share of variation in log wealth explained by talent / effort / background alone	25.1% / 1.6% / 3.2%	7.9% / 0.8% / 0.0%

In plain language: living your working life again with the same abilities but different luck, you would probably end up somewhere quite different. In the full model, fixed traits account for about a third of the variation in (log) wealth, against nearly two-thirds for lifetime earnings. Only 7.75% of the people at the very top would be there again in their second life, and 18.2% would be below the median. Yet extreme success is still far more repeatable than chance (7.75 times the chance rate in A), because talent raises the odds; relative to chance, top-1% status is more repeatable than top-10% status (2.57 times). "Mostly luck" and "strongly selected on talent" are both true of the very top.

The gap between earnings and wealth comes from the wealth events (opportunities, windfalls and losses), whose settings are assumptions. With all of them switched off, the three traits explain 60.9% of the variation in log wealth (measured by regression, the method used for variants; at baseline it gives 29.9% against the twin-life 31.2%).

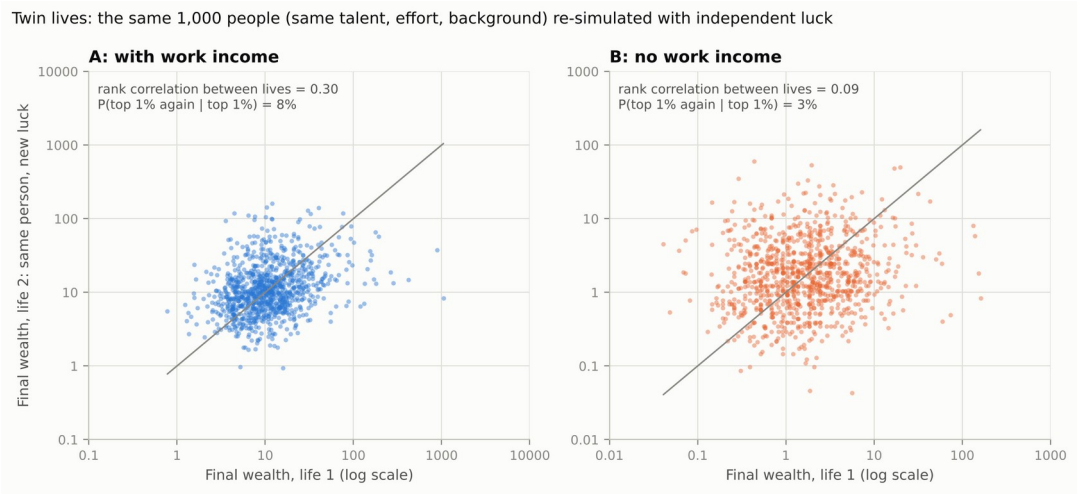


Figure 2. Final wealth of the same 1,000 people (run 0) in two lives with independent luck. Source: `results/charts/twin_lives.png` (its labels round the top-1% repeat chances to whole percentages).

4.7 Work income: the strongest and most robust equaliser

Because A and B contain the same people with the same luck, the difference between them isolates the effect of a steady income.

Result	A minus B [95% CI]	Range of A minus B across 33 paired variants
Median final wealth	+8.66 [8.65, 8.68]	+5.3 to +12.6
Gini coefficient	−0.115 [−0.117, −0.114]	−0.077 to −0.205
Top 1% share	−4.4 pp [−4.7, −4.2]	−2.7 to −9.4 pp
Share ending below start	−31.1 pp [−31.2, −31.0]	−10.5 to −67.5 pp
Spearman correlation, talent and wealth	+0.224 [0.223, 0.226]	+0.16 to +0.37

All five directions (higher median, lower Gini, lower top-1% share, fewer people ending worse off, stronger link between talent and wealth) held in 33 of 33 paired variants.

In plain language: a steady wage is a stream of many small, mostly reliable payments. It adds a large, predictable amount to everyone's wealth, which dilutes the influence of a few lucky or unlucky big events. Because earnings themselves reflect talent, effort and background, outcomes also become more closely tied to those traits. This is the review's "averaged, repeated, bounded outcomes are less luck-driven" pattern appearing inside a single model.

