Thesis booklet

Gambling behavior through the lens of big data

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Contents

1 Research background and justification for the selection of the topic

Problem gambling has been and will continue to be a lasting and extended issue affecting tens of millions worldwide, with significant socio-economic implications. The U.S. National Council on Problem Gambling (2021) concludes that 11% of gamblers have shown at least one signs of problem gambling "many times" in the preceding 12 months. In Europe, problem gambling rates vary between $.3\%$ in Ireland to 6.4% in Latvia, according to Carran (2022). The picture globally does not look much better: based on the report of the World Health Organization (2024) estimates suggest that 1.2% of the world's adult population has a gambling disorder. The rise of online gambling (combined with the fallout of the COVID-19 epidemic), including sports related and casino games have largely inflated this problem, particularly among young people, with an estimated 21% of online gambling in Europe occurring outside regulated environments.

While problem and at risk gamblers cover a fraction of total gambling population, they generate the larger part of gambling revenue, as e.g. Team et al. (2024) shown that 10% of players generated 90% of total casino expenditures in Massachusets in 2024. This expenditure leads to an increased incidence of mental illnesses and suicide instead of providing leisure and being a source of fun. While disproportionately affecting lower income households, gambling harms also include family violence, financial distress, connection to crimes, neglect of children and erosion of civil institutions via corruption and political activity. While treatments do exist, only $.14\%$ of the population is actively seeking formal or informal help for their problems (Bijker et al., 2022).

The global gambling industry have generated $\$536$bn in revenue in 2023 with an expected growth of 7% in 2024 largely driven by digital platforms, and is estimated to reach $\$700$bn by 2028 (World Health Organization, 2024). The normalization of gambling through heavy commercialization and digitization makes the market more accessible, while the industry is also working heavily toward the deregulation of online gambling. An example is how Hungary's national monopoly has been broken up through EU trade regulation principles (see European Gaming Industry News (2023)), which, while in principle meant to push online gamblers toward licensed operators, managed to increase the growth potential in online gambling markets, while left it dominated by unlicensed offshore operators (Vali (2024)). Besides this, the gambling industry's main response to treatment is the so-called responsible gambling, which - following the model of the energy and garbage (plastic) industry - is effectively blaming the end consumers, ergo the group who mainly suffers the externalities of it.

Addressing the issue of problem gambling requires both economic and psychological understanding as well as political and societal interventions. From an economic perspective, it is crucial to understand the demand for gambling services and the what and how of regulatory impact. Models can help predict the effectiveness and extent of interventions and increase the effectiveness in allocation of resources towards prevention and support. Integrating insights from economics, psychology and technology can enable policy makers to tackle the delicate issue of market regulation. Then again, the question in the end remains if the political will in representing the welfare of the general populace is stronger than the influence of an (almost) trillion dollar industry. To end this section on a brighter tone, there are signs of strengthening general regulations (e.g. Solon and Zuidijk (2024)), that is targeting to reduce the complexity of tackling online gambling with levys, personal limits and timing restrictions.

Modern machine learning technologies are being applied in marketing and widely used in other industries as well, like targeted advertisement and player retention. The basis of these, player tracking gambling datasets, have been mostly left unused by policy making (outside of the observation of generic macro-trends), besides research articles founded on proprietary datasets provided by the market or through regulators. Aligning with the zeitgeist, the attention of industry participants is shifting towards AI solutions around responsible gaming based on tracking data (see Behe (2024)), for better or worse. Thus it is a pivotal moment for research that meant to support the regulatory sides to concentrate on these data intensive issues, so it can keep up with the market competition for the gambler's attention, money and health.

As Chagas and Gomes (2017) highlights, most of the research studies on gambling before 2000 were based on experimental settings or self reports from gamblers. An icebreaker in this field was the study of Croson and Sundali (2005), who took on the enormous task of tracking hours of videotape recordings from casinos to track individual roulette sessions creating the first large empirical dataset for gambling. With the birth of online gambling, real life gambling data have started to amass in the databases of facilitators and eventually market regulators. However, very few of these datasets have been made available to the research community to conduct studies on, like Braverman and Shaffer (2012); Horváth et al. (2010); LaBrie et al. (2007); Xu and Harvey (2014) for bets tracking and Kotter et al. (2018) for self-exclusion. Although empirical analysis of behavioral tracking data contributes a lot to our understanding of risky behavior, most research is done on a few instances of sports and online casino datasets that remain largely proprietary. This also affects the value of these research papers from the point of reproducibility.

