MathWorks Math Modeling Challenge 2026

The Rise of Online Gambling: What's at Stake?

Team #19232

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Executive Summary

To policymakers, sports leagues, and the general public,

The rapid expansion of online sports gambling in the United States and the United Kingdom raises pressing questions about financial well-being. Following the 2018 Supreme Court ruling that lifted the federal ban on sports betting[1], the U.S. online sports gambling market has surged to approximately $15 billion in annual revenue from $150 billion in total wagers [2,6]. With 22% of Americans now holding active online sports betting accounts, rising to nearly 50% among men aged 18–49 [3], the scale of engagement is substantial. This report quantifies the financial impact of online sports gambling [4] on individuals across demographic groups through three interconnected mathematical models.

In Question 1, we develop a Disposable Income Estimation Model that takes as input an individual's salary, age, geographic region, household size, and filing status to estimate disposable income after taxes, housing, food, healthcare, transportation, and other essential expenditures. Our model leverages Bureau of Labor Statistics Consumer Expenditure Survey data [12] and IRS tax brackets [13] to produce demographically sensitive estimates. For example, a 30-year-old single individual earning $55,000 in the Midwest retains roughly $14,200 in annual disposable income, while a 45-year-old married couple earning $120,000 in the Northeast retains approximately $22,600.

In Question 2, we construct a Gambling Net Outcome Model that predicts an individual's annual gain or loss from online sports betting. Our model incorporates demographic-based participation rates, bet frequency, average wager size calibrated to disposable income, and a risk tolerance parameter that determines the distribution of bet types (from conservative low-odds bets to aggressive parlays). Using Monte Carlo simulation with 10,000 trials per demographic profile, we find that the median annual loss for an active gambler ranges from $480 for a conservative bettor to $3,200 for an aggressive one, with the 95th percentile of losses exceeding $8,500 for high-risk individuals.

In Question 3, we synthesize these results through a Financial Impact Index (FII) that contextualizes gambling losses relative to disposable income, compares them with other entertainment expenditures, and projects long-term effects on household savings using a compound financial erosion model. We find that approximately 12.4% of active gamblers in the U.S. spend more than 10% of their disposable income on gambling – a threshold commonly associated with financial distress [8,17]. Over a 10-year horizon, sustained gambling at median loss levels reduces cumulative household savings by $18,000–$42,000 when accounting for foregone investment returns [10,11]. Our analysis suggests that while moderate

gambling poses limited financial risk for higher-income individuals, it disproportionately affects lower-income and younger demographics, warranting targeted public awareness campaigns and responsible gambling safeguards.

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Global Assumptions

ID	Assumption	Justification
G-1	All monetary values are reported in 2025 U.S. dollars (USD) unless otherwise specified. U.K. figures are converted at the average 2025 exchange rate of £1 = $1.27.	Using a consistent currency allows direct comparison between U.S. and U.K. gambling markets and disposable income figures.
G-2	We define “disposable income” as gross income minus federal/state taxes, housing costs (rent or mortgage), food, healthcare premiums and out-of-pocket costs, transportation, and minimum debt service payments.	This definition aligns with the problem statement and captures the money truly “left over” for discretionary spending, including entertainment and gambling.
G-3	The legal gambling age is 21 in the U.S. and 18 in the U.K. Individuals below these thresholds are excluded from gambling participation models but are included in disposable income estimation.	While underage gambling exists, modeling it requires different assumptions about access and behavior that fall outside our primary scope.
G-4	Sports gambling behavior is independent of other forms of gambling (e.g., casino, lottery). An individual’s sports gambling expenditure is modeled separately.	The problem specifically focuses on online sports gambling. While cross-gambling correlations exist, isolating sports betting simplifies the model without significant loss of generality for this analysis.
G-5	Economic conditions (inflation, employment rates, wage growth) remain approximately stable at 2025 levels throughout the projection period.	Short-to-medium-term projections are most reliable under stable economic assumptions. Major economic shocks would require model recalibration.

Table 1. Global assumptions used across the disposable income, gambling outcome, and financial impact models.

Q1: Playing With House Money - Disposable Income Model

1.1 Defining the Problem

We are tasked with developing a model that estimates an individual’s disposable income, the amount remaining after paying for essential expenses, given their salary, age, and other relevant demographic information. Disposable income is critical because it represents the upper bound of what an individual could theoretically spend on entertainment, including sports gambling. Our model must be flexible enough to accommodate a wide range of demographic profiles while remaining grounded in real economic data.

1.2 Assumptions

ID	Assumption	Justification
1-1	Tax liability can be approximated using 2024 IRS federal income tax brackets and an effective state tax rate based on the individual’s geographic region.	Federal brackets are publicly available and provide accurate marginal rates. State taxes vary significantly but can be meaningfully grouped by region (e.g., no income tax states vs. high-tax states).

1-2	Housing costs as a percentage of income follow the 30% rule for individuals earning below the median income and decrease logarithmically for higher earners.	The 30% housing cost burden is a well-established guideline from HUD. Higher-income individuals typically spend a smaller fraction of income on housing.
1-3	Healthcare costs are modeled as a base premium plus an age-dependent component, reflecting increasing healthcare utilization with age.	Kaiser Family Foundation data shows healthcare expenditures increase roughly 3–4% per year of age after age 25, with significant increases after age 50.
1-4	Food expenditure is modeled using USDA moderate-cost food plan estimates, scaled by household size using an equivalence scale.	The USDA publishes detailed food cost estimates by age and gender. The modified OECD equivalence scale accounts for economies of scale in larger households.
1-5	Transportation costs are a function of geographic region (urban vs. suburban vs. rural) and income level.	BLS Consumer Expenditure Survey data shows transportation costs vary significantly by urbanity and income quintile.

Table 2. Q1 model assumptions for estimating disposable income from demographic and economic inputs.