4.8 Which sources of luck matter most

Each row switches one source of luck off (1,000 runs each). "Talent corr." is the Spearman correlation of talent with wealth.

Scenario	A: Gini	A: top 1%	A: talent corr.	B: Gini	B: top 1%	B: talent corr.	B: below start
Baseline	0.515	16.0%	0.49	0.631	20.5%	0.27	31.2%
Opportunities off	0.290	3.6%	0.37	0.380	7.1%	0.00	13.8%
Windfalls off	0.517	16.3%	0.51	0.619	21.5%	0.30	40.4%
Wealth-loss events off	0.502	16.1%	0.54	0.589	19.5%	0.32	10.5%
All wealth events off	0.223	3.1%	0.52	–	–	–	–
All earnings luck off	0.529	16.7%	0.56	–	–	–	–

In plain language: the risky opportunities create most of the inequality at the top; switching them off cuts A's top-1% share from 16.0% to 3.6%. Removing all luck from earnings (no shocks, job losses, health shocks or recession effects) barely changes wealth inequality and raises the talent correlation only from 0.49 to 0.56. Earnings luck matters a lot for earnings, but over a lifetime it averages out in wealth. In B, talent reaches wealth only through opportunities: switch them off and talent stops mattering.

4.9 What holds up and what depends on assumptions

The sensitivity analysis changed one setting at a time across its plausible range: 59 variants of A, 32 of B and 2 of C, each with 1,000 runs and the same random numbers as the baseline.

Results that held in every relevant variant:

- Work income raises the median and the talent–wealth link, and lowers the Gini, the top-1% share and the share ending worse off: 33 of 33 paired variants.
- The talent–wealth rank correlation is positive: 60 of 60 variants of A, and 31 of 33 of B. The two exceptions in B are the variants in which talent has no route to wealth (venture skill effect off, or opportunities off), where the correlation is about zero, as it should be.
- The top 1% is never less talented than the top 2–10% (no "Denrell–Liu reversal"). A reversal appeared in 0 of 60 variants of A and 1 of 33 of B. The one case is the B variant with opportunities switched off, where talent cannot affect wealth and the true gap is zero; the study treats the measured gap (−0.024 SD) as a statistical false positive.
- Fewer than 5% of people end below their starting wealth in A: 60 of 60.
- Fixed traits explain under half of the variation in log wealth in A: 59 of 60. The exception is "all wealth events off" (0.61).

Results whose size depends on assumptions (ranges over the one-at-a-time variants, excluding the switch-off variants of Section 4.8):

Result	A: baseline	A: range	B: baseline	B: range	Most influential settings
Gini coefficient	0.515	0.36–0.73	0.631	0.45–0.85	Share of wealth staked, opportunity rate (both assumptions)
Top 1% share	16.0%	6.4%–37.7%	20.5%	9.1%–47.1%	Share staked, opportunity rate; in A also talent's effect on ventures
Median final wealth	10.4	5.9–18.6	1.70	0.51–5.60	A: savings rate, return on wealth. B: starting wealth, return on wealth
Ending below start	0.05%	0.0%–4.0%	31.2%	13.0%–67.8%	A: starting wealth. B: return on wealth, share staked, loss rate
Spearman, talent and wealth	0.49	0.29–0.56	0.27	0.00–0.40	Talent's effect on ventures; A also talent's effect on earnings; B also opportunity rate
Talent percentile of richest	90th	61st–95th	84th	49th–93rd	Talent's effect on ventures
Log-wealth variation explained by traits (R^2)	0.30	0.14–0.41	0.09	0.01–0.33	A: talent's effect on ventures, target earnings share. B: unequal starting wealth