The advent of cryptocurrencies has opened up a new opportunity for this field as well, since user behavior can be tracked through the publicly available ledger of transaction history. Recent articles have only started to be published on the statistical analysis of gambling and gaming datasets collected from the Ethereum blockchain (Scholten et al., 2019, 2020). Some works also suggest that many people are using the trading space of cryptocurrencies as a form of gambling (Mills and Nower, 2019) and Conlon and McGee (2020) even suggested that gambling may have a strong effect influencing the value of BitCoin in fiat currencies.

For me, the lack of publicly available tracking datasets for gambling research provides a gap in the research space to be filled. As a first step of my research, I have gathered large datasets on gambling based on cryptocurrency data using strategies similar to Conlon and McGee (2020) and (Scholten et al., 2019).

2 Aims, objective, research questions and methods

The main goal of my PhD research was to delve into the aspects of gambling research centered around data intensive, multidisciplinary behavioral tracking approaches, and to do so in a manner that will only involve datasets and methods that can be made public at the end. To be able to deliver on these aims my foremost task was to find an eligible source and create such dataset that can be made public ethically, while still providing the critical features available in proprietary datasets.

After this, beside familiarizing myself with the research landscape of the area, I wanted to review the methodological toolbox used in these studies and provide support or pose challenge towards them through replication. I also wanted to see if I could provide industry-level tools to the effort of policy making, using or combining the contemporary modeling and intelligence approaches in an open and reproducible manner. Finally I was looking for ways to leverage the special nature of my dataset - being sourced from the crypto-space - that can extend the research focus of the current gambling studies around tracking data. The above objectives have crystallized over time around the three projects that are presented as papers in my thesis.

2.1 Approaching the Hot Hand with a Cool Head

In this project my goal was to leverage the large-scale gambling data mined from the Bitcoin-base online gamble SatoshiDice to challenge the findings of Xu and Harvey (2014) on streak-dependent gambling behavior, particularly focusing on their methodologies in investigation of the hot hand fallacy and the gambler's fallacy. My core research questions can be formalized as follows:

1. Can the observed aggregate-level trends in betting behavior - as reported in Xu and Harvey (2014) - be explained without assuming behavioral biases?
   - Null Hypothesis (H_0): The observed changes in betting behavior after streaks arise due to underlying behavioral biases (e.g., hot hand or gambler's fallacy).
   - Alternative Hypothesis (H_A): The observed changes in betting behavior can emerge without the assumption of underlying behavioral biases, such as the hot hand or gambler's fallacy.
2. Do individual gamblers exhibit consistent behavioral biases (hot hand effect or gambler's fallacy), or do aggregate-level trends emerge from a heterogeneous population of persistent risk-takers?
   - Null Hypothesis (H_0): Individual gamblers frequently adjust their betting strategy in response to winning or losing streaks, supporting the presence of hot hand and gambler's fallacies.
   - Alternative Hypothesis (H_A): Individual gamblers tend to maintain their chosen risk levels, and the observed trends in aggregate data emerge from persistent heterogeneity in risk preferences rather than systematic biases.

By analyzing these questions I directly challenge the decision-making theory of Xu and Harvey (2014) and the arguments of Xu and Harvey (2015) while making an effort to highlight the importance of methodological rigor. During the study I was trying to stay as close as possible to the methodological approach of the original article from the field of cognitive psychology. To show the presence of selection bias in their studies I was to apply empirical replication, statistical reasoning, simulation and some - albeit trivial - analytical derivation.