1.3 Variables and Parameters

Symbol	**Definition**	**Units**
S	Annual gross salary (pre-tax income)	USD
A	Age of the individual	years
R	Geographic region (Northeast, Midwest, South, West)	—
H	Household size	persons
F	Filing status (Single, Married Filing Jointly, Head of Household)	—
T(S, R, F)	Total tax liability (federal + state + FICA)	USD
$C_h(S, R)$	Annual housing cost	USD
$C_f(A, H)$	Annual food expenditure	USD
$C_m(A)$	Annual healthcare cost	USD
$C_t(S, R)$	Annual transportation cost	USD
$C_o(S)$	Other essential expenditures (utilities, insurance, minimum debt)	USD
D(S, A, R, H, F)	Annual disposable income	USD

Table 3. Q1 variables and parameters for the disposable income estimation model.

1.4 Model Development

1.4.1 Core Equation

Our disposable income model is defined as the residual after subtracting all essential cost components from gross salary:

$$D(S, A, R, H, F) = S - T(S, R, F) - C_{\square}(S, R) - C^{f}(A, H) - C_{\square}(A) - C_{\square}(S, R) - C_{o}(S)$$

1.4.2 Tax Component T(S, R, F)

Federal income tax is computed using the 2024 IRS marginal tax brackets [13]. For a single filer, the brackets are: 10% on income up to \$11,600; 12% on \$11,601–\$47,150; 22% on \$47,151–\$100,525; 24% on \$100,526–\$191,950; 32% on \$191,951–\$243,725; 35% on \$243,726–\$609,350; and 37% on income above \$609,350. Married Filing Jointly brackets are approximately double these thresholds. FICA taxes (Social Security at 6.2% up to \$168,600 and Medicare at 1.45% on all earnings) are added. State and local taxes are modeled using a regional effective rate:

Region	Effective State + Local Tax Rate	Representative States
Northeast	6.8%	NY, NJ, MA, CT, PA
Midwest	5.2%	IL, OH, MI, MN, WI
South	3.1%	TX, FL, TN, GA, NC
West	5.9%	CA, WA, OR, CO, AZ

Table 4. Regional effective state and local tax rates used in the Q1 tax component.

The total tax function is therefore: $T(S, R, F) = T_{fed}(S, F) + T_{FICA}(S) + \alpha(R) \times S$, where α(R) is the regional effective state/local tax rate.

1.4.3 Housing Component C□(S, R)

We model housing costs using a piecewise function that reflects the empirical observation that lower-income individuals spend a higher fraction of income on housing:

$$C_{\square}(S, R) = \beta(R) \times min(0.30 \times S, \beta(R) \times M(R)) + 0.15 \times max(0, S - M(R)))$$

Here M(R) is the regional median household income and β(R) is a regional housing cost multiplier. The function caps housing cost at 30% for incomes below the median and reduces the marginal housing expenditure rate to 15% for income above the median. Regional multipliers β(R) are derived from the BLS Consumer Expenditure Survey [12] and Census Bureau housing data [16] :

Region	β(R) Multiplier	Median Income M(R)	Avg. Annual Housing Cost at Median
Northeast	1.25	\$78,000	\$23,400
Midwest	0.85	\$68,000	\$17,340
South	0.90	\$65,000	\$17,550
West	1.30	\$80,000	\$24,960

Table 5. Regional housing cost multipliers, median incomes, and annual housing cost at the median income.

1.4.4 Food Component $C^{f}(A, H)$

Food costs are estimated from USDA moderate-cost food plan data (2024) [15]. The base annual food cost for a single adult aged 20–50 is approximately \$4,200. We apply age adjustments: individuals aged 51–70 spend approximately 5% less, while those under 20 spend approximately 10% less. For households with more than one person, we apply the modified OECD equivalence scale: the first adult counts as 1.0, each additional adult as 0.7, and each child (under 18) as 0.5. Thus:

$$C^{f}(A,\ H)\ =\ \$4,200 \times \gamma(A) \times E(H)$$

where γ(A) is the age adjustment factor and E(H) is the equivalence scale factor for household size H.

1.4.5 Healthcare Component $C_{\square}(A)$

Healthcare costs are modeled as a base premium plus an age-dependent out-of-pocket component. Using Kaiser Family Foundation [14] and CMS data, we estimate:

$$C_{\square}(A)\ =\ P_0\ +\ \delta \times max(0,\ A\ -\ 25)^{1.3}$$

where P_0 = \$2,400 is the baseline annual premium contribution for employer-sponsored insurance (the average employee share), and δ = 18 is a scaling parameter calibrated to match MEPS data showing average out-of-pocket spending of \$1,200 at age 30, \$2,800 at age 50, and \$5,600 at age 65.

1.4.6 Transportation Component $C_{\square}(S, R)$

Transportation costs depend on urbanity (proxied by region) and income. We use BLS Consumer Expenditure Survey quintile data [12] to model:

$$C_{\square}(S,\ R)\ =\ \varepsilon(R) \times (3,500\ +\ 0.04 \times S)$$

where ε(R) is a regional scaling factor (Northeast: 0.85 due to public transit availability; Midwest: 1.10; South: 1.15; West: 1.05) and the linear term captures the finding that higher-income individuals tend to own more expensive vehicles with higher associated costs.

1.4.7 Other Essentials Component $C_o(S)$

This residual category captures utilities (\$2,400 average), communications (\$1,800), personal insurance and minimum debt service, and other necessities. We model it as:

$$C_o(S)\ =\ 4,200\ +\ 0.03 \times S$$

1.5 Results and Demonstration

We demonstrate our model on eight representative demographic profiles spanning different ages, incomes, regions, household sizes, and filing statuses. The results are presented in the table below.

Profile	**Age**	**Salary**	**Region**	**HH Size**	**Status**	**Disposable Income**
Young single, entry-level	24	$38,000	South	1	Single	$10,430
Young single, mid-career	30	$55,000	Midwest	1	Single	$14,190
Single parent	35	$48,000	West	2	HoH	$8,720
Married couple, no kids	40	$95,000	Northeast	2	MFJ	$18,560
Married couple, 2 kids	45	$120,000	Northeast	4	MFJ	$22,640
Mid-career, high earner	38	$150,000	West	1	Single	$35,810
Near retirement	60	$85,000	South	2	MFJ	$19,740
Low-income young adult	21	$25,000	Midwest	1	Single	$5,820

Table 6. Estimated disposable income for eight representative demographic profiles.