- **How unequal wealth ends up** depends mostly on how often people get opportunities and how much of their wealth they stake. The review has no evidence on either; it lists the "frequency of major positive career events" as a gap. The opportunity rate plays the role of the lucky-event probability that Elvidge (2020) found to be the most influential input of the TvL model.
- **How strongly talent predicts wealth** depends most on how much talent raises venture success. Between the low end of the review's guidance (1.5 times, which the study reads as +1 SD against average) and the 2.07 times implied by Gompers et al.'s persistence figures, the Spearman correlation in A ranges from 0.47 to 0.56. If talent did not affect venture success, it would fall to 0.29 (and to 0.000 in B).
- **Whether people without income end worse off** ranges from 13.0% to 67.8% in B, mostly depending on the assumed return on wealth (67.8% at a 0% return, 13.0% at 5%).
- **Whether effort pays** (its correlation with wealth ranges from −0.003 to 0.252 in A) depends on whether the extra opportunities effort brings are good bets (Section 5.2).
- **The TvL outputs** are fragile: changing the event probability from 0.05 to 0.02 or 0.10 moves the Gini from 0.78 to 0.55 or 0.91, the top-1% share from 27.9% to 11.5% or 51.2%, and the talent correlation from 0.15 to 0.09 or 0.22.
- **The best-evidenced settings matter least.** Across their ranges, job-loss frequency and timing, health-shock frequency and recovery, and the size of the recession-entry effect each changed A's Gini by at most 0.004 and its talent correlation by at most 0.004. Removing Guvenen et al.'s asymmetry or the fat tails of earnings shocks raised the Gini by 0.04 and 0.05.

In plain language: the directions are robust. A steady income always equalises and always strengthens the link between talent and wealth; talent always helps; the top is always more talented on average; and in every one-at-a-time variant wealth is much more luck-driven than earnings. The sizes are not robust, and the settings that move them most are the ones nobody has measured well.

4.10 Comparison with the Talent-vs-Luck model

Version C reproduces the qualitative claims the review attributes to TvL. Capital is heavy-tailed (the top 20% hold 81.2%, close to the familiar "80/20"). The richest agents are moderately but not exceptionally talented (71st percentile on average). 67.0% of agents end poorer than they started. Run-to-run variation is very large: the richest agent's capital ranges from 320 to 5,120 across runs, a spread of 356% of the mean, which confirms Elvidge's point that single TvL runs are unreliable.

The calibrated model gives talent a much larger role than TvL: Spearman 0.49 (A) and 0.27 (B) against 0.15, and the richest person at the 90th and 84th talent percentiles against the 71st. This supports Whitmore's critique that TvL's talent effect is weak by construction: when talent's effect on success is set from the venture evidence, talent matters noticeably more.

5. Where the literature and the simulation agree and disagree

The simulation was built from the literature, so agreement on calibrated figures is there by design. The informative comparisons are results the model was not tuned to produce, and places where putting the literature's figures into one model exposes tensions between them.

Topic	Literature (confidence)	Simulation	Verdict
Luck's role grows with how extreme the outcome is	L1 (High)	Traits fixed at 23 explain 62% of lifetime-earnings variation (calibrated) but 31% of log-wealth variation (10% without income). Only 7.75% of the top 1% repeat in a second life.	**Agree.** The wealth figure depends on assumed wealth events.
Averaged, repeated, bounded outcomes are less luck-driven	The review's "most robust pattern"	A steady income changes the Gini by −0.077 to −0.205 and raises the talent rank correlation in all 33 paired variants	**Agree**
Skill shifts the odds but does not decide outcomes	L4 (High)	Talent always helps (60 of 60 variants), with large overlap between talent groups	**Agree**
Experts cannot predict venture winners	Correlation about 0.1 (Medium, one firm)	Even perfect knowledge of talent gives a correlation of 0.16	**Agree** (emerged, not targeted)
Lifetime earnings: about 55–65% fixed by 23	L2 (Medium)	62.0%	**Matches by design**; not an independent check
TvL is fragile and single runs are unreliable	Elvidge 2020; TvL rule rated Low (uncalibrated)	Run-to-run range 356% of the mean; Gini 0.55–0.91 as the event probability varies	**Agree**
TvL's talent effect is weak by construction	Whitmore (informal)	Calibrated model gives talent a much larger role	**Agree**
The very top is weaker evidence of skill than the next tier	Denrell & Liu 2012 (model result; empirical support claimed but not cited)	No reversal in any variant where talent can affect wealth	**Disagree** in this model; not a refutation
"Maximise the number of independent shots"	Practical advice, paired with "survive bad draws"	More shots raise the mean and the top-1% chance but lower the median and raise the chance of ending poorer (B)	**Partly agree**: only together with the survival advice
Skill effect of 1.5–1.7 times vs persistence of 30% / 18–21% / 20–22%	Guidance vs Gompers et al. (Medium-high)	At 1.6 times, repeat success is only 24.5%	**Tension within the literature's figures**
"Ordinary outcomes are about 60% persistent" applied to wealth	Huggett et al.: 62.4% for "wealth"	31% for accumulated wealth	**Different measures**; do not carry the 60% over
Job loss, health shocks and recession entry have large lasting effects	Natural experiments (High)	Used as inputs; they barely change wealth inequality or the talent link	**Not a contradiction**: individual effects vs population inequality
Genes and family as luck; self-serving bias; business survival	L5 (Medium), L6 (High), BLS data	Not modelled (talent and background are unchosen by assumption)	**Not tested**

