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How Bitcoin's ups and downs are changing the way you bet

Barna Bakó *, Máté Csaba Sándor

Institute of Economics, Corvinus University of Budapest, Fővám tér 8, 1093 Budapest, Hungary

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ABSTRACT

We investigate the relationship between Bitcoin price fluctuations and gambling behavior on the blockchain-based LuckyBit platform. Using transaction data spanning four years, we analyze how Bitcoin's exchange rate, price movements and volatility impact key gambling metrics, including bet size, gambling frequency, and risk appetite. Employing regression models and clustering techniques, we identify distinct behavioral responses among different gambler cohorts. Our findings reveal that higher Bitcoin price levels are associated with increased risk-taking but reduced gambling frequency, whereas higher weekly price volatility leads to a significant reduction in average bet sizes across all player groups. These results suggest that gamblers perceive Bitcoin's price movements as a psychological reference point, influencing their betting decisions in a manner similar to traditional financial decision-making.

1. Introduction

Imagine a casino where, instead of traditional chips, players use a special digital coin that displays its real-time monetary value in USD. As you hold this coin, its value fluctuates — sometimes increasing unexpectedly, making you feel wealthier and more inclined to place larger bets, and sometimes decreasing sharply, prompting caution or perhaps riskier bets in an effort to recover losses. This digital coin, with its constantly shifting value, creates a unique challenge for players as they weigh their decisions at the gambling table. This scenario encapsulates a key question: how does perceived value, especially when volatile, shape an individual's appetite for risk? This question has significant implications for understanding behavior in both gambling and financial decision-making, two areas that exhibit strikingly similar patterns and can often be analyzed using comparable metrics. The emergence of cryptocurrencies like Bitcoin, with their extreme price volatility, offers a unique lens through which to explore this dynamic.

In this study we investigate how Bitcoin's price fluctuations affect gambling behavior, focusing on three key dimensions: (i) risk appetite, (ii) bet size, and (iii) gambling intensity. To address these questions, we analyze transaction data from the Bitcoin-based gambling platform LuckyBit, linking daily Bitcoin price movements to gambling behaviors across different cohorts of players. While prior studies have explored the effects of gambling activity on financial markets, such as Conlon and McGee (2020) analysis of LuckyBit, which found that betting activity explained 32% of BTC/USD exchange rate movements over six months, less attention has been paid to the reverse relationship: how Bitcoin's price volatility shapes gambling behavior.

Research suggests that volatility significantly affects risk-taking behavior. Typically, higher volatility leads to more cautious behavior, as people become more risk-averse in uncertain situations. In finance, for instance, increased volatility often pushes investors to favor safer assets (see Huber et al., 2022), which aligns with the concept of loss aversion, where the fear of losses outweighs the potential for gains (see Kahneman and Tversky, 1979; Barberis and Huang, 2001; Schmidt and Zank, 2005; or Bakó and Neszveda, 2024). However, volatility can also encourage risk-seeking behavior, especially among traders or gamblers who see opportunities to profit from price fluctuations (see Kuhle, 2020). This dual nature of volatility, influencing both risk aversion and risk-seeking behavior, is further shaped by psychological factors like the 'house money effect' and the 'break-even effect' (see Thaler and Johnson, 1990), where past outcomes influence future risk-taking decisions. Given these insights, it would be expected that volatility would influence gamblers' behavior, particularly their risk appetite. Volatility creates an environment of uncertainty, which could cause gamblers to adjust their betting strategies based on the potential for gains or losses. However, our results indicate that while volatility does influence the size of bets placed, it does not significantly affect the level of risk taken. This suggests that volatility impacts how much gamblers are willing to stake, but not the riskiness of their bets themselves. Instead, volatility seems to affect the amount gamblers bet rather than the type of bet they choose.

Additionally, changes in the exchange rate between Bitcoin and USD could be expected to affect bet sizes. If gamblers are accounting for bets in USD, they might perceive their holdings as more valuable when

* Corresponding author.
E-mail addresses: barna.bako@uni-corvinus.hu (B. Bakó), mate.sandor2@stud.uni-corvinus.hu (M. Cs. Sándor).