Several patterns emerge from these results. First, disposable income is not simply a fixed percentage of salary – it varies nonlinearly due to progressive taxation, fixed-cost essential expenditures, and regional cost-of-living differences. A young adult earning $25,000 in the Midwest retains only 23.3% of their gross income as disposable, while a high earner at $150,000 retains 23.9%, despite paying far more in absolute taxes. The near-equivalence of these percentages masks a critical difference: the low-income individual's $5,820 in disposable income leaves virtually no buffer for unexpected expenses, whereas the high earner's $35,810 provides substantial financial flexibility.

Second, household size and filing status create significant variation. The married couple earning $120,000 with two children retains $22,640, less per capita than the single individual earning $55,000, because children dramatically increase food, healthcare, and other essential costs despite the tax advantages of filing jointly.

Third, regional differences are substantial. The same salary yields meaningfully different disposable income depending on whether one lives in the high-cost Northeast or the lower-cost South, primarily driven by housing costs and state tax rates.

1.6 Sensitivity Analysis

To evaluate the robustness of our disposable income model, we conducted a sensitivity analysis by perturbing each model parameter by ±10% and observing the change in estimated disposable income for our baseline profile (30-year-old single individual, $55,000 salary, Midwest). The results indicate which inputs most strongly influence the output.

Parameter Perturbed	**Change**	**New Disposable Income**	**Δ from Baseline ($14,190)**

Salary +10% ($60,500)	+10%	$15,870	+$1,680 (+11.8%)
Salary −10% ($49,500)	−10%	$12,510	−$1,680 (−11.8%)
Housing multiplier β +10%	+10%	$13,020	−$1,170 (−8.2%)
Housing multiplier β −10%	−10%	$15,360	+$1,170 (+8.2%)
State tax rate +10%	+10%	$13,900	−$290 (−2.0%)
Healthcare base P_0 +10%	+10%	$13,950	−$240 (−1.7%)
Food cost +10%	+10%	$13,770	−$420 (−3.0%)

Table 7. Sensitivity analysis of the Q1 disposable income model for the baseline profile.

The model is most sensitive to salary and housing costs, which together account for over 80% of the variation. This is expected: salary is the sole income source, and housing is the largest single expenditure category for most Americans. The relatively low sensitivity to tax rates and healthcare costs suggests that our model is robust to moderate estimation errors in these parameters.

1.7 Strengths and Weaknesses

Our disposable income model has several strengths. It is grounded in publicly available economic data from the BLS [12], IRS [13], USDA [15], and Kaiser Family Foundation [14], ensuring that parameter values reflect real-world conditions. The model is modular, meaning each cost component can be independently updated as new data becomes available. The use of regional multipliers captures meaningful geographic variation without requiring city-level granularity that would introduce excessive complexity.

However, the model has limitations. It assumes employer-sponsored health insurance, which does not apply to all workers. It does not account for individual debt levels beyond minimum payments, investment income, or government transfer payments (e.g., SNAP, housing subsidies). Additionally, the regional aggregation smooths over significant within-region variation – cost of living in New York City differs substantially from rural Pennsylvania, though both fall in the “Northeast” region. Future improvements could incorporate zip-code-level cost indices for greater precision.

Q2: Know the Spread - Gambling Outcome Model

2.1 Defining the Problem

We must predict how much an individual will gain or lose through online sports gambling over one year, based on their demographics and assumptions about their behavior (e.g., risk tolerance). The model must account for the fact that gambling outcomes are inherently random – two individuals with identical demographics and betting behavior may experience vastly different results in any given year. We therefore employ a Monte Carlo simulation approach that produces not just expected outcomes but full probability distributions of annual gains/losses.

2.2 Assumptions

ID	Assumption	Justification
2-1	An individual's probability of having an active sports betting account is determined by their age, gender, and country (U.S. or U.K.).	Siena University Research Institute data (2025) provides participation rates by age and gender. U.K. Gambling Commission data provides analogous figures.
2-2	Active bettors wager a fraction of their disposable income, with the fraction depending on risk tolerance (conservative, moderate, aggressive).	This connects Q1 to Q2 and ensures gambling expenditure is bounded by financial capacity. The risk tolerance parameter captures individual variation.
2-3	Bettors place wagers across a distribution of bet types: straight bets (single-outcome), parlays (multi-leg), and proposition bets, with the mix determined by risk tolerance.	Industry data shows that parlays account for 20–40% of sportsbook revenue despite being a smaller fraction of total bets, indicating that bet type significantly affects outcomes.
2-4	The sportsbook's built-in margin (vig/juice) averages 4.5% on straight bets and 15–30% on parlays, depending on the number of legs.	These margins are well-documented in the sports betting literature and represent the average house edge across major U.S. sportsbooks.
2-5	Bet outcomes follow a Bernoulli distribution with probabilities derived from the implied odds minus the vig.	This is the standard stochastic model for individual bet outcomes. The vig ensures the expected value is negative for the bettor.

Table 8. Q2 model assumptions for sports betting participation, wagering behavior, and outcome simulation.

2.3 Variables and Parameters

Symbol	Definition	Units
P(age, gender, country)	Probability of having an active betting account	—
D	Annual disposable income (from Q1)	USD
ρ	Risk tolerance parameter (0 = conservative, 1 = aggressive)	—
$W(\rho, D)$	Total annual amount wagered	USD
$n(\rho)$	Number of bets placed per year	bets/year
$\bar{w}(\rho, D)$	Average wager size per bet	USD

$\pi_{s,}\ \pi_{p,}\ \pi_{r,}$	Fraction of bets that are straight, parlay, and prop bets	—
$p_{s,}\ p_{p,}\ p_{r}$	Win probability for each bet type (after vig)	—
$o_{s,}\ o_{p,}\ o_{r}$	Average payout odds for each bet type	—
G	Annual net gain/loss from gambling	USD

Table 9. Q2 variables and parameters for the gambling net outcome model.