5.1 Where they agree

Both sources find that luck matters more as outcomes become more extreme, that skill is real but only shifts the odds, and that averaged, repeated outcomes are less luck-driven than one-shot, compounding ones. The simulation shows this pattern within a single set of people (earnings about two-thirds fixed by traits, wealth about one-third), and it confirms the critiques of the TvL model.

5.2 Where they disagree, or where combining them exposes a tension

1. Are the very top performers the most skilled? The review emphasises Denrell & Liu's result that "the very top performers are often less reliable evidence of skill than the merely very good", and advises investors to discount extreme track records. The simulation found the opposite in every version and every variant where talent can affect wealth, including the luck-heavy TvL rules: average talent rises with wealth rank right up to the richest person, the top 1% is more talented than the top 2–10% (A: +1.38 against +0.90 SD), and the top 1% is slightly *less* spread out in talent. The simulation study explains that Denrell & Liu's result needs specific conditions, for example when the most skilled avoid the high-variance strategies that produce extreme outcomes, and that its model lacks them. So this does not refute Denrell & Liu, but it shows that the reversal is not a general consequence of "luck plus rich-get-richer". Which conditions hold in real markets is not settled by either source.

2. The literature's skill guidance and its persistence data do not fit together. The review suggests a skill effect of about 1.5–1.7 times for strong versus average founders, and reads Gompers et al.'s persistence figures as a correlation of about 0.1–0.15 between consecutive outcomes. At the guidance value (1.6 times), the model gives repeat success of only 24.5% rather than 30%, success after a failure of 18.9%, and a consecutive-outcome correlation of 0.057. Matching the 30% figure would need 2.07 times per SD (correlation 0.125), but then founders who failed before would succeed only 17.5% of the time. More generally, the simulation study notes that no model in which persistence is pure hidden skill can reproduce Gompers et al.'s third figure: such a model predicts that founders who failed before should do *worse* than first-timers, but the data show them doing as well or better (20–22% against 18–21%). This fits the review's caveat that persistence partly reflects *perceived* skill, and the study suggests selection into repeat founding or learning from failure as further explanations. The simulation used the guidance value as its baseline and tested the higher value (Section 4.9).

3. "Take more shots" is two-edged. The review advises individuals to "maximise the number of independent 'shots' and survive bad draws". With venture payoffs calibrated to the review's own statistics (most fail; about 6% return over 5x and supply half of returns), the average bet returns 1.05 times the stake: close to fair on average. The simulation write-up also gives per-bet calculations (not stored in `results.json`, so not quoted here) showing that for a person of exactly average talent a bet is slightly below break-even, and that because a failure loses the whole stake, the typical outcome of a bet is negative unless talent is well above average. In the model, more shots therefore raise the mean and the chance of a top-1% result, but lower the median and raise the chance of ending poorer than you started (Section 4.5). The review's companion advice, to survive bad draws and avoid ruin, is what makes extra shots worthwhile.

4. Wealth is far more luck-driven than "ordinary outcomes are about 60% persistent" suggests. The model reproduces the 62% figure for lifetime earnings but gives only 31% for accumulated wealth (10% without income). The review quotes 62.4% for "wealth" from Huggett et al. The simulation write-up reads that figure as most likely referring to *lifetime* wealth (earnings plus initial wealth) rather than wealth after investment risk, so it does not treat this as a direct contradiction. **Flag:** that reading is the write-up's interpretation and is not confirmed in either source. Either way, the 60% figure should not be carried over to accumulated wealth.

