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How Do Financial Market Outcomes Affect Gambling?

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Abstract: A large literature in behavioral finance explores how gambling sentiments influences trading in stocks. This paper considers the reverse phenomena; the impact of financial market outcomes on aggregate gambling expenditures. We expect the wealth effect of higher realized stock returns will increase gambling (entertainment good). Similarly, we expect rising volatility will attract gamblers to equity markets seeking thrill and skewed payouts. Utilizing novel horse wagering data (1934–2020), we study the impact of these forces on gambling expenditures. Using corporate bond spreads as a proxy for business cycles, we find that, in addition to financial market outcomes, price of wagering, incomes, and availability of competing betting products are important drivers of gambling. We also find that, ceteris paribus, gambling rises during recessions. Our findings will be of interest to policy makers and the finance industry, particularly as day trading, sports betting, online casinos, and other gambling gains broad public acceptance.

Keywords: realized risk premium; market volatility; stock market's wealth effect; gambling demand; racetrack gambling; conditional elasticity

JEL Classification: D12; G10; C13; L83

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1. Introduction

Participation in games of chance as an economic activity dates back to early human civilizations. Today, the modern gambling industry offers billions of participants worldwide the opportunity to bet on a large range of random outcomes, including pari-mutuel horse racing, sports, lottery, and elections. Gambling is a booming industry around the globe, generating nearly $500 billion dollars in gross revenues in 2019. According to the American Gaming Association, the U.S. is one of the fastest growing gambling markets, a trend that is projected to continue into the foreseeable future, primarily powered by the advancement of digital technologies, and introduction of new gambling products. While critics have raised concerns about gambling's adverse societal impacts (Mosenhauer et al. 2021), with the introductions of online gaming and sports betting, participation in legal and regulated games of chance will continue to gain broad public acceptance.[1]

The proliferation of legalized gambling is due to the maturation of a highly organized industry that supplies standardized wagering products with transparent payout schemes, promotes industry oversight and submits to regulatory controls and audits. Moreover, the industry has evolved by emulating financial market intermediaries, acting as market makers that facilitate the intersection of demand and supply in games of chance. Consequently, consumers increasingly view gambling products as dual featured goods that provide direct entertainment value, but also offer the potential for large gains, albeit with a small probability.[2]

Among individual investors, trading as a form of gambling and speculation probably dates back to the opening of stock exchanges. With the arrival of online brokerages and the fall in trading commissions, stock market gambling, some argue, has morphed into a form of entertainment. A large body of academic research has studied the relationship between gambling and speculative trading in financial markets. For example, relying on data from the Taiwanese Stock Exchange, Barber et al. (2009) find that the introduction of a national lottery resulted in a large drop in stock trading volume, and Gao and Lin (2015) show that as the size of lottery jackpot grew, trading volume further declined. Dorn et al. (2014) document similar relationships for the United States and Germany. More recently, Chen et al. (2021) find that when public interest in lottery gambling is high, stocks with lottery-like characteristics earn positive returns. This literature shows that there is a "substitution effect" between gambling venues, and documents the influence of gambling sentiments on trading activity in equity markets, particularly for lottery-stocks (see survey by Arthur et al. 2016).[3]

Our study empirically investigates the equally important, but mostly overlooked, reverse phenomena; the impact of financial market outcomes on aggregate gambling expenditures. Specifically, we focus on pari-mutuel horse race gambling, which is the longest running form of legal wagering, dating back to the opening of the first racetrack in 1665, and historically accounting for the largest volume of gambling expenditures in the U.S.[4] Many advancements in today's gambling industry have emanated from horse racing. These include a continually growing menu of betting products, coupled with reliance on technology to expand market penetration. Starting with telephone wagering (1970), the pari-mutuel betting network infrastructure has grown to include gambling brokerage accounts, hand-held betting devices, thousands of off-track wagering sites that simulcast races, and the internet.[5] In essence, the racetracks and associated betting infrastructure act as exchange intermediaries that organize and promote races, collect wagers and distribute payouts, and charge a commission, which is effectively the price of pari-mutuel gambling.[6]

Moreover, financial markets and pari-mutuel horse betting operate under very similar institutional structures and share several important features, including large transaction volume facilitated by specialized intermediaries (market-makers and regulators), ease of market entry, widely available information, agents with heterogeneous beliefs (informed and noise traders), similar behavioral biases, thrill and entertainment, and professional punters and analysts that seek to profit from potential arbitrage opportunities. Finally, there is historical evidence that there is an overlap in participants between the two markets, as track attendance and racehorse ownership are often associated with higher levels of wealth, including stock ownership (Riess 2014).

Given the foregoing similarities, we are interested in determining how financial market outcomes, specifically variations in realized equity returns and return volatility, have impacted aggregate horse wagering, which, until recently, was the most prevalent form of legal gambling in the U.S. Prior studies have shown that racetrack gambling provides entertainment and the potential for monetary gains. We postulate that realized equity returns, which measure change in stock market wealth, affect demand for wagering in two opposing directions. First, rising stock market returns can increase demand for gambling as a "normal entertainment good"—a direct "wealth effect". In this regard, Poterba (2000) provides evidence that rising stock markets in the 1990's directly contributed to increased consumer expenditures and point out that changes in stock prices raise consumer expenditures, even for households without equity holdings, because it affects consumer confidence and perceived uncertainty about future economic conditions. Similarly, Guzman and Stiglitz (2021) assert that the stock market creates "pseudo-wealth", defined as "individuals' perceived wealth that is derived from expectations of gains in bets arising from heterogeneous expectations" and show that as pseudo-wealth grows, consumption rises.[7]

Conversely, rising realized returns and market momentum may draw expenditures away from gambling and into equities, dampening the stock market's wealth effect. This is particularly the case for stocks with lottery-like payouts that offer thrill, entertainment, and the potential to "get rich quick". Starting with Baker and Wurgler (2007), Dorn and Sengmueller (2009), Grinblatt and Keloharju (2009), and Kumar (2009), a large body of research has shown that thrill, entertainment, and wealth motives attract gamblers and speculators to the equity markets. Moreover, Leuz et al. (2021) show that in the case of highly speculative “penny stocks”, day-traders with short investment horizons are more likely to fall prey to “pump-and-dump” scams that generate temporary price momentum. Overall, it appears that a significant portion of “individual investors” behave as gamblers, seeking highly skewed payout opportunities. For example, Kumar et al. (2021) find that in developed countries, trading in lottery-stocks accounts for roughly 14% of market volume; roughly equivalent to 3.5 times the value of all other forms of legal gambling combined.

In a similar vein, stock market volatility likely impacts bidirectional fund flows between stocks and gambling products, resulting in further integration of these risk markets. Specifically, high volatility attracts gamblers to equity markets in search of thrill and financial gains, and simultaneously reduces demand for gambling as an entertainment good, as individuals curtail consumption in response to economic uncertainty. Other systemic forces, including shifts in business cycles and socio-political upheaval (war, elections, etc.), also affect risk preferences and consumer participation in gambling and equity markets, simultaneously. Chen et al. (2021) show that demand for lottery-like stocks are highly sensitive to market volatility and broad waves of investor sentiment.

Finally, stock market gamblers, or “irrational investors”, will be attracted to skewed payouts and the thrill offered by a variety of betting products. Moreover, even rational risk-averse investors may gamble at the racetracks, because the horse race payouts are plausibly independent of aggregate risk preferences and changing risk premia in the financial markets as a whole. For example, Gomber et al. (2008) show that strategic gambling can generate an “orthogonal risk factor” that is critical for improved portfolio diversification. Evidence suggests that investors rely on intermediaries such as betting syndicates and esoteric hedge funds in pursuit of uncorrelated payouts at the racetracks.[8] The foregoing suggests that gambling and equity markets are at least partially integrated, as both markets offer thrill, entertainment, and risk-reward opportunities to investors, gamblers, and speculators.

To study the impact of financial market outcomes on aggregate gambling at the racetracks, we augment the traditional “gambling demand” models (Thalheimer and Ali 1995). This framework enables us to assess the impact of realized equity returns and stock market volatility, while controlling for the price of gambling, income, competing gambling products (lottery), and technical change (introduction of online and off-track wagering). Various economic factors (e.g., unemployment) could drive both gambling and stock market outcomes. We utilize corporate bond spreads, as a parsimonious proxy for these factors, and the overall state of business cycles. We estimate a nonlinear demand model, in percent change form, which removes auto-correlation and delivers robust coefficient estimates. We further improve upon previous studies by controlling for the supply and quality of wagering opportunities, further reducing potential endogeneity concerns. Finally, we perform a battery of robustness tests and show that our findings remain unaffected by the choice of functional specification and the presence of outliers.

Our empirical assessment is based on novel horse wagering data, that cover all California racetracks over the period 1934–2020. We find strong evidence of a negative stock market wealth effect, as higher realized equity returns lead to lower gambling at racetracks. Our analysis suggests that a rise in realized market volatility negatively impacts gambling at racetracks. In contrast, Chen et al. (2021) find a positive correlation between investor demand for lottery-like stocks and expected market volatility (VIX). [9] Furthermore, Kumar et al. (2021) show that individuals are more likely to gamble in the stock market during recessions. Our analysis suggests that, holding all else constant, this is also true for racetrack gambling. After controlling for financial market outcomes, we find that the introduction of a lottery has a negligible impact on racetrack gambling. Finally, we find that price, income, and the supply of wagering opportunities are the main drivers of gambling; in the short-run, gambling demand is inelastic, but as technology and off-track facilities enhance access, demand becomes highly elastic.

The rest of the paper is organized as follows. In Section 2, we present historical background and describe our data. Section 3 contains the conceptual framework and our proposed econometric models. In Section 4, we present the estimation results and discuss their implications. Section 5 summarizes our findings and provides suggestions for future extensions of our analysis.

2. Prior Gambling Demand Literature

Empirical analysis of horse race wagering data started with Harville (1973) and three distinct lines of inquiry, each with a large body of economic research, has subsequently developed. Briefly, the first line of inquiry concerns the efficiency of horse wagering markets; the bettors' collective ability to uncover true winning odds and exploit profitable wagering strategies. The most celebrated subject in this vein is the favorite long-shot anomaly; the empirical finding that bettors consistently tend to over-bet long-shots and under-bet favorites. Ziemba (2021) provides a comprehensive review and assessment of this literature.