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Table 1
Summary statistics of LuckyBit games. Column descriptions are detailed in Section 2.1. While expected returns are nearly identical, the coefficient of variation (CV_i) varies significantly, offering different levels of risk exposure.

Game (i)	$\max_i M_{i,j}$	$\min_j M_{i,j}$	$\sum_{M_{i,j}\leq 1} P_{i,j}$	EP_i	CV_i
Blue	2	0.2	86.7%	98.27%	0.31
Green	21	0.4	45.4%	98.25%	0.38
Yellow	110	0.3	21.0%	98.24%	1.50
Red	998	0.2	21.0%	98.24%	6.65

Bitcoin increases in price, leading them to place smaller bets. However, our results show that exchange rate changes between Bitcoin and USD do not significantly affect bet sizes. Instead, they influence gamblers' risk appetite. This suggests that while Bitcoin's perceived value affects how much gamblers stake, it is their emotional response to risk, rather than the absolute amount they bet, that drives their behavior.

2. Data & methods

As described by Conlon and McGee (2020), the LuckyBit gambling platform operates a probabilistic game that simulates a Galton board with 17 distinct outcomes.[1] This setup defines a payout function following a binomial distribution, where each possible outcome is associated with a specific multiplier. The platform offered four different game variations, each with its own set of multipliers. Table 1 summarizes the key characteristics of these games. While the expected returns (EP_i) are nearly identical, they exhibit significant differences in overall winning probabilities and maximum multipliers, ranging from 2 to 998.

To place a bet on the site, users would send a Bitcoin transaction to a static wallet address assigned to a specific game. The amount wagered was encoded in the transaction, and the outcome was determined by the transaction ID recorded on the blockchain, ensuring provable randomness. Once evaluated, the site returned a transaction to the initiating player. This publicly recorded process makes it possible to extract and analyze gambling behavior from blockchain data, as done by Conlon and McGee (2020) and Scholten et al. (2020).

2.1. LuckyBit data

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.[2,3] 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]

One limitation, however, of blockchain-based timing is that transaction timestamps correspond to the block creation time, which fluctuates between 10 and 20 min. Therefore, exact daily assignments, particularly around GMT midnight, may introduce minor inaccuracies. We use GMT for all timestamps, including exchange rate data.[5]

To capture key aspects of gambling behavior, we define three daily-level measures.

- *Gambling intensity:* the average number of bets per player per day:

$$\widetilde{N_t} = N_t/n_t, \tag{1}$$

  where N_t is the total number of bets on day t, and n_t represents the number of active players that day.
- *Bet size:* since bet amounts vary from 0.001 BTC to 50 BTC, we apply a logarithmic transformation:

$$\widetilde{\log_{10} B_t} = \sum_{i\in t} \log_{10} B_i/N_t. \tag{2}$$

- *Risk appetite (CV_t):* The coefficient of variation for game i is calculated as:

$$CV_i = \frac{\sum_j P_{i,j}\left(M_{i,j} - EP_i\right)}{EP_i}, \tag{3}$$

  where $M_{i,j}$ is the payout multiplier, $P_{i,j}$ is the probability of outcome j, and $EP_i = \sum_j P_{i,j}M_{i,j}$ is the expected payout. The daily risk appetite for the population is given by[6]:

$$\widetilde{CV_t} = \sum_{i\in t} CV_i/N_t. \tag{4}$$

To control for days with very low participation, we exclude days with fewer than 10 bets, resulting in 1486 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 (see Fig. 1).[7]

2.2. Player cohorts

Using daily averages introduces potential bias by oversampling highly active players. Additionally, online gambling, particularly in the crypto space, may involve automated bots. To address these concerns, we apply clustering techniques to segment gamblers based on aggregated behavioral patterns.