5. The best evidence covers the parts that matter least for wealth. Job loss, health shocks, recession timing and fat-tailed earnings shocks are the most solid evidence in the review (rated High), yet varying them hardly moved wealth inequality or the talent link (Section 4.9). The simulation's headline inequality figures are driven by settings the review cannot pin down. This is not a contradiction, but it limits how much the simulation's inequality numbers can be trusted.

6. Conclusions and practical implications

6.1 Conclusions

#	Conclusion	Literature confidence	Simulation
1	The more extreme and path-dependent the outcome, the larger luck's share.	High	Agrees: traits fix 62% of lifetime-earnings variation but 31% of log-wealth variation; a top-1% result repeats only 7.75% of the time.
2	About 55–65% of the variation in lifetime earnings reflects differences already present at career start; about 35–45% reflects later shocks.	Medium	Built to match; no independent test.
3	For a single venture, lasting founder qualities explain only a minority of success.	Medium	Consistent: perfect knowledge of talent correlates 0.16 with payoffs.
4	Skill is real, cumulative and partly learnable; it shifts the odds rather than deciding outcomes.	High	Agrees: talent helped in every variant of the full model, with large overlap; the very top is both mostly luck and strongly selected on talent.

#	Conclusion	Literature confidence	Simulation
5	Counting genes, family and birth timing as luck, luck's share is larger than any of these figures.	Medium	Not tested.
6	People over-attribute their success to themselves.	High	Not tested.
7	Accumulated wealth is much more luck-driven than earnings.	Not rated; the review's 62.4% "wealth" figure may measure something different (Section 5.2)	Direction held in 59 of 60 variants; size depends on assumptions.
8	A steady income from work is the strongest equaliser and ties outcomes more closely to talent.	Not studied directly; fits the review's most robust pattern	Direction held in 33 of 33 paired variants; size depends on assumptions.
9	Whether the very top performers are weaker evidence of skill than the next tier depends on conditions neither source establishes.	Model result (Denrell & Liu)	Not found in any variant. Unresolved.

6.2 Practical implications

These are the review's implications, with what the simulation adds.

- **For individuals.** Skill raises your odds; it does not set your outcome. The review advises maximising the number of independent "shots" while surviving bad draws: keep savings buffers, avoid ruin, give priority to industry experience before founding, and judge decisions by process, not by outcomes. The simulation adds that a steady income and regular saving were the most reliable route to a good typical outcome, and that more shots raise the average but lower the typical result, so the "survive bad draws" half of the advice is essential, not optional.
- **For investors and evaluators.** The review advises discounting extreme track records, notes that the second tier can be a better skill signal (Denrell & Liu), and recommends using base rates of about 50% five-year survival and about 75% zero founder payoff. The simulation agrees that track records are weak evidence (in its full model only 7.75% of top-1% outcomes repeat with new luck), but in the model the very top was always the most talent-selected group. Whether the second tier is the better signal depends on conditions, such as whether the most skilled avoid high-variance strategies, that should be checked case by case.
- **For policy.** Because large, unchosen shocks (layoffs in recessions, health events, graduating into a downturn) have lasting effects, the review finds strong justification for insurance against them. The windfall evidence shows that access to capital changes who becomes an entrepreneur. The simulation does not test insurance. Its finding that earnings shocks barely change wealth inequality comes from a model with no debt, no consumption needs and no costly emergencies, which its authors say probably makes version A too equal and too safe at the bottom, so it should not be read as evidence against insurance.

7. Limitations and open questions

7.1 Limits of the research evidence (from the review)

- **No direct measurement of luck.** All estimates are residuals or model-based. Persistence tests confound skill with persistent non-skill advantages (wealth, networks, reputation) and with perceived skill.
- **Definitional dependence.** Whether genes and upbringing count as luck changes the answer from about 35% to well over half.
- **Data gaps.** No good direct evidence on how often major positive career events occur, and no direct estimates gathered of how often job loss or health shocks occur per career.
- **Geographic concentration.** Most evidence is from the U.S., with some Canadian, Swedish, Spanish and UK data; cross-country comparisons of the luck share are largely missing.
- **Time variation.** Persistence weakened after 2000, which suggests the skill share can change as markets mature. **Flag:** the review describes this as "VC buyout persistence", mixing two fund types it otherwise keeps apart; its earlier text attributes weak persistence to buyout funds.
- **Secondary sources.** BLS survival figures come from third-party tabulations and should be checked against BLS Table 7. The Gompers first-timer rate differs between versions (18% and 21%). The Keane & Wolpin 90% figure comes from Todd & Zhang's summary, not the original.