A second line of inquiry assumes that horse bettors are rational agents whose sole motivation for gambling is monetary gains. However, their participation in negative expected return gambles may be explained by either subjective beliefs or a flexible utility function that rationalizes gambling. This literature utilizes aggregate odds data, along with "representative agent" preferences, to conduct a race between the expected utility model versus its prospect theory alternatives.[10] In a seminal contribution, Chiappori et al. (2019) propose a framework that permits for both heterogeneous bettors and flexible risk preferences. They then undertake a comprehensive study of pari-mutuel horse betting, confirming earlier findings by Snowberg and Wolfers (2010), that prospect theory with nonlinear probability weighting fits the data better than expected utility alternatives.

Closer to our domain, there exists a third strand of literature that views horse betting, primarily as a form of entertainment. Under this perspective, people bet on horses because it is fun and stimulating, and they are prepared to pay a price to enjoy this entertainment activity. Since, for individuals, and in the aggregate, the expected payout is the amount wagered net of the tracks' commissions (the "take-out"), the latter acts as the price of gambling.[11] As Gruen (1976), Suits (1979), and Thalheimer and Ali (1995) have shown, the assumption that individuals derive utility from betting activities provides the theoretical basis for estimating a gambling demand function.

Following this later perspective, we model the dynamics of aggregate dollars wagered at all racetracks and related venues in California using annual data. We consider the impact of a standard set of explanatory variables, including per capita income, the price of wagering, variables accounting for variations in the supply of betting opportunities, and business cycle indicators.

Most importantly, we improve upon previous studies by including realized equity returns and stock market volatility.

Our focus on California is motivated by the fact that it is a major horse racing state with high payouts to horse owners, which, in turn, attracts high-quality horses and trainers to its racetracks. Few locations can match California's horse racing industry in terms of the quality of races, year-round availability, and regulatory oversight that ensures market transparency. California's historical data, which has been audited annually, is particularly accurate and clean. Focusing on a single state enables us to control for tastes and customs, which vary geographically.

3. Data and Historical Background

The annual data for our analysis are obtained from a number of sources. Annual aggregate wagers on all California horse races were collected from the annual reports of California Horse Racing Board (1934–2021) (CHRB, 1934–2020) and cross-checked for errors and updates. The CHRB was established in 1933 as an independent agency of the State of California and it acts as the regulatory body that ensures "the integrity, viability, and safety of the California horse racing industry by regulating pari-mutuel wagering for the protection of the public".[12]

The CHRB's annual reports also contain information about the number of races and race days per year, the number of operating racetracks (including state and county fairs), the number of wagering venues (on- and off-track, simulcast, telephone, and online betting), and information about regulatory mandates that influence the industry as a whole, including the payout rates to horse owners, racetracks, and related businesses, as well as the state's tax collection and distribution rules. Most importantly, the CHRB collects and audits data from all betting venues and ensures the integrity of the pari-mutuel wagering system in California.

To provide comparisons, we also collect similar data for two major California racetracks that have been in operation since the late 1930s. The Del Mar Racetrack was built in 1936 and hosts hundreds of races annually. Similarly, Santa Anita Park, which began its operations in 1934, hosts hundreds of races annually, many of which are globally recognized. Both tracks generate significant interest and betting revenues. The data for both racetracks were collected from their Annual Media Guides and were cross-referenced with CHRB's Annual Reports for accuracy.[13]

With the onset of World War II, horse betting as a form of entertainment experienced significant decline, as several California racetracks were closed during the war. For this reason, we exclude the scant data from the war period in our analysis. Subsequently, our data span the period of 1934–1941 and 1946–2020 (82 observations).[14]

A major challenge in working with annual time series that nearly span a century concerns the inevitable changes in the definition, construction, and measurement of variables of interest. In this regard, our raw CHRB data are highly consistent and reliable. For example, the annual aggregate wager has always been defined as the sum of all dollars wagered by every source (on- and off-track), across all racetracks and bet types, and for every race day in the year. Similarly, there has been no change in the calculation of aggregate payments to horse owners (the purse), calculation of tax proceeds, or the number of races and race days over time. Unfortunately, this is not the case for several potentially interesting explanatory variables, and moreover, many socioeconomic series only start in the 1960s. Mindful of this challenge, we have attempted to select covariates that date back to the 1930s and whose construction has seen few changes over time.

The aggregate wager is important to the state, equine business, racetrack operators, and the racing industry infrastructure because these economic agents derive their revenues from this single source. A common practice in prior studies (Gruen 1976; Suits 1979; Thalheimer and Ali 1995) is to normalize aggregate wagers by the population of the state or the "market area" near the racetracks and study the determinants of the per capita wager. We assert that such normalization likely biases the estimated results simply because only a subset of the population wagers on horse races.[15] Moreover, with the advances in digital technologies, and the increase in the number of off-track betting facilities, a large fraction of wagers originates from outside the state.

For these reasons, we study the impact of the explanatory variables on *Wager per Race* (WRC), defined as the annual aggregate wagers deflated by the number of races per year. High wager per race is generally reflective of higher participation by betting patrons, but also by better quality races and larger prizes for horse owners. While there are no reliable data on the number of betting patrons, we do control for improvements in race quality and the purse size.

Throughout the analysis, we work with nominal values of the variables under consideration. While it is possible to adjust the nominal variables by an inflation deflator, it is difficult to identify an "appropriate" deflator that uniformly applies to take-out, income, aggregate wagers, payments to horse owners, and other monetary values. In practice, changes to take-out, purse distribution, and taxes are determined by the CHRB, rather than adjustments caused by inflationary pressure. Furthermore, given our proposed econometric specification (percent change form), failure to deflate the monetary variables by a common inflation index should minimally impact the parameter estimates.

Figure 1 presents a time series plot of annual Wager per Race (WRC); payout to horse owners (Purse per Race, PRC); the number of operating racetracks; and the number of off-track simulcast facilities for the period 1946–2020. The timing of recessions is also marked vertically. The figure essentially captures the post-war evolution of horse race gambling in California. This evolution is composed of three distinct periods.[16] During the early years (1934–1985), WRC experiences modest annual growth while there are no significant enhancements to betting technology and the number of operating racetracks remains stable. During this era, recessionary periods appear to be accompanied with modest increases in wagering.

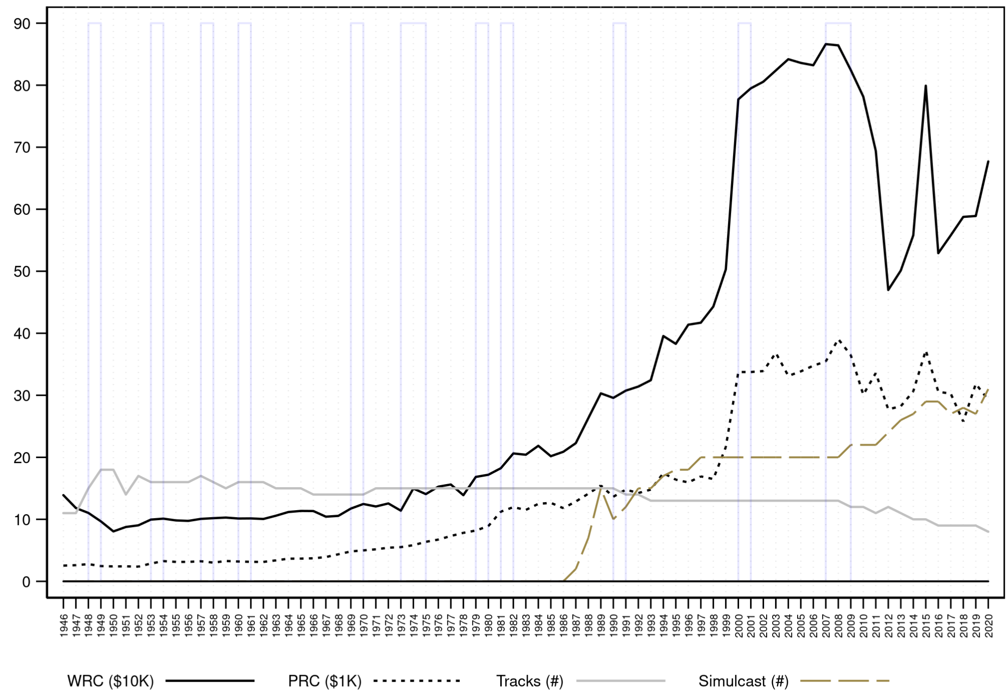

Figure 1. The evolution of the horse racing industry in California (1946–2020): Wager per Race (WRC), Purse per Race (PRC), Tracks and Simulcast Locations (Tracks), Recessions (bars).

The second period (1986–2007) is characterized by the explosive growth in aggregate wagers, despite a decline in the number of racetracks. This growth is driven by the expansion of off-track betting locations, the growth in out-of-state wagers, and numerous enhancements to wagering technologies, including the arrival of online betting, and the availability of horse betting in casinos.[17] It is during this period that lottery and Indian gaming are legalized, and gambling gains further public acceptance.

The third period (2008–present), follows the "Great Recession". During this period WRC falls precipitately, despite the initial modest rise in the number of racetracks and significant growth in simulcast locations. The decline since the "Great Recession" is attributed to proliferation of online gambling and sport betting, closure of racetracks, and the general decline of horse racing industry. More importantly, there is a disproportionate increase in payout to racetracks and the racing industry infrastructure, while payment to horse owners (PRC) remains stagnant. In short, wagering market expansion brought about by modern technologies largely favors intermediaries that process wagering dollars, with a smaller impact on the suppliers of betting opportunities (horse owner).[18] This is consistent with the findings of Kumar et al. (2021) that enhanced access to financial markets brought about by the advent of digital trading has likely lured betting dollars away from a variety of gambling activities, including horse wagering nationwide.[19]

4. Conceptual Framework

To assess the impact of financial market outcomes, we augment the traditional "gambling demand models". The extant empirical literature estimates a variant of the following constant elasticity specification:

$$E\left[W_t \mid Z, P, I\right] = e^{\sum \beta_j Z_{jt}} * P_t^{\delta} * I_t^{\eta} \quad (1)$$

where W_t represents the aggregate dollars wagered at specific racetrack(s), often normalized by the number of patrons in attendance or the size of the population residing in the vicinity of the racetrack(s); P_t is the take-out rate, which represents the "price" of gambling and δ is the "price elasticity"; I_t is per capita income and η is the "income elasticity" of wagering; Z_{it}s are a set of other relevant explanatory variables with their associated coefficients , β_is; and $E\left[W_t \mid \cdot\right]$ is the conditional expectation operator. It is important to note that the literature does not associate an "optimizing representative agent" with this demand specification. Hence, δ and η are called "elasticity" as a consequence of the functional form, rather than utility optimizing behavior, which delivers a theoretically consistent aggregate demand function.[20]

This specification—product of exponential and power functions—represents the original scale of interest for the conditional mean function. However, when elasticity estimates are the object of interest, empiricists typically rely on the logarithmic transformation to deliver an additive structure, with the appealing properties of being easy to implement and interpret. Indeed, most econometric analyses of gambling demand assume a log-linear specification and an orthogonal error structure, in conjunction with ordinary least-squares (OLS) to estimate a log-scale model.[21] However, as Manning and Mullahy (2001) and Santos-Silva and Tenreyro (2006) show, under a broad range of applications, the log-linear model estimated by OLS generates biased parameter estimates, because it fails to adequately account for the distributional characteristics of the data.