2.2 Unmasking Risky Habits: Identifying and Predicting Problem Gamblers Through Machine Learning Techniques

In this study I wanted to explore if machine learning methods can be used to identify and predict problem gambling behaviors without relying on self-labeling or psychological profiling. I also wanted to utilize a diverse set of machine learning methods using an automated modeling approach. My core research questions can be formalized as:

1. Can unsupervised machine learning techniques be used to identify problem gambling behaviors without relying on self-reported labels?
    - Null Hypothesis (H_0): Problem gambling behaviors cannot be meaningfully identified using unsupervised learning methods.
    - Alternative Hypothesis (H_A): Unsupervised learning (e.g., trimmed k-means clustering) can successfully classify gamblers into meaningful behavioral groups based on observed betting patterns.
2. How accurately can supervised machine learning models predict whether a gambler will develop problematic gambling behavior?
    - Null Hypothesis (H_0): Supervised machine learning models trained on early gambling behaviors do not perform significantly better than chance in predicting problem gambling.
    - Alternative Hypothesis (H_A): Machine learning models can accurately predict whether a gambler will exhibit problem gambling behaviors based on early gambling patterns (e.g., bet frequency, session duration, and bet size variations).

Given the limitations of self-exclusion and self-reports I wanted to explore the a data-driven alternatives in the identification of at-risk gamblers and to highlight the practical implications and power of modern machine learning forecasting methods for operators and policy makers. In this study I have leveraged methods of unsupervised learning namely trimmed k-means clustering that fit the first part of the analysis in separating groups of problem or at-risk gamblers. For forecasting I have leveraged a broader family of classification algorithms (Generalized linear models, Random forests, XGBoost and more) combined through ensembles and automation to classify and predict problem gambling tendencies effectively, comparing the strength of these algorithms comparing retention and prevention scenarios.

2.3 How Bitcoin's Ups and Downs Are Changing the Way You Bet

In this research chapter I wanted to explore the relationship between fluctuations in the price of Bitcoin and gambling behavior on the LuckyBit platform. I wanted to assess this relationship from multiple aspects of gambling behavior and to see if the results are consistent across different types of gamblers. My core research questions can be formalized as:

1. How do Bitcoin price changes impact bet sizes and gambling frequency?
   - Null Hypothesis (H_0): Bet sizes and gambling frequency remain unchanged regardless of changes in Bitcoin's price and volatility.
   - Alternative Hypothesis (H_A): Increases or decreases in Bitcoin's price and volatility significantly affect bet sizes and gambling frequency, either encouraging or discouraging betting activity.
2. Do different types of gamblers (casual, committed, extreme) respond differently to Bitcoin price fluctuations?
   - Null Hypothesis (H_0): There are no significant differences in how casual, committed, and extreme gamblers adjust their betting behavior in response to changes in Bitcoin's price and volatility.
   - Alternative Hypothesis (H_A): Different cohorts of gamblers react differently to fluctuations in Bitcoin price and volatility, with extreme gamblers potentially showing a stronger reaction due to risk-seeking tendencies or automated betting strategies.

With the rise of crypto-based gambling, it is essential to understand how external financial factors shape betting decisions. In this study I wanted to link gambling behavior to the broader financial decision-making process, to further our understanding on market-driven risk behavior and perceived wealth effects. As a first step I have used again the trimmed k-means algorithm to segment the player base, thus reducing the dimensionality of my huge panel of gamblers. I have used econometric linear modeling methods with some advanced validation techniques to control for the effects of larger models when analyzing the relationships in question.

3 Scientific results of the dissertation

3.1 Public gambling datasets

Through mining the BitCoin blockchain data and utilizing publicly available transaction data, we have managed to curate large-scale datasets describing users in the order of tens of thousands and individual bets in the millions for two popular (but now retired) online gambles. These gambling datasets provided a base for a completely reproducible way of research methodology, that makes my contributions unique in the field of gambling research on the transactional scale. The preparatory scripts and the resulting databases have been made publicly available (noted below).

3.1.1 Satoshidice

Among the early use cases of Bitcoin, the pioneering decentralized digital currency, online gambling emerged as a prominent application. Bitcoin's innovative system provided an ideal environment for experimentation, and due to its unregulated nature, numerous online gambling sites have sprung up since 2012, leveraging the Bitcoin ecosystem. One of the most successful ventures within the cryptocurrency community was Satoshidice.[1] This platform implemented a simple yet fair gambling system, offering games to players with varying odds or levels of risk. The fairness of the games was ensured through two mechanisms: the expected return for each game was fixed, thereby creating a house cut that remained independent of the risk level. Additionally, the game outcomes were determined by a "dice roll" generated by combining information from the Bitcoin ledger related to the bet itself and a pre-set secret, which could be independently verified by the players.