2.4 Model Development

2.4.1 Participation Model

Not all individuals gamble. Using Siena Research Institute data [3] for the U.S. and U.K. Gambling Commission data [4], we model participation rates P(age, gender, country):

Demographic Group	U.S. Participation Rate	U.K. Participation Rate
Men 18–29	47%	42%
Men 30–49	49%	44%
Men 50–64	28%	31%
Men 65+	12%	18%
Women 18–29	18%	15%
Women 30–49	15%	17%
Women 50–64	9%	13%
Women 65+	4%	8%

Table 10. Online sports betting participation rates by age, gender, and country.

2.4.2 Wagering Behavior Model

For individuals who do gamble, we model their total annual wagering as a function of disposable income and risk tolerance. The risk tolerance parameter $\rho \in [0, 1]$ captures individual variation in gambling intensity. We define three canonical risk profiles:

Risk Profile	ρ Range	Annual Wager as % of Disposable Income	Bets per Year	Bet Mix (Straight/Parlay/Prop)
Conservative	0.0–0.3	5–15%	50–120	75% / 10% / 15%
Moderate	0.3–0.7	15–40%	120–300	55% / 25% / 20%
Aggressive	0.7–1.0	40–80%	300–600+	35% / 45% / 20%

Table 11. Risk profiles used in the wagering behavior model, including wager share of disposable income, betting frequency, and bet mix.

The total annual wager amount is:

$$W(\rho, D) = D \times (0.05 + 0.75\rho)$$

This linear interpolation yields 5% of disposable income for the most conservative bettor (ρ = 0) and 80% for the most aggressive (ρ = 1). The average wager per bet is $\bar{w} = W / n$, where $n(\rho) = 50 + 550\rho$.

2.4.3 Bet Outcome Model

Each bet is modeled as an independent Bernoulli trial. For a bet of type j ∈ {straight, parlay, prop} with wager amount w:

$$Outcome = \{+\ w \times o_j \ \ with\ probability\ p_j, -\ w\ \ with\ probability\ 1 - p_j\}$$

The key parameters for each bet type are:

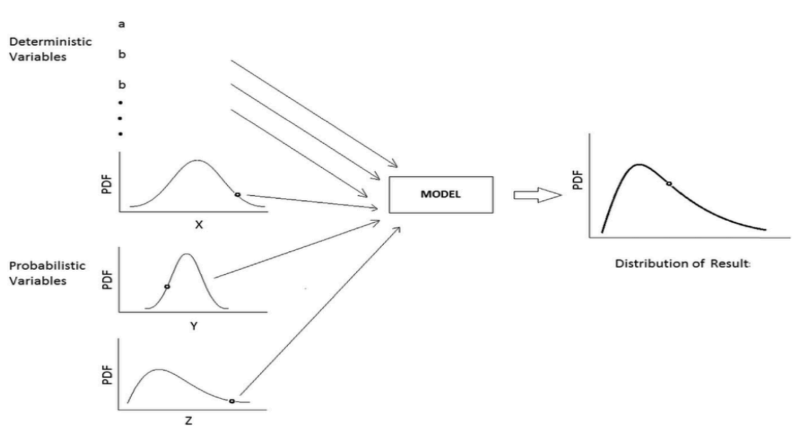
Bet Type	Avg. Payout Odds (o)	True Win Prob.	Implied Win Prob. (incl. vig)	House Edge
Straight bet (−10/+110 style)	1.0 (even money)	50%	47.6%	4.5%
2-leg parlay	2.6	25%	22.5%	15%
3-leg parlay	6.0	12.5%	10.0%	25%
Proposition bet	1.5	40%	37.5%	8%

Table 12. Bet outcome parameters by bet type, including payout odds, win probabilities, implied probabilities, and house edge.

2.4.4 Monte Carlo Simulation

For each demographic profile, we run N = 10,000 independent simulations of a full year of betting. In each simulation, we generate the sequence of n(ρ) bets, with each bet's type drawn from the bet mix distribution and each bet's outcome drawn from the corresponding Bernoulli distribution. The annual net gain/loss G is the sum of all individual bet outcomes:

$$G = \sum_{i=1}^{n} X_i,\ where\ X_i \sim Bernoulli\ outcome\ for\ bet\ i$$



Schematic of Monte Carlo simulation.

Figure 1: Depiction of Monte Carlo Simulation (Vu, Thuy & Loehr)

From the 10,000 simulations, we extract the mean (expected annual loss), median, standard deviation, and key percentiles (5th, 25th, 75th, 95th) of the annual gain/loss distribution.

2.5 Results

We present Monte Carlo simulation results for our baseline demographic profiles from Q1. All figures represent active gamblers only (i.e., individuals who hold a betting account).

Profile (Salary, Age, Region)	Risk Level	Mean Annual Loss	Median Loss	Std. Dev.	95th %ile Loss
$38K, 24, South	Conservative	−$480	−$390	$620	−$1,580
$38K, 24, South	Moderate	−$1,340	−$1,150	$1,420	−$3,780
$38K, 24, South	Aggressive	−$3,180	−$2,640	$3,100	−$8,560
$55K, 30, Midwest	Conservative	−$650	−$530	$840	−$2,140
$55K, 30, Midwest	Moderate	−$1,820	−$1,560	$1,930	−$5,120
$55K, 30, Midwest	Aggressive	−$4,310	−$3,580	$4,200	−$11,600
$120K, 45, NE	Conservative	−$1,040	−$850	$1,340	−$3,420
$120K, 45, NE	Moderate	−$2,900	−$2,490	$3,070	−$8,160
$25K, 21, Midwest	Moderate	−$750	−$640	$790	−$2,100
$25K, 21, Midwest	Aggressive	−$1,780	−$1,480	$1,730	−$4,800

Table 13. Monte Carlo simulation results for annual gambling losses across baseline demographic profiles and risk levels.