Considering the foregoing, it is apparent that the results in existing studies of gambling demand should be viewed with caution. For example, early papers by Gruen (1976) and Suits (1979) use time series and panel data for several racetracks in conjunction with a linear specification and OLS, but these authors overlook the fact that W_t, which represents aggregate wagers, is strictly positive and has a truncated distribution. Consequently, their OLS estimates are likely to suffer from instability caused by excess skewness, and be inefficient due to heteroskedasticity in wagers data. Recognizing these issues, Thalheimer and Ali (1995) and subsequent studies utilized a log-linear or semi-logarithmic specification and OLS but likely obtained biased parameter estimates (Santos-Silva and Tenreyro 2006). Consequently, the magnitude of elasticity estimates reported in prior studies fall within a wide range of values (price elasticity estimates of -1.3 to -3.1).[22]

In light of these issues, estimation based on improved econometric techniques and comprehensive data is important, regardless of whether new covariates are included in this type of analysis.

Aside from the specification choice, a number of other econometric issues should be carefully considered when estimating gambling demand models. First, excess kurtosis, right skewness, and heteroskedasticity are prominent features of wagering data. Second, the "relevant" explanatory variables utilized are often highly correlated. Finally, the residuals of estimated models exhibit strong serial correlation due to the persistence of both the dependent and explanatory variables.

In our analysis, we overcome these issues by first normalizing wager and related variables by the number of races, which reduces skewness and heteroskedasticity. We then convert the continuous variables to "percent change," which is a straightforward method to alleviate collinearity and serial correlation in time series data. Finally, we posit that demand parameters will likely vary with the supply of wagering opportunities and propose a flexible specification that captures this type of dynamic effect. Our proposed models are then estimated by nonlinear least squares (NLS).

Following Ramezani and Ahern (2022), suppose Wager per Race (WRC_t) follows a linear dynamic as, $WRC_t = WRC_{t-1} * (1 + R_t)$, where R_t, is the percent change in WRC over the period t. Then the distribution of R_t, is conditional on two sets of explanatory variables, as follows:

$$R_t = \alpha + \beta e^{\tau} + \epsilon_t = \sum \alpha_i X_{it} + \left[\sum \beta_j Z_{jt} \right] * e^{\theta * O_t} + \epsilon_t \quad (2)$$

where ϵ_t is an IID error term, X_{it}s are the financial market indicators, whose impact on R_t is constant and independent of other explanatory variables. On the other hand, Z_{jt}s are economic and racing industry variables, whose impact is conditional on the supply of wagering opportunities, O_t. Hence, the term (βe^{τ}) captures potential nonlinear interactions between Z_{jt}s and O_t, and their dynamic impact on the distribution of R.[23] Under this specification, variations in WRC_t are driven by R_t, which is in turn determined by the dynamics of X_is, Z_{jt}s and O_t, and the marginal impact of exogenous variables on R_t are imputed from their partial derivatives:

$$\text{Financial indicators and Lottery:} \quad \hat{\alpha}_i = \frac{\partial E[R \mid_{X_i, Z_j, O}]}{\partial X_i}$$

$$\text{Economic and Racing Industry:} \quad \hat{\delta}_{jt} = \frac{\partial E[R_t \mid_{X_i, Z_j, O_t}]}{\partial Z_j} = \hat{\beta}_j * e^{\hat{\theta} * O_t} \quad (3)$$

Since Equation (2) is linear in X_i, its marginal impact $(\hat{\alpha}_i)$ is constant. In contrast, $\hat{\delta}_{jt}$ that captures the marginal effect of Z_j, is time varying in the sense that its value is dependent upon the level of O_t. Moreover, when X_i is measured in percentage, $\hat{\alpha}_i$ is a direct elasticity estimate. Similarly, when Z_j is measured in percent change, $\hat{\delta}_{jt}$ is a conditional semi-elasticity estimate, which is a desirable feature of the interaction effects proposed in Equation (2).[24]

Explanatory Variables

Next, we present the explanatory variables utilized in this study. Following prior studies, we include variables that are standard in the literature. Additionally, we contribute to the body of knowledge in gambling research by examining the impact of two important factors that have not been considered in previous studies.

The first factor is a set of financial market indicators that capture the state of macroeconomic conditions, including economy-wide risk appetite.

The second factor measures the relative payout to horse owners and the racing industry infrastructure, which in turn affects the supply of wagering opportunities.

Since the aggregate wager and other race-related variables are measured in accordance with California's fiscal year (30 June–1 July), all other variables are constructed to match this calendar format. Table 1 presents the variables we utilize. In the remainder of this section, we provide a brief description of each and the rationale for its inclusion in our analysis.

Financial Market Indicators and Lottery (X_is): We assess the impact of financial market condition on aggregate wagers by utilizing standard equity and bond market indicators. We also include lottery as a competing betting product.

Equity Market Indexes: We use realized excess returns, defined as the difference between the rate of return on a broad market index and the yield on a risk-free asset, as a proxy for change in stock market wealth.[25] From a macroeconomic perspective, the realized equity returns reflect the broader outlook on the whole economy including economic growth, consumer demand, inflation expectation, investors' risk appetite and geopolitical risks. As noted above, we conjecture that realized market returns could affect aggregate wagering in two opposing directions. Our empirical model will deliver estimates of the net effect of the two countervailing forces.

Because the stock selection criterion underlying market indexes has changed over time, we construct the annual market returns using three different market portfolios: The Center for Research in Security Prices value weighted (CRSP-VW) index, the S&P-500 index, and Shiller's "total market returns" index. Following the literature, we use the yield on seasoned three-month treasury bills as a proxy for the risk-free rate. For each year, we use the average of monthly realized excess returns, and the trailing 12 months standard deviation of the monthly returns.[26]

Table 1. Definition of the Dependent and Explanatory Variables (Annual Data 1934–2020).

Dependent Variables	
R_t (% Change in WRC)	Wager Per Race, (WRC, $) WRC = Aggregate Wagers/number of races, by year Similarly defined for Del Mar and Santa Anita Tracks
Explanatory Variables	
Financial Market Outcomes and Lottery	
Bond Spread	Average of Moody's Monthly Yield Spread (Baa-AAA)
CRSP-VW Premium	Average of Monthly CRSP-VW Excess Returns
CRSP-VW Volatility	Standard Deviation of Monthly CRSP-VW Returns
S&P Premium	Average of Monthly S&P-500 Excess Returns
S&P Volatility	Standard Deviation of Monthly S&P-500 Returns
Shiller Premium	Average of Monthly Shiller's Excess Returns
Shiller Volatility	Standard Deviation of Shiller's Monthly Returns
Lottery	California Lottery Dummy Variable
Economic and Racing Industry Variables	
Price (Take-out Rate)	Fraction of Aggregate Wagers distributed to racetracks, horse owners and taxes.
Income, $	California Income deflated by Population
Purse per Race, $	Purse Proceeds / number of races
Off-Track Wager	Fraction of Aggregate Wagers originating from off-track facilities
Purse Proceeds, $	Aggregate Dollars distributed to horse owners, $
Track Proceeds, $	Aggregate Dollars distributed to racetracks & affiliated businesses
Relative Incentive	Purse Proceeds / Track Proceeds
Relative Compensation Index	RCI = (Relative Incentive) × (number of operating racetracks)

Business Cycle Indicator: Following Kumar et al. (2021), we conjuncture that aggregate wagers will likely increase during recessions. We utilize bond spreads as an informative proxy for the phase of business cycle. Starting with Jaffee (1975), a large body of literature has shown that corporate bond spreads significantly impact macroeconomic conditions.[27] We use the yield spread between the Moody's seasoned Baa and Aaa rated corporate bonds, where Aaa is at the top and Baa is at the bottom of the investment grade bond ratings (one grade above junk rating). The Baa-Aaa spread, referred to as *"quality spread"* or *"default spread"*, is widely utilized as a conditioning variable in empirical macroeconomic and asset pricing studies.[28]

Duca (1999) shows that quality spread rises during recessions (a coincident indicator), and is predictive of current and future economic activity (a leading indicator). Recent studies confirm that quality spreads contain useful information about overall macroeconomic conditions, including credit availability, inflation expectations, changes in consumer sentiment, and expected economic growth (Faust et al. 2013; Kang and Pflueger 2015; Zhang 2002). Similarly, Fama and French (1989) and Schwert (1989) find that the dynamics of the quality spread is a predictor of investors' risk appetite and the future stock price movements.

Lottery: The California State Lottery was legalized in 1984, with sales commencing in 1985.[29] The expansion of state lottery and other forms of gambling, such as Indian casinos and sports betting, is likely to carry significant consequences for aggregate horse wagering, the racing industry and the state's tax revenues. An important empirical question is whether lottery is a substitute or complement to other gambling products. Simmons and Sharp (1987) find that competition from lottery lead to higher price elasticity of horse wagering (a substitute). Gramm et al. (2007) find that lottery does not have a statistically significant impact on horse wagering. More recently, Grote and Matheson (2013) summarizes previous studies and concludes that lottery and other forms of gambling are substitutes for horse betting.

Economic and Racing Industry Variables (Z_{jt}s): Following prior studies, we examine the effect of several economic and industry variables, including price, per capita income, and purse size.

Price: Take-out represents the price of betting, and in the aggregate, it ensures that bettors collect less than the total amount wagered. The take-out rate for different wager types is set and adjusted over time by the state regulators (CHRB). Additionally, racetracks cannot alter the take-out in response to changes in demand. Therefore, endogeneity arising from the simultaneous determination of price and quantity will have minimal impact on our results.

