

From Epidemic to Pandemic-Like Diffusion: A Dynamic SIRS Model of Bitcoin Adoption

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Abstract

The present study employs the Susceptible–Infected–Recovered–Susceptible (SIRS) model to analyze the evolution of Bitcoin adoption, considering user participation as the infection process. The series cover the period from 1 February 2012 to 31 July 2026, based on daily frequencies. This model explores the transition between susceptible users (open wallets), infected (active addresses) users, and recovered (inactive addresses) users, concurrently allowing inactive users to re-enter the market. The analysis focuses on major bubble periods, during which the infection, recovery, and re-entry rates were assessed, in addition to the reproduction number and the duration of the infectious and immunity states. The findings indicate significant alterations in Bitcoin's infectious characteristics over time. The 2013–2014 period is characterized by a rapid infection rate within a small population of participants. However, the speculative cycles of 2017–2018, 2020–2021, and 2024–2025 exhibit lower reproduction numbers but longer infectious periods. This demonstrates a shift from fast and short-lived contagion to slower and longer-lasting participation in a larger ecosystem. In an epidemiological context, Bitcoin initially exhibited characteristics of epidemics, whereas later cycles display a pandemic-like pattern. Overall, contagion evolves from highly infectious diseases like measles and pertussis to broader, persistent forms like COVID-19 and influenza. Theoretically, the present study expands the application of epidemiological models by offering a novel perspective on the contagious behavior of highly speculative securities. From a managerial perspective, the findings assist investors and policymakers to better understand how Bitcoin contagion spreads, persists, and re-emerges during various speculative cycles.

Keywords: Bitcoin; SIRS model; Epidemic-like diffusion; Pandemic-like diffusion; Financial contagion

JEL Classification: G40; G41; G17

Declaration of competing interest:

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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1. Introduction

Bitcoin has transformed from a small-scale technological experiment into an internationally recognized asset class. The early adoption was primarily associated with technology-oriented participants, while later developments expanded to a much broader segments of the population (Steinmetz et al.,2021; Catalini and Tucker, 2016). The potential for rapid gains and losses has attracted the attention of retail investors, institutional participants, researchers, and policymakers. Bitcoin (BTC hereafter) has repeatedly demonstrated patterns of bubble formation, frequently followed by market corrections (Oldani et al.,2025; Podhorsky, 2024; Geuder et al.,2019). Concurrent with these developments, there have been shifts in trading activity, investors interest, and market participation. The interplay of rapid expansion, speculative enthusiasm, and market cycles makes these dynamics hard to explain through standard financial models alone. In fact, the cryptocurrency market displays notable behavioral tendencies. These include herding and contagion, where the price of BTC exerts significant influence on other altcoins (Ballis and Drakos, 2020; Silva et al.,2019). The characteristics exhibited by the BTC market bubble extend beyond mere price fluctuations. The analysis shows that these characteristics are accompanied by ongoing changes in investor involvement and collective behavior.

Another important characteristic is that BTC ecosystem evolves alongside the spread of information, narratives, expectations, and speculative activity in digital and social networks. Koch and Dimpfl (2023) show that investor attention leads to stronger cryptocurrency price synchronization, with BTC being the primary driver. In the same vein, Zhang et al., (2021) illustrate a dynamic interaction between internet attention and the BTC market. Their findings reveal a particularly strong interaction between attention and BTC market activity, particularly during speculative cycles. An additional element of investor attention is manifested in the returns and liquidity of the cryptocurrency market. Smales (2022) provided evidence that heightened investor attention, as measured by Google search activity, is correlated with enhanced returns in the cryptocurrency ecosystem and reduced market liquidity. The relationship between attention and the cryptocurrency market is characterized by distinct differences in the way information channels are generated. Li et al., (2021) documented two-way associations between cryptocurrency returns and investor engagement. Their findings reveal that the information presented to users by search engines and social media platforms varies in terms of relevance to specific cryptocurrencies. Concurrently, the narratives underpinning cryptocurrencies also exert a substantial influence on participant behavior, prices and market volatility. In their study, Nguyen et al., (2023) stress that coins with strong narratives tend to demonstrate high performance, while rising prices generate further interest in these narratives. These findings suggest that participation in the BTC market is also a socially transmitted process influenced by narratives and participant behavior. These factors, among others, have the potential to influence the entry and exit of investors in the marketplace.