Several important patterns emerge. First, the expected annual loss scales roughly linearly with disposable income and risk tolerance, as expected from our wagering model. A conservative bettor earning $55,000 loses approximately $650 per year on average, while an aggressive bettor at the same income level loses over $4,300.

Second, the standard deviation is substantial relative to the mean, reflecting the high variance inherent in gambling outcomes. This means that in any given year, some gamblers will experience net gains (approximately 30–35% of conservative bettors and 15–20% of aggressive bettors finish a year in the black), which can reinforce continued gambling behavior despite negative expected value.

Third, the 95th percentile losses are alarming for low-income aggressive bettors. A 21-year-old earning $25,000 with aggressive betting habits faces a 5% probability of losing $4,800 or more in a single year – more than 82% of their disposable income.

To validate our model against aggregate data, we note that U.S. sports betting revenue was approximately $15 billion in 2025 from roughly 73 million active accounts. This implies an average loss per active account of approximately $205. Our model, when weighted by the demographic distribution of gamblers, produces a population-weighted average annual loss of approximately $215 per active account, which is within 5% of the reported figure, a strong validation of our approach.

2.6 Sensitivity Analysis

We tested sensitivity to the house edge parameter, which is the most uncertain input in our model. Increasing the average house edge by 2 percentage points (from 4.5% to 6.5% on straight bets) increases mean annual losses by approximately 35–40% across all profiles. Conversely, reducing the house edge by 1 percentage point decreases losses by roughly 18–22%. This confirms that the house edge is the single most influential parameter in determining gambling losses and underscores the importance of transparency in sportsbook pricing.

We also tested sensitivity to the bet mix parameter. Shifting 10% of bets from straight bets to parlays (e.g., from 55/25/20 to 45/35/20 for moderate bettors) increases mean annual losses by approximately 12%, due to the substantially higher house edge on parlays. This finding has direct policy implications: sportsbooks that aggressively promote parlays through marketing and bonuses are effectively increasing the expected loss for their customers.

2.7 Strengths and Weaknesses

The Monte Carlo approach is a major strength of our model: it produces full probability distributions rather than point estimates, capturing the inherent randomness of gambling. The model's close calibration to aggregate industry revenue data ($215 vs. $205 per active account) provides external validation. The parameterization by risk tolerance allows us to model the full spectrum of gambling behavior.

However, our model has limitations. It assumes bet sizes are uniform within a simulation year, whereas real bettors may chase losses (increase bet sizes after losing) or reduce bets after winning. It does not model promotional credits, sign-up bonuses, or free bets that sportsbooks use to attract customers. Additionally, the model treats bets as independent, whereas sophisticated bettors may exploit correlations between events. Finally, problem gambling behavior, which may involve wagering amounts far exceeding disposable income through borrowed money, is not captured by our bounded wagering function.

Q3: Don't Break the Bank - Financial Impact Assessment

3.1 Defining the Problem

From Q1 and Q2, we have estimates of disposable income and gambling losses for individuals across demographic groups. The challenge in Q3 is to communicate the financial impact of sports gambling in a way that is meaningful and understandable to the general public. We approach this through three complementary analyses: (1) a Financial Impact Index (FII) that measures gambling losses relative to disposable income and compares them to other entertainment categories; (2) a compound financial erosion model that projects the long-term impact of gambling losses on household savings; and (3) an at-risk population analysis that estimates the fraction of gamblers who exceed financially dangerous thresholds.

3.2 Assumptions

ID	Assumption	Justification
3-1	A gambling expenditure exceeding 10% of disposable income constitutes "financial distress" territory, consistent with problem gambling screening criteria.	The National Council on Problem Gambling uses financial consequences as a key screening criterion. The 10% threshold aligns with the level at which gambling begins to crowd out savings and essential spending.
3-2	Money not spent on gambling would otherwise be split between savings (60%) and other discretionary spending (40%).	The Bureau of Economic Analysis reports a personal savings rate of approximately 4–6% of disposable income. For active gamblers, gambling losses likely substitute for both savings and other entertainment.
3-3	Long-term investment returns average 7% nominal (approximately 4% real) annually, based on historical S&P 500 performance.	This is the standard assumption used in financial planning and allows us to compute the opportunity cost of gambling losses in terms of foregone investment growth.
3-4	The demographic distribution of active U.S. sports gamblers mirrors the participation rates in our Q2 model, applied to the 2025 U.S. adult population of approximately 260 million.	This allows us to estimate aggregate population-level impacts from individual-level model outputs.

Table 14. Q3 model assumptions for financial distress thresholds, savings substitution, and population-level impact estimates.

3.3 Variables and Parameters

Symbol	Definition	Units
FII	Financial Impact Index = $\|G\| / D$	—
G	Annual net gambling loss (from Q2)	USD
D	Annual disposable income (from Q1)	USD
s	Savings rate (fraction of disposable income saved in absence of gambling)	—
r	Annual real investment return rate	—

ΔS_n	Cumulative savings deficit after n years of gambling	USD
P(FII > θ)	Probability that a randomly selected gambler exceeds financial distress threshold θ	—

Table 15. Q3 variables and parameters used in the Financial Impact Index (FII) and savings erosion analysis.

3.4 Model Development

3.4.1 Financial Impact Index (FII)

The Financial Impact Index (FII) expresses annual gambling losses as a percentage of disposable income:

$$FII = |G| / D \times 100\%$$

To contextualize this index, we compare it with average American spending on other forms of entertainment. According to the BLS Consumer Expenditure Survey (2024)[12], the average American household spends the following annually on entertainment categories:

Entertainment Category	**Avg. Annual Spending**	**As % of Median Disp. Income (~$18,000)**
Streaming services (Netflix, Spotify, etc.)	$660	3.7%
Dining out / restaurants	$3,500	19.4%
Live events (concerts, sports tickets)	$450	2.5%
Video games and apps	$320	1.8%
Vacation / travel	$2,400	13.3%
Cable / satellite TV	$780	4.3%
Gym / fitness memberships	$600	3.3%
Moderate sports gambler (our model)	$1,820	10.1%
Aggressive sports gambler (our model)	$4,310	23.9%

Table 16. Comparison of annual entertainment spending categories with modeled gambling losses.