We use the average take-out across all wager types as the effective price of gambling. We expect an increase in the betting price to result in a lower amount wagered, while holding other covariates constant.

Income: Per capita income is a significant factor in the demand for gambling. Prior studies typically use nominal per capita income and we follow the literature for consistency.[30] While estimates of income elasticity of gambling vary widely, empirical research reports elasticity estimates that are close to unity, suggesting that a relatively greater percentage of income is spent on horse wagering at lower income levels (Gruen 1976; Thalheimer and Ali 1995). As in previous studies, we assume income is an exogenous variable. This assumption is justified on the grounds that the aggregate wager is a minuscule fraction of the California economy and changes in the aggregate wager are assumed to have no impact on per capita incomes.[31]

Purse per Race: The purse is the fraction of aggregate wagers distributed among the horse owners. The purse distribution rule is set by the CHRB, often months in advance. For major races, small additions to the purse (a subsidy) are negotiated between racetracks and horse owners, and are approved by regulators. Purse per Race (PRC) is the aggregate purse divided by number of races by year. As Figure 1 shows, the rise in WRC has been accompanied by rising PRC. Gramm et al. (2007) and DeGennaro and Gillette (2013) assert that large purses attract quality horses, leading to bigger wager pools.

Off-Track Wager: In California, off-track betting began in 1985 and by 2020, over 90% of dollars wagered originated from outside the racetrack facilities. Technological change that has enhanced access to horse betting has been the key driver of this growth.[32] The most important impact of technology has been a reduction in transaction costs of visiting racetracks.

Supply of Wagering Opportunities: Figure 2 shows the distribution of take-out revenues among the racing industry infrastructure (track operators, simulcast facilities and off-track service providers), horse owners (purses), and the state (taxes). The figure shows that as price of horse gambling has risen and taxes have decreased, the distribution of the remaining take-out between the racing industry infrastructure (gambling intermediaries) and horse owners (purveyors of quality races) has varied over time. Economic theory suggests that in addition to price and income, the availability of high-caliber races (quality) and low-cost access to wagering facilities (infrastructure) will lead to higher aggregate gambling expenditures. We propose a simple index to capture the variation in relative payout to horse owners and the gambling intermediaries, which together determine the supply of quality betting opportunities.

We define *relative incentive* as payment to horse owners per dollar paid to the racing industry infrastructure. This ratio rose from a low of $0.30 in early years to a peak of nearly $1.50 in 1985. Since then, the relative payout to horse owners has steadily declined to below $0.30 in 2020. We hypothesize that, holding the number of racetracks constant, higher relative payout to horse owners increases investments in breeding and training race horses, and subsequently enhances the supply of high-caliber races; i.e., high entertainment value and large wager pool for winners.

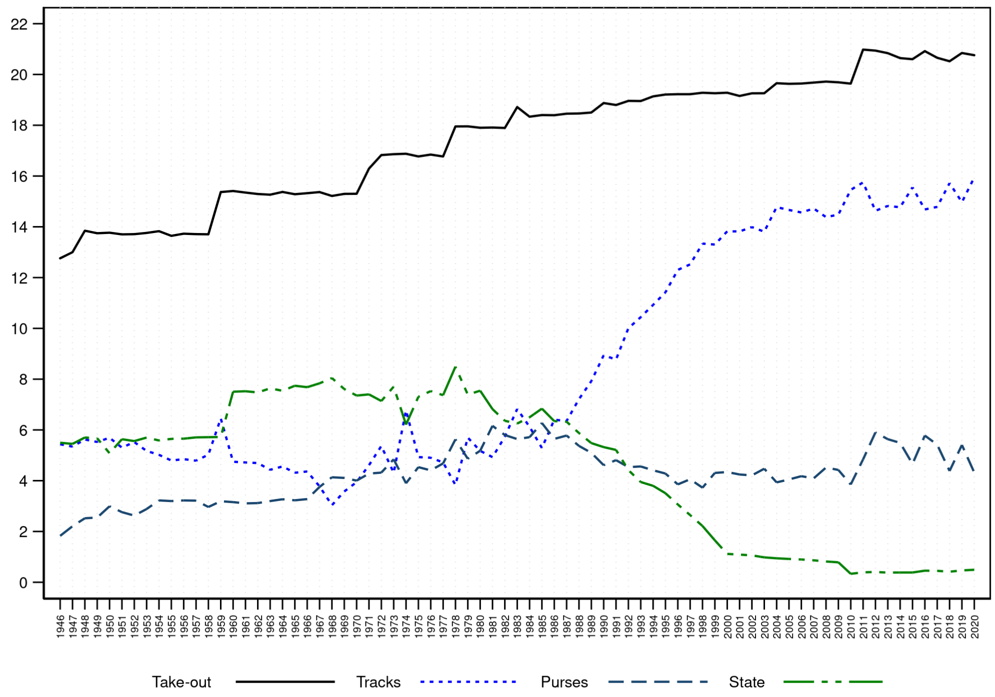

Figure 2. Distribution of Take-out (1946–2020) Percent of Aggregate Wagers Allocated to Racetracks, Purses, and the State.

Prior studies have relied on Purse per Race (PRC) as a broad measure of race quality. However, PRC is only reflective of revenues flowing to horse owners, rather than the actual division of net industry revenues. As Figure 2 shows, before the introduction of off-track betting in 1985, purses and racetrack revenues moved in tandem and were nearly equal. With the proliferation of exotic wagers and explosive growth in off-track wagering, these payouts diverged such that by 2020, the racing industry's revenues per race were nearly four times the horse owner proceeds. Hence, while PRC has improved, it has not kept pace with the blistering growth in racing infrastructure revenues. Hence, our proposed relative incentive ratio captures the decline in "entertainment quality" of wagering, since off-track betting simply offers thrill of winning, rather than the enjoyment of in person gambling at the tracks.

We scale the relative incentive ratio by the number of operating racetracks to arrive at our proposed *Relative Compensation Index (RCI)*, denoted by O_t. Scaling by the number of racetracks will ensure that shifts in relative incentive are not simply due to changes in the number of racetracks. Hence, RCI proxies for both entertainment value and the supply of wagering opportunities. Holding the number of tracks fixed, we expect smaller gambling price elasticity for high-quality races (high relative incentive). Conversely, higher price elasticity will be associated with expansion of gambling infrastructure, particularly off-track facilities (low relative incentive). While prior studies have been suggestive of this possibility, to the best of our knowledge, no other study has considered this form of conditional demand elasticity.[33]

Table 2 provides basic statistics on the distributional characteristics of the variables described above. We note that from the perspective of this study, the most important advantage of the proposed covariates is the fact that their construction has remained reasonably consistent for nearly a century. Furthermore, our data span several business cycles, offering the opportunity to assess the validity of the proposed hypothesis through different macroeconomic conditions.

Table 2. Statistics for Dependent and the Explanatory Variables, 1935–2020 (Annual, N = 81) All figures have been rounded to two decimal points for this table.

	Mean	St. Dev.	Skewness	Kurtosis	Min	Max
Dependent Variables						
Wager Per Race-California ($)	309,383	268,865	0.93	2.40	18,627	866,227
R_t (% Change in WRC)	0.05	0.15	1.01	6.30	−0.34	0.57
R_t-Del Mar (N = 79)	0.05	0.13	1.90	12.93	−0.30	0.74
R_t-Santa Anita	0.04	0.13	0.84	8.30	−0.42	0.61
Explanatory Variables						
Financial Market Outcomes and Lottery						
Bond Spreads—(Baa-AAA)	0.01	0.00	1.35	4.46	0.00	0.03
CRSP-VW Excess Returns	0.08	0.16	−0.38	3.12	−0.35	0.45
CRSP-VW Market Volatility	0.04	0.02	1.84	8.16	0.02	0.13
S&P Excess Returns	0.05	0.15	−0.37	3.21	−0.38	0.45
S&P Market Volatility	0.04	0.02	2.17	9.96	0.02	0.14
Shiller Excess Returns	0.03	0.17	−0.37	2.94	−0.36	0.40
Shiller Market Volatility	0.03	0.02	1.36	4.61	0.01	0.08
Lottery Dummy	0.44	0.50	0.22	1.05	0.00	1.00
Economic and Racing Industry Variables						
Price (Per $ of Wager)	0.17	0.03	−0.22	1.65	0.12	0.21
% Change in Price	0.01	0.03	0.93	9.44	−0.09	0.12
Income($)	19,248	19,391	0.96	2.80	776	71,261
% Change in Income	0.05	0.04	0.82	6.04	−0.04	0.21
Purse (Per $ of Wager)	0.04	0.01	0.08	2.26	0.02	0.06
Track (Per $ of Wager)	0.08	0.04	0.58	1.62	0.03	0.16
Purse Proceeds/Track Proceeds	0.60	0.29	0.89	3.06	0.25	1.47
Number of Tracks—California	14	2.22	−0.55	3.35	8	19
Relative Compensation Index (RCI)	8.63	4.73	0.59	2.51	2.17	22.03
Purse Per Race (PRC) ($)	13,790	12,327	0.73	2.02	585	39,068
% Change in PRC	0.05	0.13	1.52	7.24	−0.18	0.56
% Change in PRC—Del Mar (N = 79)	0.05	0.11	1.00	9.47	−0.37	0.56
% Change in PRC—Santa Anita	0.05	0.17	0.78	5.89	−0.46	0.62
Number of Races	6107	2430	0.24	1.89	2113	10,590
% Change in Number of Races (NRC)	0.01	0.11	0.92	9.91	−0.33	0.47
% Change in NRC—Del Mar (N = 79)	0.01	0.10	2.37	14.39	−0.32	0.48
% Change in NRC—Santa Anita	0.01	0.11	1.94	12.81	−0.36	0.56
Off-Track Wager (Fraction of Wagers)	0.31	0.39	0.55	1.41	0.00	0.93
% Change in Off-Track Wager	0.01	0.03	5.35	35.48	−0.00	0.25

5. Results

In a prior study, Ramezani and Ahern (2022) empirically estimated the *percent change specification* in Equation (2). In this paper, we extend their analysis by undertaking a set of robustness tests, including assessing the influence of outliers, and evaluating whether additional coefficients, for example $\hat{\alpha}_i$s, should also be conditioned on O_t.[34] The models presented below are estimated using nonlinear least-squares with heteroskedasticity robust standard errors. We test the null hypothesis that the residuals are white noise using a standard test for serial correlation. We utilize Shapiro-Wilks statistics to test for normality of the residuals. Other diagnostic tests appear in the tables and are discussed below.