In addition to analyses of BTC and cryptocurrencies, epidemiological models find application also in other domains of financial contagion. For example, Zhang and Pan (2022) use the SIRS model to analyze the spread of corporate financialization, treating firms as agents that can transition between different SIRS categories. The study uses a large set of Chinese manufacturing company data from 2007–18 to show how corporate financialization maintain contagion effects. The results imply that an increase in financial asset investment by one firm can influence the behavior of other firms in a similar manner. A considerable body of research has previously utilized epidemiological models to assess the contagion attributes of the global financial system. In their study, Aliu et al., (2026) examine the financial contagion of the thirteen largest European banks. Despite the lessons learned from the financial crisis of 2008–09, the findings suggest that the European banking system is still highly susceptible to price contagion. This suggests that the potential failure of a major banking institution could lead to the breakdown of the European financial system.

Concurrently, the notion of financial contagion finds application in the field of risk management, whereby distress or risk can propagate from one financial institution to another using epidemiological models. The study by Dehshalie et al., (2021) examine credit-risk contagion using a time-delay SIR model to investigate the conditions for controlling and stabilizing financial risk transmission. They categorize susceptible agents as financially healthy, infected agents as financially distressed, and recovered agents as those no longer in distress. These applications show that epidemiological models can be used not only to model biological infections, but also financial behavior, risk and economic distress too.

The use of epidemiological methods has expanded beyond infectious diseases to include the assessment of financial contagion. Using the dynamic SIR model with time delay, Aliano et al., (2025) have investigated financial risk between firms. This is achieved through supply-chain relationships, which spread financial risk and delay captures temporary financial immunity after recovery. The study shows that the system achieves a steady state of risk, in which financial distress can be either temporary or persistent. Building on this idea, Aliano and Ragni (2026) use a combination of the SIR model and game theory concepts to inspect risk contagion and collaborative behavior among cryptocurrency exchanges. They found that such cooperation can mitigate systemic risk while improving market efficiency and resilience. In the domain of cryptocurrency markets, investor behavior is profoundly influenced by sentiment, information, and social interaction. Consequently, narratives can emerge as a powerful mechanism driving price movements. The seminal work of Shiller (2017) offers a novel perspective on the propagation of the BTC narrative, drawing parallels with the infectious diseases. He proposes that the narrative and stories surrounding BTC can be deconstructed through the lens of Ebola outbreaks. However, it must be noted that BTC is distributed globally and exhibits characteristics associated with pandemics rather than localized epidemics. More relevant to the present topic, Aliu (2024) uses the standard SIR framework to identify BTC price bubbles. The author compares BTC price patterns with those of the SARS-CoV-2 virus, focusing on modelling the susceptible, infected and recovered states. A subsequent study by Aliu (2025) builds upon this approach by employing a time-dependent SIR model. This study classifies open wallets as susceptible, active wallets as infected and inactive wallets as recovered. Meanwhile, he observes BTC spreading like measles and recovering slowly, like the tuberculosis. In contrast, the present study proposes an extension to the SIRS dynamic model, thereby facilitating a transition from recovered participants back to susceptible state via the re-entry rate parameter. This enables previously inactive participants to return to the BTC ecosystem. It is important to emphasize that model estimates, including infection, recovery and re-entry rates, are subject to continuous changes in response to evolving market conditions. The existing models represent these rates using a limited number of static estimates at each period. Rather than presenting BTC as a single epidemiological profile, the aim of this study is to show how it evolves from an epidemic-like contagion to a pandemic-like diffusion.

The evolution of BTC is closely linked to the constant movement of individuals into and out of active market participation. From an epidemiological perspective, these movements can be interpreted as a contagion-like processes in which participation spreads, disappears, and may subsequently re-emerge. In the SIRS model, participants in the BTC ecosystem fall into one of three main categories. The susceptible group comprises individuals who are in the ecosystem, yet not active. In our case, this is represented numerically by the total number of open wallets. Open wallets are regarded as being susceptible due to their ability to become active when market conditions change. This tendency manifests during periods of heightened or diminished enthusiasm surrounding the BTC price changes. The infected group comprises actively engaged participants who are directly involved in transactions or investments. The recovered category represents inactive participants resulting from reduced interest, market corrections or speculative losses. In this regard, SIRS model can assess whether BTC cycles are driven by rapid contagion within a small population or by more persistent participation within an increasingly large ecosystem.