- **Toy models.** The TvL model is uncalibrated and sensitive to its parameters; it should not be cited as an empirical estimate.
- **Search budget.** The review notes that its search was finite.

7.2 Limits of the simulation (from the study)

- **Built from the literature.** Where it matches the literature on calibrated figures, the match is by design.
- **Assumptions drive the headline sizes.** 34 of 60 settings are assumptions, including the two most influential for inequality (opportunity rate and share staked) and the overall spread of earnings (an SD of 0.6 in log earnings, which the study says is not from the review). Talent, effort and background are given equal weight in earnings, and talent and effort are unrelated at baseline; both are assumptions.
- **Not modelled:** debt and negative wealth; consumption needs and dissaving; market-wide investment risk; economic shocks common to a whole cohort; ventures that take several years; talent that reduces exposure to losses; the costs of effort; and traits that change over life. The study says these omissions probably make version A too equal and too safe at the bottom.
- **Not varied in the sensitivity analysis:** the age–earnings profile, windfall size, the evidence-based sizes of the health shock and job-loss losses (only the share of job losses in bad times was varied), the probability and disadvantage gradient of recession entry, and the TvL talent distribution.
- **Twin lives only at baseline.** For variants, the regression R^2 of log wealth on the three traits is used instead; at baseline the two agree closely (0.30 against 0.31).
- **One simulated population is not enough to measure the top.** With identical settings, the top-1% share of version A ranged from 9.2% to 33.9% across runs.

7.3 Inconsistencies and weak points found in the source files

None of these changes a conclusion of this report.

#	Where	Issue	How this report handles it
1	Literature review	The lifetime-earnings share is given as 61.5%, 60–66%, 54–66% and 55–65% in different places; the underlying estimates run from 53.8% to 66.0%.	Each quoted where used.
2	Literature review	Gompers et al.'s first-timer success rate is 18% (working paper) or 21% (published); five-year BLS survival is 50.2% or 50.6% depending on the tabulation. Both flagged by the review itself.	Both values given.
3	Literature review	The empirical support claimed for Denrell & Liu is not cited specifically (links are a press release and a summary site).	Treated as a model result.
4	Literature review	Some links do not point to the cited work: the Hamada (2023) sentence links to Elvidge's ResearchGate page; one Bermejo et al. link points to a page titled "Politicians' Luck of the Draw: Evidence from the Spanish Christmas Lottery", apparently a different study; Denrell & Kovács (2008) links to a Google Scholar profile; the description of the TvL rules links to Hamada (2023) rather than the original paper.	Links kept as given (Section 8); not verified further.
5	Literature review	"VC buyout persistence weakened after 2000" mixes buyout and VC funds.	Flagged in Section 7.1.
6	Literature review	The headline rates precise entrepreneurship "luck %" figures Low, while conclusion L3 is rated Medium. These are different claims (a precise share versus "a minority"), but easy to misread.	Both ratings shown.
7	Simulation write-up vs `results.json`	Rounding differences: talent of B's top 2–10% shown as +0.55 (`results.json`: 0.5448); talent of C's top 1% +0.62 (0.6147); B's effort-decile-8 median 1.57 (1.5646); upper run range of C's Pearson correlation 0.17 (0.1649); TvL top-1% share at event probability 0.02 shown as 12% (11.49%).	`results.json` values used.
8	Simulation write-up	Some figures are not stored in `results.json`: per-bet break-even and typical-outcome figures for ventures, the share of the top 10% drawn from the top talent decile, development diagnostics, and the general-knowledge comparison with real U.S. wealth.	Described without numbers or omitted. The per-bet figures, re-derived from parameters in `results.json`, agree within rounding.
9	Simulation write-up	It says average talent rises "monotonically" with wealth rank; the stored averages show small dips between neighbouring ranks (for example, in C rank 4 is slightly above rank 3), though the overall rise and the richest-is-most-talented pattern hold.	Described as a steady rise.
10	Simulation write-up	It says the opportunity rate and share staked are "also the most influential inputs in Elvidge's analysis of TvL"; the review reports Elvidge's finding only for the lucky-event probability, and TvL has no stake setting.	Only the opportunity-rate parallel is stated.