Under the proposed specification, the percent change in wager per race (R_t) is determined by covariates with percent units, except the lottery dummy variable. As expected, this specification addresses the econometric problems associated with collinearity and serial correlation.[35] Table 3 contains the estimated coefficients, where each column shows the inclusion of a subset of explanatory variables; column 1 shows the impact of financial market indicators and lottery. Similarly, column 2 and 3 contain estimates of economic and racing industry variables. Column 4 includes all covariates, without the dynamic interaction effects (henceforth the static model). The last three columns show results for the full model under each equity market index.[36]

Table 3. Distribution of % Change—Wager per Race, R_t (1935–2020).

Explanatory Variables	α_is (S&P)	γ and η	β_is	Static	S&P	CRSP	Schiller
Financial Market Outcomes and Lottery							
Bond-Spread α_1	4.130 0.98			3.917 1.66	7.190 *** 3.96	7.215 *** 3.56	6.308 ** 2.30
Excess Returns α_2	0.015 0.13			−0.082 −0.93	−0.154 ** −2.23	−0.123 * −1.87	−0.092 −1.22
Market Volatility α_3	0.128 0.13			−1.231 −1.52	−1.793 *** −2.80	−1.679 ** −2.50	−1.814 *** −2.81
California Lottery α_4 Dummy Var.	−0.004 −0.12			−0.014 −0.79	−0.059 ** −2.55	−0.064 ** −2.59	−0.069 *** −2.73
Economic and Racing Industry Variables							
Price γ		−0.77 −1.28		−0.678 −1.17	−2.402 ** −2.34	−2.449 ** −2.38	−2.330 ** −2.01
Income η		1.00 *** 3.07		0.877 ** 2.18	2.593 *** 4.52	2.646 *** 4.40	2.689 *** 3.99
Purse per Race β_1			0.653 *** 5.83	0.543 *** 4.87	0.921 *** 3.68	0.927 *** 3.42	0.880 *** 3.32
Number of Races β_2			−0.452 *** −4.57	−0.549 *** −6.16	−0.741 *** −7.86	−0.757 *** −7.78	−0.836 *** −7.04
Off Track Wager β_3			0.438 *** 4.38	0.488 *** 2.83	2.168 * 1.96	2.223 * 1.91	2.276 * 1.69
Relative Comp. Index θ RCI				$\theta \equiv 0$	−0.103 *** −2.99	−0.107 *** −2.91	−0.114 *** −3.06
Model Diagnostics							
Adj. R^2	0.06	0.16	0.61	0.67	0.73	0.72	0.71
Fit	0.02	0.09	0.59	0.67	0.74	0.73	0.72
Serial Correlation (p-value)	0.89	0.58	0.17	0.34	0.63	0.57	0.46
Normality (p-value)	0.00	0.00	0.00	0.04	0.32	0.16	0.25
Log-Likelihood	42	45	77	87	96	95	93
AIC	−76	−87	−147	−155	−172	−170	−166
BIC	−67	−82	−140	−134	−148	−146	−142
Num. of Iterations	-	-	-	-	19	22	30

All models are estimated using nonlinear least-squares, in conjunction with `robust` standard errors; t-values appear below the estimates ('*' for $p < 0.10$, '**' for $p < 0.05$, and '***' for $p < 0.01$).

Before discussing the estimated coefficients, we consider the test statistics associated with each column. First, the correlation among the covariates is low, as reflected in "Fit" and adjusted R^2s. Similarly, there is no evidence of serial correlation, up to six lags, in the residuals. The Shapiro-Wilks statistics for columns 1 through 4 reject the null hypothesis that the residuals are normality distributed. We therefore cannot compare the log-likelihoods and test the null hypothesis that, relative to column 1, the extra variables in column 2 or the last columns are unnecessary. On the other hand, residuals for the full models appear to be normally distributed.

Staring with the financial market indicators, we find that the impact of these variables on horse wagering is large and statistically significant. Bond spread, which is an informative proxy for overall macroeconomic conditions, has a large positive and statistically significant impact on R_t. Since larger bond spreads are associated with deeper recessions, our results suggest that individuals wager more when the economy slumps and unemployment rises.

Such behavior may be driven by the prospects of winning a big payout at the tracks, and increased demand for affordable entertainment during bad economic times.[37]

The gambling literature provides evidence of this type of behavior in other betting markets as well; Kumar et al. (2021) shows that individuals are more likely to gamble in the stock market during recessions. Herskowitz (2021) provides evidence that the propensity to gamble is higher among credit constrained individuals for whom gambling offers the potential to generate liquidity. Overall, our findings improve upon prior studies that rely on a recession dummy variable to assess this phenomenon.

The evidence on equity market indicators is also compelling. We have argued that realized equity returns have opposing effects on wagering demand. Our results indicate that the overall effect of increasing realized equity returns on the demand for horse wagering is negative and statistically significant. We have also hypothesized that stock market volatility may attract certain racetrack gamblers to equity markets, while others may reduce their wagering activities due to economic uncertainty. Once again, our findings demonstrate that the overall effect of rising market volatility on the demand for horse wagering is negative and statistically significant.

As noted earlier, the impact of lottery on horse wagering is important to racing industry and policy makers. The reported findings in prior studies are generally inconclusive and often conflicting. Controlling for the influence of financial market outcomes, we find that lottery is a weak substitute for horse betting and its economic impact is negligible. This is unsurprising, because, relative to playing lottery, horse wagering (stock picking) is more engaging, offering additional entertainment value, including the ability to study each horse's characteristic and to learn from the wagers placed by other bettors (public odds).

Next we consider the economic and racing industry variables. The coefficient of price and income are statistically significant and their imputed elasticity are within the range of values reported in prior studies. We find that growth in payout to horse owners has a positive impact and growth in number of races has a negative impact on R_t. As expected, Off-track wager has a large and highly significant impact, affirming the role of technology in expanding access to wagering. Clearly, economic and racing industry factors as a group are the most important determinants of R_t. However, their impact varies dynamically with the relative compensation index, O_t. We discuss the dynamic elasticity estimates ($\hat{\delta}_{jt}$ in Equation (3)), after our robustness analysis.

5.1. Robustness Analysis

Politics, War, and Other Socioeconomic Variables: The long period under consideration (1934–2020) contains several periods of majority political alignment, where the house, the senate, and the presidency are held by the same party. We included a binary variable that captures such party alignments, a dummy variable for major wars, as well as variables measuring national crime rate, and broad inflation indexes. These socioeconomic indicators were statistically insignificant, most likely because their impact is already captured by the included financial market indicators.

Evidence from Del Mar and Santa Anita Tracks: Table 4 presents the estimation results for two major California racetracks. The dependent variable, R_t, is the percent change in annual wager per race at each facility. Explanatory variables specific to each track include PRC, number of races, and fraction of off-track wagers. We find that the evidence from individual tracks is generally mixed; financial market indicators, lottery, income and price are generally insignificant. But, as expected, the racing industry variables are highly significant.

These findings seem unsurprising, as both racing facilities are premier racetracks that cater to more experienced patrons, who likely engage in sophisticated betting strategies that are independent of the financial market outcomes, and the introduction of lottery. Furthermore, the distribution of effective take-out rate at these tracks are likely to be different than the average take-out rate used in California models. On the other hand, we find that industry variables are the key drivers of wagering demand at these tracks.

Table 4. Distribution of R_t for Del Mar and Santa Anita Racetracks (1935–2020).

Explanatory Variables	Del Mar			Santa Anita		
	S&P	CRSP	Schiller	S&P	CRSP	Schiller
Financial Market Outcomes and Lottery						
Bond-Spread α_1	0.494 0.20	1.199 0.47	0.251 0.08	7.200 ** 2.42	7.073 ** 2.35	6.104 ** 2.25
Excess Returns α_2	−0.103 −1.51	−0.062 −1.04	−0.052 −0.84	−0.06 −0.93	−0.067 −1.03	−0.042 −0.60
Market Volatility α_3	−0.538 −0.71	−0.688 −0.91	−0.438 −0.47	−1.089 −1.40	−1.01 −1.32	−0.937 −1.25
California Lottery α_4 Dummy Var.	−0.034 −1.52	−0.037 −1.59	−0.039 −1.64	−0.057 ** −2.06	−0.059 ** −2.15	−0.062 ** −2.24
Economic and Racing Industry Variables						
Price γ	−0.622 −1.22	−0.672 −1.21	−0.590 −1.03	−2.111 −1.14	−2.139 −1.15	−2.170 −1.01
Income η	1.116 ** 2.29	1.104 ** 2.22	1.007 ** 2.03	1.632 1.59	1.742 1.63	1.779 1.48
Purse per Race β_1	0.535 *** 8.25	0.535 *** 7.84	0.520 *** 7.37	1.092 ** 2.49	1.112 ** 2.51	1.169 ** 2.27
Number of Races β_2	−0.359 ** −2.07	−0.358 ** −2.05	−0.349 * −1.90	0.143 0.29	0.132 0.26	0.152 0.27
Off Track Wager β_3	1.859 *** 2.77	1.905 *** 2.74	1.873 ** 2.50	2.264 1.42	2.322 1.43	2.639 1.36
Relative Comp. Index θ RCI	−0.008 −0.42	−0.008 −0.41	−0.008 −0.37	−0.185 ** −2.44	−0.188 ** −2.46	−0.207 ** −2.27
Model Diagnostics						
Adj. R^2	0.69	0.69	0.68	0.47	0.47	0.46
Fit	0.68	0.68	0.68	0.50	0.50	0.49
Serial Correlation (p-value)	0.50	0.43	0.32	0.21	0.22	0.26
Normality (p-value)	0.17	0.05	0.05	0.49	0.57	0.46
Log-Likelihood	95	95	94	79	79	79
AIC	−170	−169	−168	−139	−139	−137
BIC	−146	−146	−144	−115	−115	−113
Num. of Iterations	16	16	19	21	21	23

All models are estimated using nonlinear least-squares, in conjunction with `robust` standard errors; t-values appear below the estimates ('*' for $p < 0.10$, '**' for $p < 0.05$, and '***' for $p < 0.01$).