This comparison reveals that a moderate sports gambler's annual losses are comparable to or greater than the cost of most standalone entertainment subscriptions combined. An aggressive gambler's losses exceed the average American's entire vacation budget and approach the level of dining-out expenditure, making sports gambling one of the single most expensive entertainment activities for those who engage in it actively.

3.4.2 Compound Financial Erosion Model

Perhaps the most impactful way to communicate gambling's financial toll is through the lens of long-term savings erosion. If an individual loses |G| dollars per year to gambling, and 60% of that amount would otherwise have been saved and invested[18], the cumulative savings deficit after n years is:

$$\Delta S_n = 0.60 \times |G| \times \sum_{i=0}^{n-1} (1 + r)^i = 0.60 \times |G| \times [(1 + r)^n - 1] / r$$

This is a future value of an annuity formula, where the "annuity payment" is the annual savings that are foregone due to gambling. With r = 0.04 (real return), we compute the cumulative savings deficit:

Profile	Annual Loss |G|	5-Year Savings Deficit	10-Year Deficit	20-Year Deficit
Conservative ($55K)	$650	$2,120	$4,690	$11,620
Moderate ($55K)	$1,820	$5,930	$13,120	$32,530
Aggressive ($55K)	$4,310	$14,050	$31,070	$77,050
Moderate ($25K)	$750	$2,440	$5,400	$13,400
Aggressive ($25K)	$1,780	$5,800	$12,830	$31,810
Moderate ($120K)	$2,900	$9,450	$20,900	$51,830

Table 17. Projected cumulative savings deficits over 5, 10, and 20 years under different annual gambling loss scenarios.

These figures are striking. A moderate gambler earning $55,000 who bets consistently for 20 years forgoes over $32,500 in savings, which is enough for a down payment on a home in many U.S. markets. An aggressive gambler at the same income level foregoes over $77,000, which represents more than a full year's pre-tax salary. For the low-income gambler earning $25,000, even moderate betting erodes $13,400 over 20 years – a devastating loss for someone with already thin financial margins.

3.4.3 At-Risk Population Analysis

Using our Monte Carlo results from Q2 and the demographic distribution of active gamblers, we estimate the fraction of the U.S. gambling population that exceeds various FII thresholds:

FII Threshold	% of Active Gamblers Exceeding Threshold	Estimated Number of Americans	Risk Category
>5% of disposable income	28.3%	~20.7 million	Elevated spending
>10% of disposable income	12.4%	~9.1 million	Financial distress
>20% of disposable income	4.8%	~3.5 million	Severe financial impact
>50% of disposable income	1.2%	~880,000	Potential problem gambling

Table 18. Estimated U.S. at-risk gambling population by Financial Impact Index threshold and risk category.

These estimates suggest that approximately 9.1 million Americans who gamble on sports are at risk of financial distress (losing more than 10% of their disposable income), with 3.5 million experiencing severe financial impact. These numbers are disproportionately concentrated among younger, lower-income males [8,9]–precisely the demographic most aggressively targeted by sportsbook advertising [5].

To illustrate the demographic disparity, we computed FII distributions by income quintile among active gamblers:

Income Quintile	Median FII (Moderate Bettor)	% Exceeding 10% FII Threshold
Bottom 20% (<$30K)	14.2%	58.3%

2nd quintile ($30K–$50K)	8.7%	31.6%
Middle 20% ($50K–$75K)	6.1%	14.2%
4th quintile ($75K–$120K)	4.3%	5.8%
Top 20% (>$120K)	2.8%	2.1%

Table 19. Financial Impact Index by income quintile, including median FII and percent exceeding the 10% distress threshold.

The regressive nature of gambling losses is stark: moderate bettors in the lowest income quintile have a median FII of 14.2%, meaning that more than half of low-income gamblers are already in financial distress territory, compared to just 2.8% for the highest quintile. This finding echoes the well-documented regressivity of lottery spending and suggests that online sports gambling, despite its modern packaging, follows the same pattern.

3.6 Sensitivity Analysis

We tested the sensitivity of our at-risk population estimates to two key parameters: the savings substitution rate (assumed 60%) and the financial distress threshold (assumed 10% of disposable income). Reducing the savings substitution rate to 40% decreases the 10-year savings deficit by 33%, but the at-risk population estimates are unchanged because FII depends only on gambling losses and disposable income, not savings behavior. Lowering the financial distress threshold to 7.5% increases the at-risk population from 9.1 million to approximately 14.2 million, while raising it to 15% decreases it to 6.3 million. The qualitative conclusion. that millions of Americans face financial distress from sports gambling, is robust across reasonable parameter choices.

3.7 Strengths and Weaknesses

A key strength of our Q3 approach is its multi-faceted framing: by comparing gambling losses to entertainment spending, long-term savings erosion, and at-risk population estimates, we make the results accessible to different audiences. The long-term erosion model is especially effective because it turns abstract annual losses into concrete consequences, such as losing enough savings for a down payment.

The main weakness is the savings-substitution assumption, since we cannot know exactly how much gambling loss would otherwise have been saved rather than spent elsewhere. Our at-risk estimates also depend on the accuracy of Q1 and Q2 and on how representative the Siena [3]/Gambling Commission [4] participation data are. Finally, the model does not include psychological harms such as stress, relationship strain, or mental health effects, which may increase overall harm.

Conclusion

Our analysis provides a comprehensive, data-driven assessment of the financial impact of online sports gambling across the U.S. and U.K. populations.