As shown by Braverman and Shaffer (2012), k-means clustering can effectively distinguish casual players from problem gamblers. Furthermore, Sándor and Bakó (2024) demonstrate that trimmed k-means clustering is particularly useful for identifying players exhibiting extreme behavior, which may include automated bettors or bots.[8]

To segment players, we compute several behavioral metrics: the total number of bets placed (N_{total}), the number of active calendar days (D), the coefficient of variance of their bet portfolio weighted by bets placed ($CV_p = \sum_i CV_i \cdot B_{i,p}/\sum_i B_{i,p}$), and both the total ($log_{10}\left(\sum_i B_{i,p}\right)$) and maximum ($\max\left[log_{10}\left(B_p\right)\right]$) wager placed, measured on a logarithmic scale. A logarithmic transformation is applied to wagers beforehand for normalization.

[1] 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/.

[2] See the shared dataset `luckybit_names_address.csv` for the map of addresses.

[3] Our dataset concludes in February 2018 because in early 2018 the platform introduced a registration-based, closed-account system that swiftly overtake its publicly visible "direct-betting" interface in popularity, due to decreased transaction costs and an increase in evaluation speed. This change effectively removed public access to wager information, leaving only a handful of observable bets during the transition and none thereafter, so systematic data collection beyond 2018 is not feasible.

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

[5] The dataset does not include nationality or socioeconomic details about users, preserving anonymity and ensuring ethical use of the data.

[6] We have used the multipliers in the equation instead of the payouts (that is multiplier times bet size) to keep the wager and variance risk dimensions separate in the analysis. A combined measure (that is weighting with bets sizes) brings almost identical overall conclusions to the study.

[7] Scripts used for data preparation and analysis are made publicly available at github.com/sampaat/luckybit_gambling.

[8] Our classification of the trimmed group as potentially containing bots is based on the assumption that bots place a high number of bets over either a short or extended period. As a result, they are separated from the rest of the player base based on the total number of bets or the days played descriptor used in the clustering process.