#	Where	Issue	How this report handles it
11	Simulation write-up	Explaining the one Denrell–Liu reversal, it says "With 93 tests, one false positive at the 5% level is expected"; this arithmetic is loose, since most variants have a clearly non-zero true gap. The conclusion rests on the simpler point that the reversal occurred only where the true gap is exactly zero.	Simpler point reported.
12	Simulation write-up	"93" is used for two different sets: the 93 sensitivity variants (59 + 32 + 2) and the 93 baseline-plus-variant runs of A and B (60 + 33).	Counts stated explicitly.
13	Simulation parameters	The health-shock setting's note says about 35% of people are hit at least once; `results.json` reports 37.0%.	`results.json` value noted.
14	Simulation vs literature	The model's share of ventures paying nothing (79.8%) is above the review's 73–75% for founders.	Flagged in Section 4.2.
15	Simulation write-up	Its reading of Huggett et al.'s 62.4% "wealth" figure as lifetime wealth is not confirmed in either source.	Flagged in Section 5.2.

7.4 Open questions

From the review:

- Can the hidden-skill share in venture success be estimated directly, for example with Bayesian models on serial-founder panels?
- How do platform economies, with stronger rich-get-richer dynamics, change the luck share?
- How large are the long-run effects of positive shocks compared with negative ones?

Raised by the simulation:

- How often do people actually meet major business or investment opportunities, and how much of their wealth do they stake? These two unmeasured settings drive most of the simulated inequality.
- Under what real-world conditions does the Denrell–Liu reversal appear?
- Why do founders who failed before do as well as first-timers: selection into repeat founding, learning from failure, or perceived skill?

8. References

Links are those given in the source files; link labels are the short site names the review used.

8.1 Research cited in the literature review

- Azoulay, Jones, Kim & Miranda (2020). Age and High-Growth Entrepreneurship. *AER: Insights* 2(1):65–82. DOI 10.1257/aeri.20180582. Links: ssrn, aeaweb.
- Bermejo, Ferreira, Wolfenzon & Zambrana (2022). Title not given in the review; a study of the Spanish Christmas Lottery and firm creation. Nova SBE Working Paper 651; CEPR Discussion Paper 14638. Links: unl, researchgate. (see Section 7.3, item 4)
- Cesarini, Lindqvist, Notowidigdo & Östling (2017). The Effect of Wealth on Individual and Household Labor Supply. *American Economic Review*. Links: aeaweb.
- Challet, Pluchino, Biondo & Rapisarda (2020). The Origins of Extreme Wealth Inequality in the Talent versus Luck Model. arXiv 1907.04237. Links: arxiv.
- Davis & von Wachter (2011). Recessions and the Costs of Job Loss. *Brookings Papers on Economic Activity* (Fall). Links: repec, brookings.
- Denrell & Kovács (2008). Title not given in the review; work on selective sampling. *Administrative Science Quarterly*. Links: google. (see Section 7.3, item 4)
- Denrell & Liu (2012). Top performers are not the most impressive when extreme performance indicates unreliability. *PNAS* 109(24):9331–9336. DOI 10.1073/pnas.1116048109. Links: sciencedaily, managementcraft.
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- Elvidge (2020). The Luck in 'Talent versus Luck' Modeling. *Advances in Complex Systems* 23(03):2050007. DOI 10.1142/S0219525920500071. Links: worldscientific, researchgate.
- Gompers, Kovner, Lerner & Scharfstein (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics* 96(1):18–32. DOI 10.1016/j.jfineco.2009.11.001. Working-paper version: NBER WP 12592 (2006). Links: repec, qcconference.
- Guvenen, Karahan, Ozkan & Song (2021). What Do Data on Millions of U.S. Workers Reveal About Lifecycle Earnings Dynamics? *Econometrica* 89(5):2303–2339. Links: ssrn, repec.
- Hall & Woodward (2010). The Burden of the Nondiversifiable Risk of Entrepreneurship. *American Economic Review*. Links: stanford, openicpsr.