Outliers: The dependent and explanatory variables we utilize have occasional extreme values, which coincide with major economic events during the period 1934–2020. There are numerous methods for handling outliers, including dropping or "winsorizing" extreme observations. These methods are add-hoc and impractical for our small sample size. Instead, we opt for a simpler solution by creating a new variable, labeled "Tail Impact", that assumes the value of the first and last deciles of purse per race (18 observations), and zero otherwise. Extreme PRC values coincide with large outcomes for other variables, particularly R_t, bond spread, and market volatility. The coefficient of Tail Impact measures the effect of PRC outliers and is simple to interpret. However, under this specification, positive and negative outliers are assumed to have symmetrical impact on the dependent variable.[38]

Table 5 presents the estimation results after we include Tail Impact in the models. The first three columns of the table show estimated coefficients for California under different equity market indexes. The last two columns are for Del Mar and Santa Anita. A comparison with estimates in Tables 3 and 4 shows that the parameter estimates are slightly smaller post the outliers adjustment. Most importantly, the sign and statistical significance of all covariates are unchanged and our prior conclusions remain intact.

Table 5. Distribution of R_t with Adjustment for Extreme Values (1935–2020).

Explanatory Variables		**California**		**Del Mar**	**Santa Anita**
	S&P	**CRSP**	**Schiller**	**S&P**	**S&P**
Financial Market Outcomes and Lottery					
Tail Impact α_0	0.477 *** 3.19	0.509 *** 3.41	0.497 *** 3.31	0.155 *** 7.98	0.177 *** 14.71
Bond-Spread α_1	6.015 *** 3.19	6.130 *** 3.03	4.861 * 1.97	1.470 0.83	4.634 * 1.89
Excess Returns α_2	−0.129 * −1.92	−0.122 * −1.84	−0.081 −1.10	−0.058 −1.36	−0.014 −0.29
Market Volatility α_3	−1.490 ** −2.58	−1.414 ** −2.38	−1.351 * −1.93	0.316 0.70	−0.734 −1.35
California Lottery α_4 Dummy Var.	−0.052 ** −2.22	−0.055 ** −2.33	−0.060 ** −2.28	−0.019 −1.34	−0.020 −0.89
Economic and Racing Industry Variables					
Price γ	−2.072 * −1.85	−2.150 * −1.90	−2.045 * −1.67	−0.217 −1.12	−0.410 −0.60
Income η	2.280 *** 3.13	2.404 *** 3.16	2.398 *** 2.77	0.210 1.09	0.750 1.52
Purse per Race β_1	0.423 ** 2.25	0.398 ** 2.12	0.360 * 1.70	0.154 ** 2.34	0.363 ** 2.22
Number of Races β_2	−0.556 *** −5.28	−0.551 *** −5.16	−0.612 *** −4.98	−0.114 −1.21	0.340 ** 2.16
Off Track Wager β_3	1.985 * 1.67	2.072 1.66	2.106 1.46	0.854 * 1.96	0.084 0.35
Relative Comp. Index θ RCI	−0.101 ** −2.55	−0.108 ** −2.59	−0.115 ** −2.58	0.042 1.13	−0.081 −1.40
Model Diagnostics					
Adj. R^2	0.77	0.77	0.75	0.84	0.80
Fit	0.78	0.78	0.76	0.84	0.81
Serial Correlation (p-value)	0.44	0.35	0.21	0.80	0.37
Normality (p-value)	0.10	0.11	0.06	0.73	0.24
Log-Likelihood	102	102	100	123	119
AIC	−183	−183	−178	−223	−215
BIC	−157	−157	−151	−197	−189
Num. of Iterations	21	24	33	23	16

All models are estimated using nonlinear least-squares, in conjunction with `robust` standard errors; t-values appear below the estimates ('*' for $p < 0.10$, '**' for $p < 0.05$, and '***' for $p < 0.01$).

Alternative Specifications: In our proposed econometric specification (Equation (2)), the impact of economic and racing industry variables on wager-per-race rate (R_t) is dependent upon the quality and availability of wagering opportunities (O_t). This form of interactions in effect enables us to ask, for example, whether price elasticity of wagering falls as the quality of races improve (higher wager pool). In this section, we address a similar question: is the impact of financial market outcomes also dependent upon the supply of quality betting opportunities?

Table 6 presents the estimation results for the most general form of interactions effect, where all coefficients are conditioned on the level of O_t, as follows:

$$R_t = \left[\sum \alpha_i * X_{it} + \gamma * P_t + \eta * I_t + \sum \beta_j Z_{jt}\right] * e^{(\theta * O_t)} + \epsilon_t \quad (5)$$

The columns labeled "Simple" ("Improved") in Table 6 show the results when Tail Impact is excluded (included) in the model. Comparison with parameters in Table 3 shows that there is no change in sign and significance of most coefficients, except the coefficient of realized excess returns becomes statistically insignificant. On the other hand, other coefficients become disproportionately larger, suggesting that imposing a nonlinear structure on financial market indicators may be overkill. Indeed, the improvements from conditioning financial market indicators on O_t is very small, suggesting that Equation (2) provides an adequate fit for the distribution of R_t.

Table 6. Distribution of R_t With General Interaction Effects (1935–2020).

Explanatory Variables	**Simple**			**Improved**		
	S&P	**CRSP**	**Schiller**	**S&P**	**CRSP**	**Schiller**
Financial Market Outcomes and Lottery						
Tail Impact α_0				0.444 *** 2.95	0.470 *** 3.20	0.443 *** 3.10
Bond-Spread α_1	22.748 *** 3.02	25.492 *** 3.40	30.416 *** 3.10	17.438 ** 2.06	19.775 ** 2.36	23.819 ** 2.10
Excess Returns α_2	−0.323 −1.65	−0.286 −1.50	−0.236 −1.09	−0.282 −1.30	−0.310 −1.46	−0.223 −0.90
Market Volatility α_3	−4.334 ** −2.51	−4.451 *** −2.65	−5.669 *** −2.83	−3.412 * −1.84	−3.636 ** −2.02	−4.482 * −1.89
California Lottery α_4 Dummy Var.	−0.174 *** −2.65	−0.193 *** −2.81	−0.258 *** −3.23	−0.147 ** −2.15	−0.159 ** −2.30	−0.223 ** −2.30
Economic and Racing Industry Variables						
Price γ	−3.405 *** −3.39	−3.556 *** −3.69	−3.892 *** −3.46	−2.952 ** −2.40	−3.122 ** −2.60	−3.478 ** −2.48
Income η	3.284 *** 4.58	3.381 *** 4.33	3.662 *** 4.33	3.000 *** 2.94	3.217 *** 3.11	3.444 *** 2.81
Purse per Race β_1	0.996 *** 4.50	0.991 *** 4.51	0.874 *** 3.59	0.478 ** 2.17	0.443 ** 2.18	0.356 1.59
Number of Races β_2	−0.970 *** −7.28	−1.016 *** −7.68	−1.241 *** −6.13	−0.821 *** −4.93	−0.846 *** −5.10	−1.056 *** −4.33
Off Track Wager β_3	2.607 ** 2.19	2.651 ** 2.20	3.072 * 1.74	2.396 * 1.81	2.446 * 1.87	2.888 1.51
Relative Comp. Index θ RCI	−0.138 *** −4.48	−0.144 *** −4.69	−0.161 *** −4.14	−0.137 *** −3.30	−0.144 *** −3.57	−0.165 *** −3.29
Model Diagnostics						
Adj. R^2	0.74	0.74	0.74	0.77	0.78	0.77
Fit	0.75	0.75	0.75	0.79	0.79	0.78
Serial Correlation (p-value)	0.59	0.53	0.52	0.33	0.24	0.25
Normality (p-value)	0.16	0.10	0.04	0.18	0.15	0.07
Log-Likelihood	98	98	97	104	104	103
AIC	−176	−175	−174	−185	−187	−184
BIC	−152	−151	−150	−159	−160	−158
Num. of Iterations	14	14	14	15	14	16

All models are estimated using nonlinear least-squares, in conjunction with `robust` standard errors; t-values appear below the estimates ('*' for $p < 0.10$, '**' for $p < 0.05$, and '***' for $p < 0.01$).

5.2. The Dynamics of the Economic and Racing Industry Parameters

Since the introduction of regulated gambling, economists have pointed out that the size of price and income elasticity of wagering has significant implications for oversight of legal gaming operations, which essentially conduct business as regulated monopolies. Because winnings and the track industry's take-out revenues are taxed, knowledge of price elasticity is deemed critical to designing tax policies that optimize the state's revenues. Moreover, income elasticity estimates can help determine if taxes on gambling are progressive or regressive (see Chapter 2 in Grote and Matheson 2013, and Sauer 1998). These parameters are also important to track operators and racing industry infrastructure. Specifically, the elasticity estimates provide valuable information that is critical for reversing the recent decline in horse wagering.

In this section we present conditional elasticity estimates for price, income, and the other racing industry variables. The elasticities are imputed for each value of RCI, using Equation (3) and parameter estimates in Tables 3 and 5. The elasticities are imputed for both the "Simple" and the "Improved" versions of the model so that the influence of outliers can be assessed. The equity market index utilized is the S&P, but other indexes generate similar results.

Figures 3 and 4 present time series plots for the imputed elasticities since the end of World War II in 1946. We also fit a Kernel Smoother (Parzan) to the imputed values. These plots show that price and income elasticity have increased significantly, particularly since the introduction of lottery, legalization of Indian casinos, proliferation of online gaming, and the expansion of off-track facilities in the mid-1980s. On the other hand, the elasticity with respect to purse and number of races, while changing over time, has remained within a narrow range of values.

Table 7 shows the distributional characteristics of dynamic elasticity estimate imputed from Equation (3) and parameters in Tables 3 and 5, including estimates from the static specification. Comparison with prior studies suggests that the static elasticity estimates reported in the literature (DeGennaro and Gillette 2013; Gramm et al. 2007) fall within the range of values generated by the dynamic specification (Equation (2)). Based on our historical data and the flexible specification estimated, we conclude that studies that overlook the role of financial market outcomes, and improvements in supply of gambling opportunities due to technical change, will produce unreliable estimates and erroneous policy prescriptions.

Table 7. Price, Income, and Industry Elasticity Estimates (1935–2020).

	Static	Simple				Improved			
	% Change	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Price	−0.68	−1.10 ***	0.46	−1.92	−0.25	−0.96 **	0.40	−1.66	−0.22
Income	0.88 **	1.18 ***	0.50	0.27	2.07	1.06 ***	0.44	0.25	1.83
PRC	0.54 ***	0.25 ***	0.11	0.06	0.43	0.20 **	0.08	0.05	0.34
No. of Races	−0.55 ***	−0.25 ***	0.11	−0.44	−0.06	−0.26 ***	0.11	−0.45	−0.06
Off-Track	0.49 ***	1.35 **	0.30	0.53	1.77	1.16 **	0.26	0.47	1.52

Significance level is based on the estimated coefficient estimates $\hat{\beta}_j$s and $\hat{\theta}$ ('**' for $p < 0.05$, and '***' for $p < 0.01$).