The game process was straightforward. Players selected their desired level of risk by choosing a specific game from a predefined list, which presented various winning probabilities (inversely proportional to the odds) alongside a unique wallet address. By initiating a transaction to one of these addresses, the player placed a bet with the sent amount (within specific bet limits). The site assessed the bet based on transaction details and the secret key, promptly sending a return transaction reflecting the outcome. Although blockchain confirmation times in 2013 typically ranged from 5-7 minutes, most bets received instantaneous responses from the site.

Given the blockchain's public nature, it is possible to extract a comprehensive history of all incoming and outgoing transactions associated with any address on the network. We collected all bets placed at and return transactions sent by SatoshiDice during its operational period in the specified form (the site transitioned to a prepay system in 2014). Our dataset comprises a complete longitudinal observation set of betting transactions, with five 21-day periods used to assess the robustness of our procedure over different samples and time frames (see details at Table 1). For detailed information on the data gathering methodology and resources, see B. Bakó, M. C. Sándor (2021)[2]. This dataset has been leveraged for the first two paper of my thesis work.

[1] see https://web.archive.org/web/20121103121459/http://www.satoshidice.com/

[2] The dataset used for the analysis can be accessed at DOI: 10.5281/zenodo.5600259.

	Start date	Number of bets	Number of users	Total bets placed (BTC)	Median bet size (BTC)	Mean daily price (USD/BTC)
A	2012-05-02	119,399	1002	46,649	0.04	5
B	2012-09-17	129,265	2114	85,280	0.06	12
C	2012-12-17	252,301	3405	407,140	0.04	13
D	2013-05-04	329,155	3432	100,430	0.02	111
E	2013-09-11	86,520	1400	62,920	0.03	123

Table 1: *Summary statistics of the subsets of the observed gambling history used. The exchange rates have been sourced from the public historical data published by the online cryptocurrency exchange aggregator BitCoinCharts (see http://www.bitcoincharts.com)*

3.1.2 LuckyBit

As described by Conlon and McGee (2020), the LuckyBit gambling platform operates a probabilistic game that simulates a Galton board with 17 distinct outcomes.[3]

To gather Bitcoin transaction records related to LuckyBit, we utilized the Bitcoin ledger dataset curated by Kondor et al. (2014), which has been extended through February 7, 2018. Unlike in Conlon and McGee (2020), our dataset includes entity-level approximations, allowing us to examine user-specific behavior rather than only individual bets.[4] To control for days with very low participation, we exclude days with fewer than 10 bets, resulting in 1,486 days of observations between October 20, 2013, and February 7, 2018, covering 2,060,601 bets from 18,220 unique players. This period includes Bitcoin price fluctuations from a low of $171 to a high of $1280 per BTC, featuring extreme price jumps and volatility. This dataset was the subject of investigation in the third article.

3.2 Approaching the Hot Hand with a Cool Head

By replicating the analytical steps in producing the results of Xu and Harvey (2014) we were able to reproduce their results over all our samples from the SatoshiDice dataset. On the same population of gamblers we have analyzed if the underlying population indeed shows the consistent behaviors hinting at the presence Hot Hand fallacy and found that, both for winning and losing streaks, this trend is indeed not present for overwhelming parts of the population. We have also constructed simulations and showed through elementary probability theory that the trends in risk taking read over subpopulations experiencing longer and longer outcome streaks will emerge with gambling agents only being consistent in participation but not changing their risk-taking behavior otherwise whatsoever. If, however we construct a measure to quantify expected change in risk taking behavior after streaks (see Figure 1), we have found that rather than increasing their risk appetite, gamblers show signs of conservative decreases that dampens as the streak length increases - the exact opposite of what was theorized by Xu and Harvey (2014).

To complete our study we have corrected a methodological error in Xu and Harvey

[3]A representative archive version of the website containing most graphical elements and the gambling rules is available at the web archives https://web.archive.org/web/20150314200358/http://luckyb.it/.

[4]The dataset used for the analysis can be publicly accessed at DOI: 10.5281/zenodo.14926295.