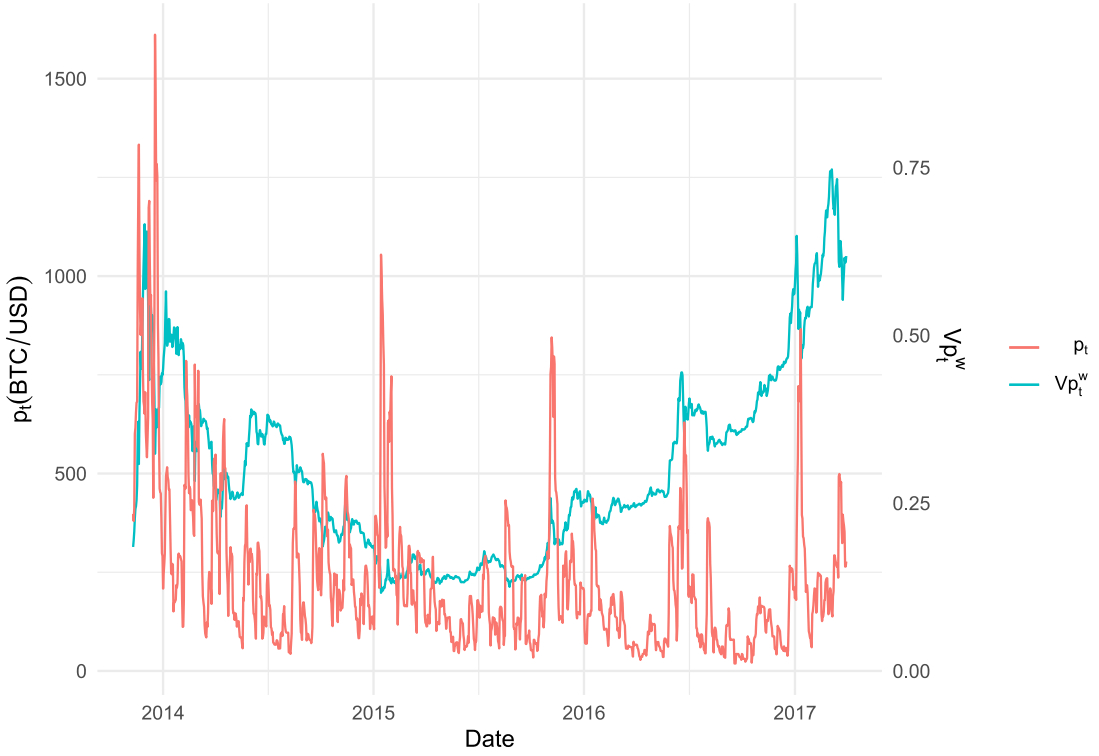

Fig. 1. Bitcoin exchange price p_t and weekly volatility Vp_t^w over the observed period. We can see that over the 4 years of the discussed timeline both the price and the volatility had similar high and low values and clusters over time providing a great variability of effect combinations from these two aspects of the exchange rate. Data shown is gathered from the publicly available historic records of Coinmarketcap (see Section 3).

Table 2
Corhort sizes ($N_{players}$) and median (IQR) descriptors of the whole player base and the three cohorts separated by the clustering (Casual and Committed) and trimming (Extreme). The bet values are represented on a logarithmic base of 10 in BTC.

Cluster	$N_{players}$	N_{total}	D	CV_p	$\max\left[log_{10}\left(B_p\right)\right]$	$log_{10}\left(\sum_i B_{i,p}\right)$
All players	18 220	4(21)	1(1)	1.47(4.57)	−2.43(−7.28)	−2(−1.38)
Casual	11 329	2(6)	1(0)	1.5(6.27)	−2.67(−7.44)	−2.52(−2.27)
Committed	6709	24(99)	2(3)	1.03(2.32)	−1.85(−7.03)	−1.16(−0.91)
Extreme	182	1432(4209)	63(85)	1.68(2.96)	−2.47(−7.15)	−0.89(0)

For clustering, we set $k = 2$ cohorts with a 1% trimming limit. As shown in Table 2, the primary distinguishing factors are the total number of bets placed and the average bet size. While some overlap exists, other dimensions also offer insights into group characteristics. For instance, more committed players tend to place larger but less risky bets compared to those who gamble only occasionally, whom we label as casual players. The trimmed cohort consists of clear outliers, either pathological gamblers or bots executing a specific strategy.

3. Influence of the price of Bitcoin

We use the USD/BTC exchange rate to capture the risk associated with Bitcoin's value.[9] To further break down the risk within the exchange rate, we derive the following price markers:

- Daily mid rate: p_t
- Relative daily return: $\delta p_t = \frac{p_t}{p_{t-1}}$
- A proxy for the relative intra-day price volatility: $Vp_t = \frac{p_t^{high} - p_t^{low}}{p_t}$

To account for the fact that while many Bitcoin holders are active investors, others may react to price information more slowly, we also included:

- Weekly return: $\delta p_t^w = \frac{p_t}{p_{t-7}}$
- Weekly volatility: $Vp_t^w = \frac{\max_{t\ldots t-7} p_\tau^{high} - \min_{t\ldots t-7} p_\tau^{low}}{p_t}$.

Before estimating the regressions, all dependent and explanatory variables were standardized to mean zero and unit variance, which makes coefficients directly comparable across specifications. To assess collinearity among the five price-related regressors, we conducted a principal component analysis (PCA): the first component explains only 36% of the total variance, and three components are required to exceed 90%. This pattern indicates overlap in information but not a single dominant (i.e., highly collinear) dimension. Because pure LASSO can drop one variable from a correlated set, we employed Elastic Net regularization to retain its selection ability while adding ridge-type shrinkage.[10] In applications with strong collinearity, a balanced mix of the two penalties (e.g., $\alpha = 0.5$) is often used; in our case collinearity is modest, so we set $\alpha = 0.7$ to preserve some grouping while favoring sparsity. The penalty parameter λ was chosen by ten-fold cross-validation, and predictors with non-zero coefficients were then entered into the ordinary least squares models reported in Table 3.[11]

[9] We used the publicly available historic data of Coinmarketcap at https://coinmarketcap.com/currencies/bitcoin/historical-data/.