In conclusion, we proposed and estimated several parsimonious models that explain the dynamic variations in aggregate gambling. The proposed specifications reduced correlations among the covariates and removed residual serial correlation, providing reliable parameter estimates. Despite their relative simplicity, the models enable us to estimate conditional demand parameters and the results are robust to the choice of covariates, model specification and outliers. We find that racing industry variables alone are the most important drivers of variations in gambling demand. We also find that the proposed RCI is statistically significant and its impacts on betting demand is economically meaningful. Finally, we find that financial market outcomes significantly impact aggregate wagering at the racetracks.

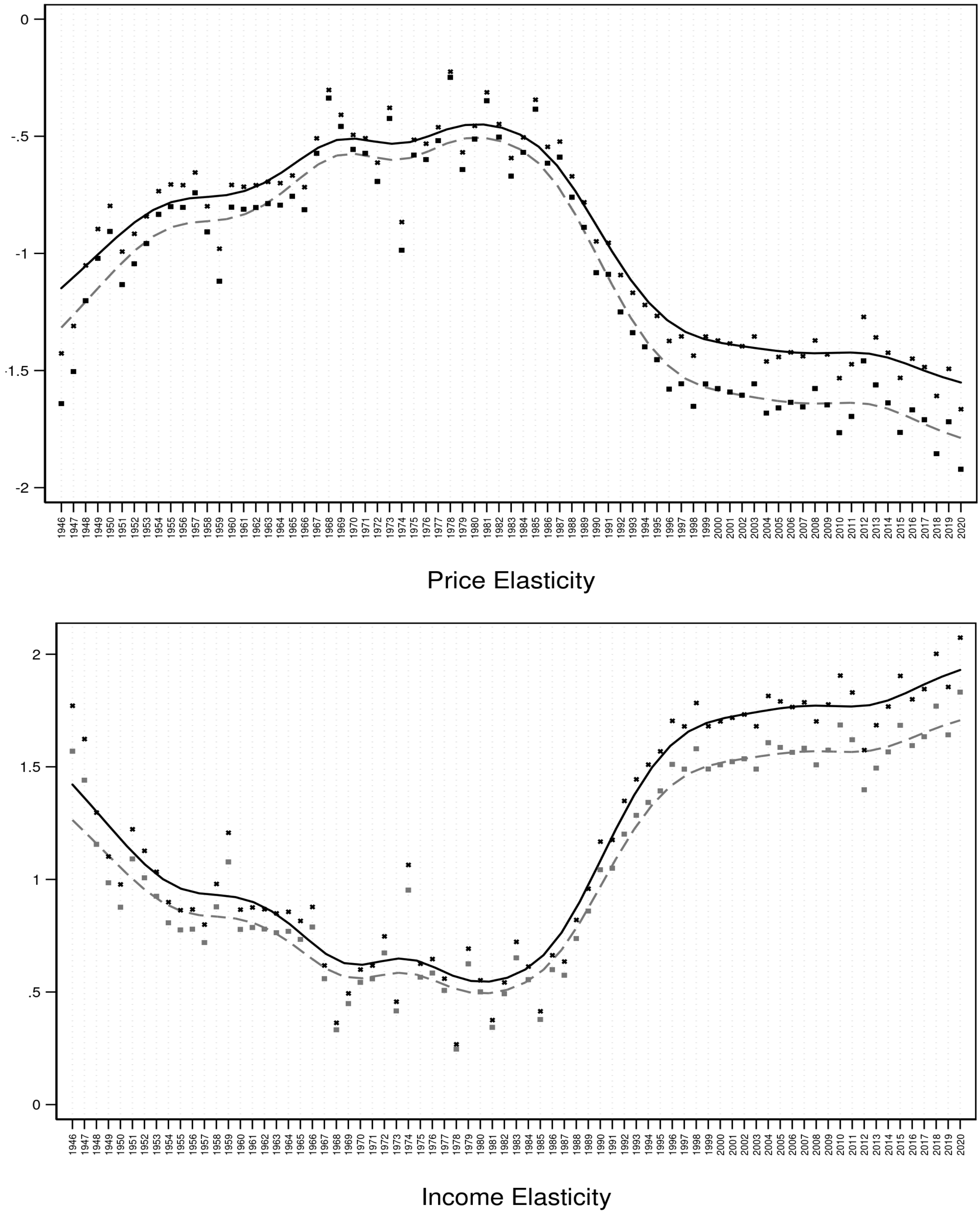

Figure 3. The Dynamics of Price and Income Elasticities (1946−2020). Simple Model: Solid black line, data (x). Improved Model: Dashed gray line, data (squares).

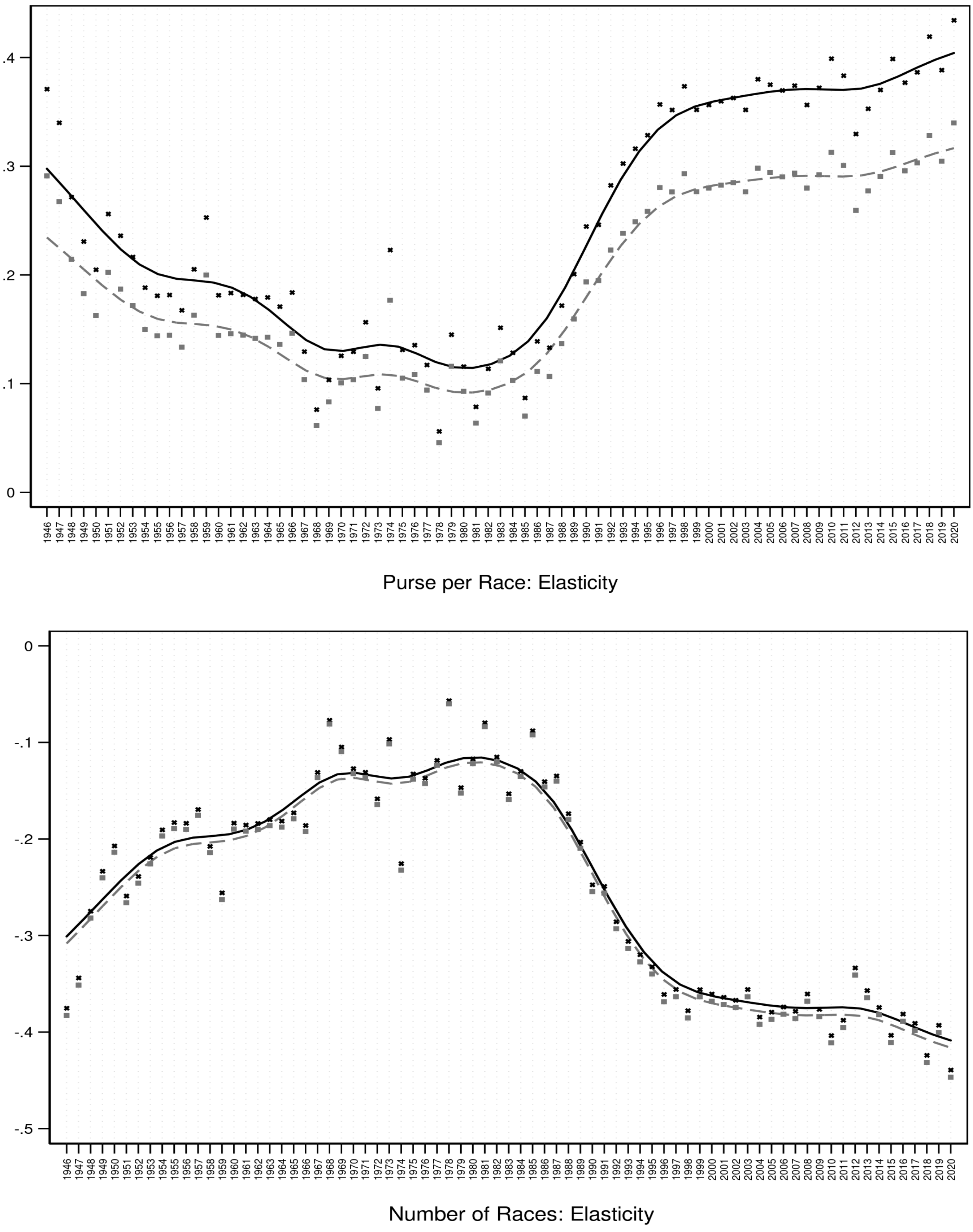

Figure 4. The Dynamics of PRC and No. of Races (Elasticities, 1946−2020). Simple Model: Solid black line, data (x). Improved Model: Dashed gray line, data (squares).

6. Conclusions and Directions for Future Research

There is a large body of academic evidence suggesting that gambling, particularly at racetracks, offers both entertainment value and the possibility of large monetary payouts. Utilizing horse betting data that span eight decades, we estimated several wagering demand models that account for these dual characteristics of gambling products. We hypothesized that realized excess returns and stock market volatility are likely to impact gambling demand. We also addressed whether lottery is a substitute for betting at the racetracks. Finally, we proposed a proxy for the supply of wagering opportunities, which accounts for relative compensation to horse owners and the racing industry infrastructure, and evaluated the role of important racing industry variables.

We estimated a dynamic betting demand model and found that financial market conditions significantly impact gambling. Specifically, we found that rising realized excess returns and stock market volatility negatively impacts racetrack wagering. The existing literature has shown that individuals are attracted to traditional gambling activities, particularly casinos, during bad economic times. We also find that widening corporate bond spreads, which occur during recessions, have a large positive impact on racetrack wagering. Our analysis indicates that lottery is a weak substitute for racetrack wagering. Finally, we found that racing industry variables are the main drivers of gambling demand. Our analysis suggests that, in the short-run, horse betting demand is inelastic, but as the number of off-track facilities rise and digital access to wagering improves, it becomes highly elastic.

There are a number of limitations that can be addressed in future research. First, our findings could be corroborated by utilizing data from other major horse racing states and countries. Second, higher frequency data may prove useful to ascertain the role of stock market outcomes and industry variables in driving the dynamics of horse wagering demand. Such research can assist the horse race industry to innovate and compete with new forms of legalized gambling, potentially reversing its recent decline. Finally, Weidner (2022) argues that financial markets and the gambling industry share many common features, particularly excessive risk-seeking behavior and addiction. These authors point out that regulators must design policies that reduce these adverse effects. Future extensions of our work can promote scientific development of such mitigation strategies.