- Hamada (2023). Luck of Outcome in the Talent versus Luck Model. *Advances in Complex Systems*. DOI 10.1142/S021952592350008X. Links: worldscientific, researchgate, as linked. (see Section 7.3, item 4)
- Hamilton (2000). Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-Employment. *Journal of Political Economy* 108(3):604–631. DOI 10.1086/262131. Links: uchicago, edegan.
- Harris, Jenkinson, Kaplan & Stucke (2020/2023). Title not given in the review; a study of persistence in buyout and VC fund performance. NBER WP 28109, DOI 10.3386/w28109; *Journal of Corporate Finance* 2023. Links: nber, repec, researchgate.
- Huggett, Ventura & Yaron (2011). Sources of Lifetime Inequality. *American Economic Review* 101(7):2923–54. DOI 10.1257/aer.101.7.2923. Links: georgetown.
- Kaplan & Schoar (2005). Title not given in the review; *Journal of Finance* study of persistence across successive funds. Links: uncipc.
- Keane & Wolpin (1997). The Career Decisions of Young Men. *Journal of Political Economy* 105(3):473–522.
- Kerr, Nanda & Rhodes-Kropf (2014). Entrepreneurship as Experimentation. *Journal of Economic Perspectives* 28(3):25–48. DOI 10.1257/jep.28.3.25. Links: harvard, researchgate, nber.
- Levine & Rubinstein (2017). Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More? *Quarterly Journal of Economics* 132(2):963–1018. Links: repec, nber, nber, nyu.
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- Nicolaou, Shane, Cherkas, Hunkin & Spector (2008). Is the Tendency to Engage in Entrepreneurship Genetic? *Management Science* 54(1):167–179. DOI 10.1287/mnsc.1070.0761. Links: informs, planbinstitute.
- Oreopoulos, von Wachter & Heisz (2012). The Short- and Long-Term Career Effects of Graduating in a Recession. *AEJ: Applied Economics* 4(1):1–29. DOI 10.1257/app.4.1.1. Links: aeaweb, nber.
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- Storesletten, Telmer & Yaron (2004). Title not given in the review; *Journal of Monetary Economics*.
- Todd & Zhang (2020). Title not given in the review; *Quantitative Economics*. DOI 10.3982/QE890.
- U.S. Bureau of Labor Statistics, Business Employment Dynamics, Table 7 (data to March 2025), via secondary tabulations. Links: workspace369, thebrokershopinc.
- van de Rijt and colleagues (2014). Field experiments of success-breeds-success dynamics. *PNAS*. DOI 10.1073/pnas.1316836111. Links: pnas.

8.2 Informal, secondary and unverified sources (labelled as such by the review)

- J.B. Whitmore. Informal reimplementation and critique of the TvL model (not peer-reviewed). Links: github.
- AI-generated “living paper” replication of the TvL model (unverified). Links: github.
- Blog commentary on the heritability of entrepreneurship. Links: Substack.
- Blog summary of attribution research (secondary source for Mezulis et al.). Links: Substack.
- Press release on Denrell & Liu (2012). Links: sciencedaily.
- The review’s note on sources also lists strategy+business summaries and textbook summaries of Mezulis et al. as secondary sources, without identifying specific items.

8.3 Books mentioned but not relied on for figures

- Mauboussin. *The Success Equation*.
- Frank. *Success and Luck*.

8.4 Simulation study

- `simulation/model.py` and `simulation/README.md`: model code and documentation (agent-based Monte Carlo model; parameter table with sources).
- `results/results.json`: all simulation results (1,000 runs × 1,000 agents per version; Python 3.13.18, numpy 2.5.3; random seeds in `meta.seeds`).
- `results/simulation_results.md`: written results; `results/charts/`: charts used in Figures 1–2 (`results/charts/key_metrics_comparison.png` shows the headline table of Section 4.3 as a chart).