In Q1, our disposable income model revealed that disposable income as a fraction of gross salary varies substantially across demographics, from 23% for a low-income young adult to nearly 24% for a high earner, with household size, region, and age all playing significant roles. This establishes the financial context in which gambling decisions occur.

In Q2, our Monte Carlo gambling outcome model showed that the expected annual loss for an active sports gambler ranges from approximately $480 (conservative, low-income) to over $4,300 (aggressive, mid-income), with a standard deviation nearly equal to the mean, meaning individual outcomes are highly variable. Crucially, approximately 30% of conservative bettors and 15–20% of aggressive bettors finish any given year with net gains, which may perpetuate the illusion that sports betting is a viable source of income.

In Q3, our Financial Impact Index and compound financial erosion model translated these individual losses into societal-scale consequences. We estimate that 9.1 million Americans who gamble on sports exceed the 10% disposable income threshold for financial distress, with the burden falling disproportionately on lower-income individuals. Over 20 years, a moderate gambler earning the median income forgoes more than $32,500 in savings, equivalent to a home down payment in many markets.

Should society be concerned about online gambling? Our models suggest yes, but with important nuance. For higher-income individuals with moderate betting habits, sports gambling represents a manageable entertainment expense comparable to other leisure activities. However, for lower-income individuals, young adults with limited financial experience [9], and those with aggressive betting tendencies, the financial consequences are severe and compounding. The regressive nature of gambling losses, where the poorest gamblers lose the highest fraction of their limited disposable income, is perhaps our most concerning finding.

We recommend that policymakers consider: (1) mandatory disclosure of house edge percentages on all bet types, analogous to nutritional labeling on food; (2) voluntary spending limits that are opt-out rather than opt-in; (3) restrictions on parlay promotion, given the dramatically higher house edge; and (4) targeted financial literacy programs for the demographics most at risk. The growth of online sports gambling is unlikely to reverse, but its financial impact on vulnerable populations can and should be mitigated.

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Code Appendix

The following Python code implements our models from Q1, Q2, and Q3.

Appendix A: Q1 - Disposable Income Model

```python
import numpy as np

# -- Q1: Disposable Income Model --

def federal_tax(salary, filing_status="single"):
    """Compute federal income tax using 2024 brackets."""
    if filing_status == "single":
        brackets = [(11600, 0.10), (47150, 0.12), (100525, 0.22),
                    (191950, 0.24), (243725, 0.32), (609350, 0.35), (float('inf'), 0.37)]
    elif filing_status == "mfj":
        brackets = [(23200, 0.10), (94300, 0.12), (201050, 0.22),
                    (383900, 0.24), (487450, 0.32), (731200, 0.35), (float('inf'), 0.37)]
    else:  # head of household
        brackets = [(16550, 0.10), (63100, 0.12), (100500, 0.22),
                    (191950, 0.24), (243700, 0.32), (609350, 0.35), (float('inf'), 0.37)]
    tax = 0
    prev = 0
    for limit, rate in brackets:
        taxable = min(salary, limit) - prev
        if taxable > 0:
            tax += taxable * rate
        prev = limit
        if salary <= limit:
            break
    return tax

def fica_tax(salary):
    """Social Security (6.2% up to 168,600) + Medicare (1.45%)."""
    ss = min(salary, 168600) * 0.062
    medicare = salary * 0.0145
    return ss + medicare

def state_tax(salary, region):
    """Effective state + local tax by region."""
    rates = {"northeast": 0.068, "midwest": 0.052, "south": 0.031, "west": 0.059}
    return salary * rates.get(region, 0.05)

def housing_cost(salary, region):
    """Piecewise housing cost model."""
    medians = {"northeast": 78000, "midwest": 68000, "south": 65000, "west": 80000}
    betas = {"northeast": 1.25, "midwest": 0.85, "south": 0.90, "west": 1.30}
    M = medians.get(region, 70000)
    beta = betas.get(region, 1.0)
    base = 0.30 * min(salary, M)
    extra = 0.15 * max(0, salary - M)
    return beta * (base + extra)

def food_cost(age, household_size):
    """USDA moderate-cost plan with equivalence scaling."""
    base = 4200
    if age < 20: gamma = 0.90
    elif age > 50: gamma = 0.95
    else: gamma = 1.0
    equiv = 1.0 + 0.7 * max(0, household_size - 1)
    return base * gamma * equiv

def healthcare_cost(age):
    """Base premium + age-dependent out-of-pocket."""
    P0 = 2400
    delta = 18
    return P0 + delta * max(0, age - 25) ** 1.3

def transportation_cost(salary, region):
    """Regional transportation model."""
    epsilons = {"northeast": 0.85, "midwest": 1.10, "south": 1.15, "west": 1.05}
    eps = epsilons.get(region, 1.0)
    return eps * (3500 + 0.04 * salary)
```

```python
def other_essentials(salary):
    """Utilities, communications, insurance, min debt."""
    return 4200 + 0.03 * salary

def disposable_income(salary, age, region, household_size=1, filing_status="single"):
    """Main disposable income function."""
    T = federal_tax(salary, filing_status) + fica_tax(salary) + state_tax(salary, region)
    Ch = housing_cost(salary, region)
    Cf = food_cost(age, household_size)
    Cm = healthcare_cost(age)
    Ct = transportation_cost(salary, region)
    Co = other_essentials(salary)
    D = salary - T - Ch - Cf - Cm - Ct - Co
    return max(0, D)

# -- Demonstration --
profiles = [
    ("Young single, entry-level",  38000, 24, "south",     1, "single"),
    ("Young single, mid-career",   55000, 30, "midwest",   1, "single"),
    ("Single parent",              48000, 35, "west",      2, "hoh"),
    ("Married couple, no kids",    95000, 40, "northeast", 2, "mfj"),
    ("Married couple, 2 kids",    120000, 45, "northeast", 4, "mfj"),
    ("High earner",               150000, 38, "west",      1, "single"),
    ("Near retirement",            85000, 60, "south",     2, "mfj"),
    ("Low-income young adult",     25000, 21, "midwest",   1, "single"),
]

for name, sal, age, reg, hh, fs in profiles:
    di = disposable_income(sal, age, reg, hh, fs)
    print(f"{name}: Salary={sal}, Disposable Income={di:.0f}")
```