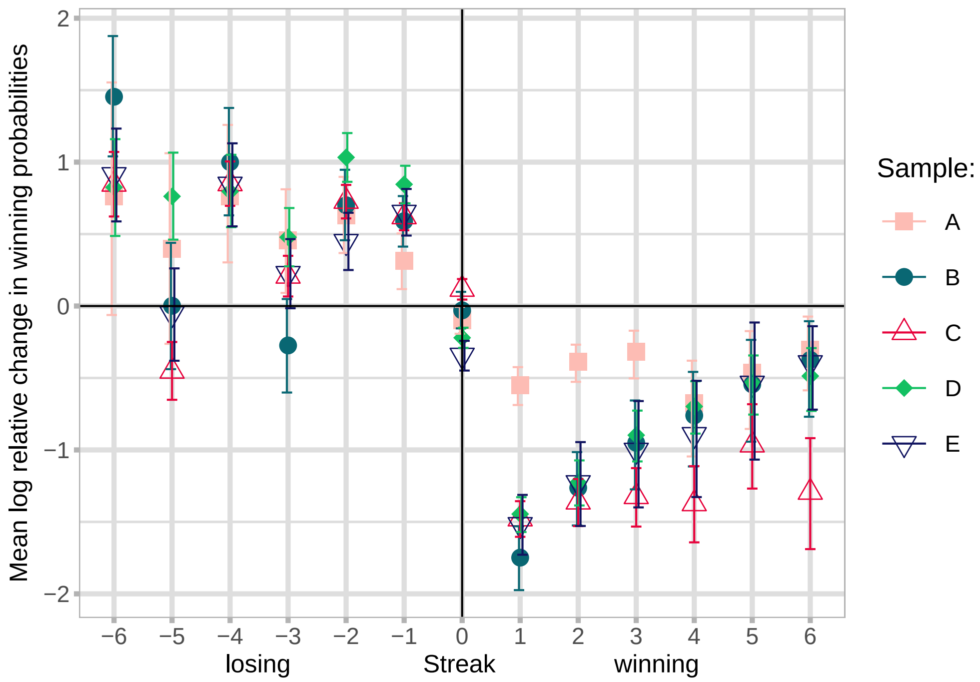

Figure 1: *Means of the relative logarithmic changes in chosen winning probabilities ($E\left[\log_2 \frac{\rho_{n+1}}{\rho_n}\right]$) for different streak lengths over the observed periods. Error bars indicate 99% bootstrap confidence intervals (CIs) of the means. Positive changes indicate an increase, negative ones a decrease in the winning probability.*

(2015) - their answer provided to methodological critique towards their approach - regarding order of summation, and thus we have also shown that - if carried out correctly - this examination also fails to back up any signs of the Hot Hand fallacy being present in our sample.

3.3 Unmasking Risky Habits: Identifying and Predicting Problem Gamblers Through Machine Learning Techniques

Using the trimmed k-means method, we have been able to show a separation of our gambler base into two groups consistently over the SatoshiDice samples, where the smaller groups consistently identified at-risk and/or problem gamblers. The identified clusters exhibit distinct behavioral patterns (see Table 2), with the intensive group demonstrating a higher frequency of gambling, risk taking, and bet sizes, resulting in higher expected losses due to the nature of the game's fairness. These patterns overlap heavily with the behavioral markers referenced in the DSM-5 guidelines (American Psychiatric Association et al., 2013): a tendency to play more frequently over the days, with multiple sessions (bets placed within a day with at least a 4-hour pause between) results in orders of magnitudes more total bets placed. This combined with a distinctly more risk taking behavior in choosing scenarios and occasionally placing much larger bets results in higher overall losses and volatility in payout.