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Notes

1. After a Supreme Court ruling that legalized sport betting in 2018, wagering has expanded across the U.S. Currently 34 states and the District of Columbia permit online and in-person sport wagering. According to the American Gaming Association, sport wagering generated $4.3B in revenues in 2021. For a detailed analysis of sport betting markets see Mosenhauer et al. (2021).
2. The history of gambling in the U.S. includes periods with no legal constraints on gambling, followed by episodes of stringent federal and state prohibitions (Schwartz 2013). In recent decades, firms within the gambling industry have become public companies. A move that has resulted in a flow of Wall Street investments and increased public scrutiny. The profitability of these

firms is directly tied to consumers' acceptance of gambling as a form of entertainment, and ubiquitous gaming advertisements attest to this fact.

3 Lottery-stocks are shares of unprofitable firms in financial distress, which have negative expected returns, high volatility, and highly skewed returns.

4 By the late 1800s, there were over 300 racetracks in operations across the U.S. Bookmaking was replaced with the regulated pari-mutuel betting system starting in 1908. Under the pari-mutuel wagering system, players bet on random outcomes and winners share, in proportion to their wagers, the pool of all bets net of the racetrack's commissions and state taxes—the "take-out rate".

5 Starting in the early 1980s, racetracks began offering Advance Deposit Wagering (ADW) accounts, which are similar to electronic brokerage accounts at financial institutions. The horse racing industry infrastructure supports betting from multiple states and internationally. For a detailed historical background see Liebman (2017).

6 Pari-mutuel betting institutions function in a similar manner as the financial system, fulfilling important services, as outlined in Merton (1995). Merton's functional perspective framework rests on the premise that financial functions, such as fulfilling demand for games of chance, are stable over time and market institutions, including the gambling industry, evolve to serve such functions.

7 Relying on more recent data, Maggio et al. (2020) empirically demonstrate that consumption responds to changes in stock market returns. These authors suggest that households treat capital gains and dividends as separate sources of income and show that consumption is highly responsive to both. Furthermore, Chodorow-Reich et al. (2021) demonstrate that, in addition to consumption, changes in stock market wealth also affect employment and the real economy.

8 Kaplan (2002) notes that since the 1980's, the racing industry has witnessed significant proliferation of such intermediaries, generating a large flow of funds into horse wagering. Apparently, these hedge funds rely on exotic wagers with low probability but high payouts, for instance, superfecta, and picking winners in multiple races. Such bets are similar to the purchase of deep out-of-the-money options. A successful strategy generates small steady losses with infrequent but large gains. It is important to note, however, that the ability of horse betting markets to absorb a large flow of funds is limited by the number of tracks and available races. There is also a long tradition of racetrack gamblers and handicappers, becoming traders and stock pickers, and vice versa. Warren Buffet and Charlie Munger are two prime examples of horse race handicappers that became stock pickers.

9 This is not surprising, as rising VIX likely signals higher volatility of lottery-stocks and more skewed returns. Rising realized stock market volatility is unlikely to impact gambling payoffs at racetracks.

10 Under cumulative prospect theory, gamblers may act in a risk-loving manner as a consequence of over weighting small probability outcomes. On the application of prospect theory to gambling, see Barberis (2012) and Barberis (2013) and for a survey of economic models of risk aversion, see O'Donoghue and Somerville (2018) and their references.

11 As Conlisk (1993) has shown, this perspective is also consistent with the expected utility model. All that is needed to adequately explain the individual's demand for gambles is a tiny felicity of gambling appended to any proposed utility function. For an interesting application of felicity of gambling in the horse wagering context see Green et al. (2020).

12 It is impossible to incorporate illegal wagering among individuals or through bookmakers in our analysis. In any case, the magnitude of illegal wagering likely dwindled as telephone and simulcast betting were introduced, starting in 1980's.

13 Detailed historical information about these tracks and their Media Guides are available at https://www.dmtc.com/ and https://www.santaanita.com/, both accessed on 29 May 2023. After the Pearl Harbor attack (1941), both racetracks were closed (1942–1945) and were used as temporary internment camps for Japanese Americans.

14 The data for Del Mar Racetrack is available starting in 1938, its first operating year, resulting in 79 observations.

15 Over the long span of time we study, the per capita wager in California has declined because the cumulative growth rate of the population, which is always positive with little variability, mostly exceeds the cumulative growth rate of aggregate wagers, which is subject to large positive and negative annual fluctuations.

16 History of gambling in California is detailed in Atkinson (1998) and California Legislative Analyst Office (2019).

17 Gramm et al. (2007) note similar trends across the United States: "From 1985 to 2002, the total wagered on Thoroughbred races in North America increased from $8.25 billion to $15.62 billion, despite the fact that the number of races dropped over 20 percent."

18 In response to falling aggregate wagers, a host of new wagering products are introduced during this period. These include, exchange wagering (direct bettor to bettor wagers); futures wagering; track-subsidized and guaranteed wagering pools; wagering on the success rate of jockeys or trainers; take-out rebates to larger bettors; fantasy horse racing; wagering on previously-run races; and the ability to include fixed-odds wagering.

19 Surprisingly, during the COVID-19 pandemic, aggregate wagering on California races nearly matched its 2019 level, despite an 18% decline in the number of races. A similar phenomenon occurred for the U.S. as a whole.

20 Chiappori and Ekeland (2011) provide a detailed discussion of aggregate demand functions and the required assumptions for summing demand across individuals.

21 The specification in (1) and its logarithmic variants are popular in several areas of empirical economics; for example, estimation of CES-type production (utility, cost, other) functions. Following the introduction of the Box-Cox transformation, the search for

"optimal variable transformation" has produced several useful methods to linearize Equation (1), as discussed in a recent survey by Atkinson et al. (2021).

22 See Grote and Matheson (2013) for a survey of the empirical literature and elasticity estimates for a variety of gambling activities, including horse wagering and lottery.

23 Modeling and interpreting linear and nonlinear interaction affects are discussed in Balli and Sørensen (2013) and Greene (2010).

24 While it is possible to model interaction effects by using the product of Z_{jt}s and O_t, our proposed specification provides better fits for the distribution of R. As Equation (3) shows, the term $(e^{\hat{\theta}*O_t})$ essentially acts as a weighting function that adjusts $\hat{\beta}_j$s over the range of O_t. As seen below, this structure captures the dynamics of R_t quite well.

25 We utilize the current realized excess returns, i.e., the current "premium" relative to the risk-free rate. In contrast, "equity risk premium" is typically estimated from long time series (Siegel 2017). We refrain from using the term "premium", because it is often associated with expectations, rather than a single period of realized excess returns.

26 CRSP-VW and S&P-500 indexes are obtained from Wharton Research Data Services (https://wrds-www.wharton.upenn.edu/). Shiller's total market returns are obtained from Yale University (http://www.econ.yale.edu/~shiller/data.htm). We also considered the Dow Industrial index. While we obtained similar results, we believe comparisons with the Dow is problematic because the Dow is a price-weighted index and has few constituents (30 stocks), and additions/deletions to this index are less reflective of the state of the economy. In any case, using the Dow will not change our results because it is highly correlated with the S&P 500 and CRSP indexes. The treasury bill data (https://fred.stlouisfed.org/series/TB3MS) and the monthly Aaa and Baa bond yields (https://fred.stlouisfed.org/series/AAA) are obtained from the Federal Reserve Bank of St. Louis. (These sources were last accessed on 29 May 2023).

27 Relative to a "recession dummy", bond spread is more informative, as its magnitude captures the extent of recession or expansion.

28 Another measure of the credit market condition is the *term spread*, defined as the yield difference between corporate and treasury bonds with similar maturity. However, as Duca (1999) has shown, the term spread is a less informative measure due to the differences in the associated bonds' covenants, for example callability provisions. The quality spread uses bonds with similar covenants and maturity, and is therefore subject to fewer complications arising from provisions that result in differential prepayment risk. Note that the quality spread is simply the difference between the *term spreads* of Baa and Aaa bonds relative to treasuries.

29 Under the current California law, at least 50% of the total sales revenues must be returned to the public in the form of prizes (take-out rate of 50%) and the remainder will be used to support public education (37%) and cover the lottery's administrative costs (maximum of 13%).

30 We obtain the California annual per capita income from Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/CAPCPI, accessed on 29 May 2023.

31 We also considered the effect of the state unemployment rate. However, the coefficient is not significant and it is highly correlated with income. We therefore dropped unemployment rate from the estimation.

32 At off-track betting sites, races are simulcast from different tracks, allowing patrons to bet on a multitude of races. Nationwide, the ability to bet on horse races dramatically increased when off-track betting was legalized, first in New York (1970), and subsequently in other states. A second expansion of betting opportunities was brought about by inter-track wagering (simulcasts from one track to another). It is interesting to note that, Schwab implemented TeleBroker, the first trading application using the phone in 1989, nearly two decades after horse wagering by phone started in 1971.

33 Olmstead et al. (2007) estimate a water demand function in which price elasticity is conditional on the prevailing price structure, i.e., pricing is nonlinear such that higher marginal prices are charged for higher quantities consumed. Non-linearity arises from the fact the quantity consumed is conditional on individual's "consumption block", where different blocks have their own marginal pricing scheme.

34 Estimation results for the levels specification (Equation (1)) are consistent with the results for percent change specification (Equation (2)). However, the levels model suffers from major statistical shortcomings and biased coefficient estimates, as noted earlier. The results for levels specification are available upon request.

35 In the special case where errors in the nonlinear model are homoskedastic and orthogonal, NLS is efficient among estimators that only require the first two moments of residuals distribution (Cameron and Trivedi 2005). The percent change specification is more likely to be consistent with these requirements.

36 In the context of nonlinear models, the usefulness of adjusted R^2 has been a subject of debate. The row labeled "Fit" in the tables reports the squared correlation between the dependent variable and the model's predicted values, and serves an alternative goodness-of-fit metric for nonlinear models.

37 For an interesting historical exposé regarding horse wagering during the Great Depression, see https://www.pbs.org/wgbh/americanexperience/features/seabiscuit-racing-depression/, accessed on 29 May 2023.

38 We included a dummy variable for each tail separately, but the estimated coefficients remained unchanged. We opted for a symmetrical "Tail Impact" to keep the models parsimonious and save degrees of freedom.

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