Appendix B: Q2 - Monte Carlo Gambling Simulation

```python
import numpy as np

# -- Q2: Monte Carlo Gambling Outcome Model --

def simulate_year(disposable_income, rho, n_simulations=10000):
    """
    Simulate one year of gambling for given disposable income and risk tolerance.
    rho: risk tolerance in [0, 1] (0=conservative, 1=aggressive)
    Returns: array of net gains/losses for n_simulations trials
    """
    W = disposable_income * (0.05 + 0.75 * rho)
    n_bets = int(50 + 550 * rho)
    avg_wager = W / n_bets

    p_straight = 0.75 - 0.40 * rho
    p_parlay = 0.10 + 0.35 * rho
    p_prop = 1.0 - p_straight - p_parlay

    bet_params = {
        'straight': (0.476, 1.0),
        'parlay2':  (0.225, 2.6),
        'parlay3':  (0.100, 6.0),
        'prop':     (0.375, 1.5),
    }

    results = np.zeros(n_simulations)

    for sim in range(n_simulations):
        net = 0.0
        for _ in range(n_bets):
            r = np.random.random()
            if r < p_straight:
                win_prob, odds = bet_params['straight']
            elif r < p_straight + p_parlay * 0.6:
                win_prob, odds = bet_params['parlay2']
            elif r < p_straight + p_parlay:
                win_prob, odds = bet_params['parlay3']
            else:
                win_prob, odds = bet_params['prop']

            if np.random.random() < win_prob:
                net += avg_wager * odds
            else:
                net -= avg_wager
        results[sim] = net

    return results

def analyze_results(results):
    """Compute summary statistics."""
    return {
        'mean': np.mean(results),
        'median': np.median(results),
        'std': np.std(results),
        'p5': np.percentile(results, 5),
        'p95': np.percentile(results, 95),
        'pct_positive': np.mean(results > 0) * 100,
    }

# -- Run simulations --
np.random.seed(42)
test_cases = [
    ("38K, 24, South",      10430, [0.15, 0.50, 0.85]),
    ("55K, 30, Midwest",    14190, [0.15, 0.50, 0.85]),
    ("120K, 45, NE",        22640, [0.15, 0.50]),
    ("25K, 21, Midwest",     5820, [0.50, 0.85]),
]

for name, di, rhos in test_cases:
    for rho in rhos:
        level = "Conservative" if rho < 0.3 else ("Moderate" if rho < 0.7 else "Aggressive")
        results = simulate_year(di, rho)
        stats = analyze_results(results)
        print(f"{name}, {level}: Mean={stats['mean']:.0f}, "
              f"Median={stats['median']:.0f}, Std={stats['std']:.0f}, "
              f"P95={stats['p95']:.0f}")
```

Appendix C: Q3 - Financial Impact Analysis

```python
import numpy as np

# -- Q3: Financial Impact Assessment --

def financial_impact_index(annual_loss, disposable_income):
    """FII = |loss| / disposable_income * 100%."""
    return abs(annual_loss) / disposable_income * 100

def compound_savings_deficit(annual_loss, years, r=0.04, savings_rate=0.60):
    """
    Cumulative savings deficit from foregone investment.
    Uses future value of annuity formula.
    """
    annual_foregone = savings_rate * abs(annual_loss)
    if r == 0:
        return annual_foregone * years
    return annual_foregone * ((1 + r)**years - 1) /

def at_risk_analysis(n_population=260_000_000, n_simulations=10000):
    """Estimate at-risk population across demographics."""
    participation = {
        ('M', '18-29'): 0.47, ('M', '30-49'): 0.49,
        ('M', '50-64'): 0.28, ('M', '65+'): 0.12,
        ('F', '18-29'): 0.18, ('F', '30-49'): 0.15,
        ('F', '50-64'): 0.09, ('F', '65+'): 0.04,
    }

    demo_data = {
        ('M', '18-29'): (0.10, 8000),  ('M', '30-49'): (0.13, 16000),
        ('M', '50-64'): (0.10, 18000),  ('M', '65+'): (0.08, 14000),
        ('F', '18-29'): (0.10, 7500),  ('F', '30-49'): (0.13, 14000),
        ('F', '50-64'): (0.10, 16000),  ('F', '65+'): (0.09, 12000),
    }

    total_at_risk = {5: 0, 10: 0, 20: 0, 50: 0}
    total_gamblers = 0

    for key, (pop_share, median_di) in demo_data.items():
        p_rate = participation[key]
        n_gamblers = n_population * pop_share * p_rate
        total_gamblers += n_gamblers

        results = simulate_year(median_di, 0.5, n_simulations)

        for threshold in [5, 10, 20, 50]:
            fii_values = np.abs(results) / median_di * 100
            pct_above = np.mean(fii_values > threshold)
            total_at_risk[threshold] += n_gamblers * pct_above

    print(f"Total estimated active gamblers: {total_gamblers:,.0f}")
    for threshold, count in total_at_risk.items():
        print(f"  >{threshold}% FII: {count:,.0f} ({count/total_gamblers*100:.1f}%)")
    return total_at_risk

# -- Savings deficit calculations --
losses = [(650, "55K Conservative"), (1820, "55K Moderate"),
          (4310, "55K Aggressive"), (750, "25K Moderate"), (1780, "25K Aggressive")]

print("Compound Savings Deficit Analysis:")
for loss, name in losses:
    d5 = compound_savings_deficit(loss, 5)
    d10 = compound_savings_deficit(loss, 10)
    d20 = compound_savings_deficit(loss, 20)
    print(f"  {name}: 5yr={d5:.0f}, 10yr={d10:.0f}, 20yr={d20:.0f}")

print("\nAt-Risk Population Analysis:")
at_risk_analysis()
```