In our prediction exercised we took our samples apart for 3 day training set with per-

	Group	Games	Days	Sessions	Median risk	Risk range	Mean bet	Max bet	Total payout
A	-	6 (4)	2 (2)	1.5 (0.8)	48.8 (25.0)	0.0 (36.6)	0.07 (13.53)	0.18 (10.00)	-0.10 (0.44)
	+	89 (5)*	6 (3)*	2.8 (1.0)*	48.8 (24.4)	42.5 (52.6)*	0.13 (18.52)†	2.00 (7.98)*	-0.33 (3.67)
B	-	7 (6)	1 (2)	1.5 (1.0)	48.8 (28.1)	0.0 (24.4)	0.05 (12.81)	0.20 (10.00)	-0.02 (0.42)
	+	99 (6)*	6 (3)*	2.1 (1.4)*	48.8 (36.6)	48.8 (48.8)*	0.15 (10.08)†	2.48 (9.87)*	-0.57 (6.78)
C	-	9 (7)	2 (2)	1.5 (1.0)	50.0 (24.4)	1.2 (32.6)	0.07 (17.79)	0.37 (40.00)	-0.04 (0.68)
	+	303 (8)*	6 (3)*	2.3 (1.2)*	48.8 (13.4)	71.7 (47.3)*	0.05 (9.12)	2.56 (9.43)*	-0.70 (7.79)†
D	-	7 (7)	2 (3)	1.5 (1.3)	48.8 (13.4)	6.1 (67.1)	0.02 (5.80)	0.04 (9.29)	-0.03 (2.45)
	+	105 (5)*	6 (2)*	2.6 (1.0)*	48.8 (37.8)†	48.7 (36.6)*	0.04 (3.33)†	0.85 (9.05)*	-0.32 (0.12)
E	-	6 (5)	2 (2)	1.6 (0.8)	48.8 (54.9)	0.0 (25.6)	0.02 (7.33)	0.04 (12.31)	-0.02 (0.18)
	+	62 (5)*	6 (3)*	2.5 (1.4)*	48.8 (31.7)	50.0 (40.0)*	0.03 (5.28)†	0.47 (14.27)*	-0.15 (1.81)

Table 2: *Median (IQR) statistics of the clusters identified in the data samples (described in Table 1.). The groups labeled to be the intensive gamblers are signed with a + in the group column and highlighted with gray background. The results of Kruskal-Wallis rank sum tests for difference between the group descriptors are signed on the intensive group values (P-levels:* $\dagger .05, * .001$*). The separation of the groups is consistent in the dimensions of game frequency (games, days active and sessions per day) and also the wider risk and bet size range.*

sonal daily behavioral indicators and training models to see if in the following seven day period they: ceased to participate in the game (retention) or got identified as participants of the at-risk and/or problem gamblers group (identification). We have found that user retention is more prevalent and can be forecasted with great accuracy, we were able to create models with strong predictive power for falling into the problem gambling group. We have also shown that if considerable care has been put into the preparation of descriptors, the models themselves can be highly automated using autoML solutions, thus providing generalizability to the solution.

The point of the exercise was to show that facilitators of the gambling industry have the power to create predictive power over retention and possible increase in gambling intensity and can adjust their designs or add incentives to target these user groups. But what is business problem for them is a creation of health risk externality for the players and society and thus regulatory steps should be established for data provision by these facilitators for counteracting research and a targeted policy about self regulation to promote harm reduction, utilizing the same predictive exercise and applying defensive nudges.

3.4 How Bitcoin's Ups and Downs Are Changing the Way You Bet

To determine the BitCoin price's effect on gambling behavior we have created variables capturing price level, change and volatility aspects on daily and (for the last two) weekly level. Using our LuckyBit dataset, first we have categorized our users into cohorts using trimmed k-means clustering and then created daily aggregates of behavioral indicators capturing intensity and aspects of risk taking. To examine correlation between our explanatory (BitCoin price) and target variables (bet size, frequency and risk), first we have performed variable selection trough Elastic Net, then performed an OLS regression with the remaining set.

The OLS outputs (see Table 3) indicate that price factors can explain a small but significant portion of betting behavior. Notably, the mean daily bet size is negatively affected by weekly volatility across all cohorts. A 10% increase in weekly volatility corresponds to a 1.9% decrease in average bet size, suggesting that gamblers adopt a more cautious ap-