[10] Elastic Net, introduced by Zou and Hastie (2005), combines the variable-selection power of LASSO with the grouping effect of ridge regression, promoting both sparsity and the joint retention of correlated predictors.

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.

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%

* P-levels: .1.
** P-levels: .05.
*** P-levels: 001.

The results 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 approach 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.

4. Conclusions

Our results demonstrate that the USD/BTC exchange rate 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 increase risk propensity while simultaneously decreasing 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 reduces 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.

These changes in behavior can also be interpreted through the lens of perceived wealth by viewing USD/BTC price movements as proxies for wealth shocks. When prices rise, players may feel wealthier and become more willing to take risks, consistent with the house money effect, where recent gains encourage bolder decisions (Thaler and Johnson, 1990). Conversely, falling prices create a sense of financial loss. While this does not appear to reduce players' overall risk appetite, it is associated with a clear reduction in wager size, particularly under conditions of high volatility. This may reflect the break-even effect (Thaler and Johnson, 1990), where individuals continue to pursue risky outcomes to recover earlier losses while limiting the size of their financial exposure.

Our results suggest that perceived changes in wealth affect different dimensions of gambling behavior. Risk appetite is more responsive to the level of Bitcoin prices than to volatility or recent declines, indicating that perceived gains influence the types of bets players choose. Bet size, on the other hand, reacts more strongly to price uncertainty, especially during downward trends, suggesting that players reduce their stakes when they feel financially less secure, even if their risk preferences remain unchanged. Differences across player cohorts support this interpretation. Casual players show the most pronounced reduction in bet size during volatile or declining periods, suggesting greater sensitivity to perceived losses. Committed players, by contrast, respond more to rising prices, consistent with a stronger house money effect and a greater responsiveness to perceived gains. Gamblers classified as Extreme show a more erratic response, likely reflecting a mix of behavioral extremes, including automated betting or persistent loss-chasing. While they, too, reduce bet sizes in volatile conditions, their risk-taking appears less systematically tied to perceived wealth, suggesting that other factors, such as algorithmic strategies or compulsive tendencies, may dominate. Framing these results in terms of financial perception helps explain not only the average effects of market conditions on behavior, but also the asymmetries across different types of players.

These findings have several important implications. First, they highlight the broader psychological and financial risks associated with cryptocurrency-based gambling. Unlike traditional gambling environments where currency values remain stable, crypto gamblers must navigate not only their own risk preferences but also external financial volatility, which may amplify risky decision-making or trigger more conservative betting patterns depending on the context. The stronger behavioral shifts observed among casual and committed players suggest that different types of gamblers are uniquely vulnerable to market-induced pressures, warranting a differentiated approach in regulatory and harm reduction strategies.

Furthermore, 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.

In the context of a global online gambling surge and heightened economic uncertainty, our findings emphasize the urgent need for regulatory interventions. Policymakers must consider the role of digital

[11] Using $\alpha = 0.5$ retained a few additional regressors, but none was statistically significant nor did they improve model fit, and the resulting selection was identical to that obtained with pure LASSO ($\alpha = 1$).

currencies in facilitating new forms of gambling, particularly those that appeal to younger or more vulnerable populations.[12]

Stronger consumer protections, responsible gambling initiatives, and public awareness campaigns could help mitigate the risks posed by the intersection of digital finance and gambling. As cryptocurrencies and blockchain-based betting platforms continue to evolve, understanding their psychological and economic effects on gamblers will be essential for developing effective policy responses and harm reduction strategies.

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Data availability

I have shared the link to the data and code used in the manuscript.

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[12] This is especially relevant given the increasing use of digital currencies to enable gambling-like reward systems in video games targeted at teenagers and young adults, as discussed by Kim et al. (2023).