Behavior	Cluster	p_t	δp_t	Vp_t	δp_t^w	Vp_t^w	$R^2_{adj.}$
$\widetilde{log_{10}}B_t$	All players			-0.07*		-0.19***	5.6%
	Casual	0.08*	0.01	-0.03**	0.06**	-0.28***	9.2%
	Committed				0.06**	-0.2***	4.1%
	Extreme			-0.04**		-0.13***	2.7%
$\widetilde{N_t}$	All players	-0.39***			-0.06**		16.3%
	Casual	-0.12***	-0.06*	-0.04	0.06*	0.17***	2.5%
	Committed	-0.24***			-0.05*	-0.04	6.6%
	Extreme	-0.1***	-0.06*	0.11***	-0.05*	0.18***	8.7%
$\widetilde{CV}_t$	All players	0.29***	0.02	-0.04	-0.04	-0.05	7.6%
	Casual	0.32***	0.07**		-0.1***	-0.06**	9.6%
	Committed	0.34***			-0.03	-0.12***	11.0%
	Extreme	0.21***		-0.05		-0.05	4.5%

Table 3: *OLS regression coefficients and adjusted R^2 of the models organized by the targeted population behavior and the clusters created. Only those coefficients are shown with values that were pre-selected using Elastic Net regression (P-levels: $^{*}.1;^{**}.05;^{***}.001$).*

proach during periods of high volatility. This effect is particularly strong for casual players, who also tend to place larger bets when Bitcoin prices are higher. For daily betting frequency, there is a general negative correlation with price levels, with the strongest effect observed among committed players. However, weekly volatility appears to have a positive impact on betting frequency for both casual and extreme players. When examining risk-taking behavior, we find that higher price levels consistently correspond to greater risk propensity across all cohorts. Some counteracting effects emerge from weekly returns and volatility, though these influences are neither as strong nor as consistent across different player groups.

Our results demonstrate that the USD/BTC exchange rate - given all other factors unchanged - plays a partial but meaningful role in shaping the behavior of Bitcoin gamblers, with consistent effects observed across different player segments, including casual users, highly addicted individuals, and potentially automated betting programs. This highlights the influence of cryptocurrency market dynamics on gambling patterns, reinforcing the idea that digital asset volatility can significantly impact financial decision-making in high-risk environments.

One of the key findings is that higher Bitcoin price levels tend to correlate with an increase in risk propensity while simultaneous decrease in betting frequency. This suggests that when Bitcoin prices rise, players may feel more confident, leading them to take greater risks with individual wagers. However, the reduction in betting frequency indicates a more selective approach, where players place fewer but potentially larger bets. These effects are more pronounced among committed gamblers than casual ones, implying that engagement level plays a crucial role in shaping how individuals respond to price fluctuations.

Regarding the impact of directional price changes and volatility, our findings suggest that gamblers respond to price movements on a weekly rather than daily basis. This indicates a longer memory in their behavior, meaning that players do not react instantaneously to market changes but instead adjust their gambling patterns based on sustained trends. Notably, higher weekly price volatility coincides with reduced wager sizes across all cohorts, with the strongest effect observed among casual players. This suggests that uncertainty in Bitcoin's value leads to more cautious betting behavior, particularly among those who are less engaged in gambling.

Our study underscores the growing overlap between online gambling, speculative trading, and digital asset markets as also discussed by Delfabbro et al. (2021). As the boundaries between these activities become less distinct, understanding how market trends influence betting behavior is increasingly important. The fact that gamblers appear to react more to weekly trends than daily fluctuations suggests that exposure to cryptocurrency markets may shape their decision-making processes. This raises concerns about the potential for crypto volatility to exacerbate gambling addiction or financial losses, particularly among players who lack the experience or knowledge to navigate these risks effectively.

4 Scientific contributions

4.1 Journal publications

1. **M. C. Sándor**, B. Bakó Unmasking risky habits: Identifying and predicting problem gamblers through machine learning techniques. *Journal of Gambling Studies*, 40, 1367–1377, 2024.

2. B. Bakó, **M. C. Sándor** How Bitcoin's ups and downs are changing the way you bet. *Economics Letters*, 225, 112564, 2025.

4.2 Other publications

1. B. Bakó, **M. C. Sándor** Approaching the hot hand with a cool head. Under review, draft accessible at *SSRN*, 3952051, 2021.

2. **M. C. Sándor** SaoshiDice [Dataset]. On *Zenodo*, 5600259, 2021.

3. **M. C. Sándor** LuckyBit bets [Dataset]. On *Zenodo*, 14926295, 2025.

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