The present study makes several contributions to the existing literature. Firstly, it extends the existing static BTC SIR application to a dynamic SIRS framework. The dynamic process in this case enables previously inactive participants to become susceptible and enter the active marketplace. This demonstrates precisely how participation in the network fluctuates in accordance with the evolution of market conditions. Secondly, the SIRS model offers an alternative to conventional bubble-detection techniques. It is evident that models such as the Augmented Dickey–Fuller (ADF), recursive right-tailed ADF (ARDAF), the Supremum ADF (SADF), and Generalized Supremum ADF (GSADF) are primarily dependent on a single variable, such as asset-price series. In contrast, the SIRS model examines the bubble creations using three compartments: susceptible (S), infected (I), and recovered (R). At the same time, the system also allows recovered participants to become susceptible again. Contrary to the standard techniques of analyzing bubble formation from abnormal price behavior alone, dynamic SIRS captures a more comprehensive set of factors. This includes how participants become infected, recover, and subsequently re-enter during speculative episodes. In conclusion, it provides behavioral and participant-based perspectives on the bubble formations that complement standard bubble models. Thirdly, it employs reproduction numbers and infectious periods to benchmark BTC adoption dynamics against those of representative infectious diseases. This comparison extends the epidemiological interpretation of BTC contagion, by identifying the types of infectious diseases that most closely resemble its transmission dynamics.

The remainder of this paper is structured as follows. Section 2 reviews the literature on herding behavior and discusses infectious diseases analogous to BTC. Section 3 describes the data, construction of variables, and descriptive statistics. The dynamic SIRS methodology is presented in Section 4, while the empirical results – including the evaluation of BTC contagion across speculative cycles – are covered in Section 5. Finally, Section 6 concludes the paper and discusses the main implications.

2. Related Literature

The related literature is categorized into two distinct parts. Section 2.1 explores herding behavior in the cryptocurrency market, while Section 2.2 examines infectious diseases and epidemiological parameters comparable to BTC's adoption characteristics.

2.1. Herding Behavior in Cryptocurrency Markets

Herd-based behavior has been identified as a significant explanatory factor in understanding the actions of participants in the cryptocurrency market. The phenomenon occurs when investors consistently follow the decisions and expectations of their peers instead of relying on their own information or beliefs. The mechanism is relevant for the cryptocurrency market, where determining intrinsic value is difficult and participation depends on market sentiment. The study by Almeida and Gonçalves (2023) argue that herding is a key part of cryptocurrency investors investment strategy. Their findings emphasize the critical role of social media, public sentiment, and speculative decisions in influencing herding behavior. The research demonstrates that the intensity of herding exhibits significant fluctuations over time and is subject to variation across diverse market conditions. Bouri et al., (2019) reveal that herding becomes more prevalent in the cryptocurrency market when uncertainty rises. For this purpose, herding is not a long-lasting part of cryptocurrency trading, but it's more common during market shocks. Concurrently, Ballis and Drakos (2020) posit that cryptocurrency investors tend to imitate the actions of other investors rather than exercising independent judgment. Their findings suggest that herding is not just a random feature of cryptocurrency markets, but a key behavioral mechanism that becomes especially influential when uncertainty, sentiment and market movements intensify.

Concurrent studies suggest that herding tendency is asymmetric, depending upon the prevailing state of the cryptocurrency market. Vidal-Tomás et al., (2019) provide evidence that herding is particularly evident during periods of significant decline in the cryptocurrency market. Their estimates indicate that during these periods, low-market-capitalization cryptocurrencies reveal a propensity to gravitate towards dominant ones. As illustrated by Ali (2022), herd-based behavior is shown to vary depending on the investment horizon and market dynamics. His results determine that herding exerts a more distinct effect in the short term, while its efficacy diminishes over the medium and long term. In summary, evidence suggests that herding is dynamic within the cryptocurrency ecosystem, intensifying when investors face elevated uncertainties. Moreover, these studies imply that the actions of market participants are not entirely independent. The expectations and attention of participants under specific circumstances are aligned with the actions of others. This provides an important behavioral foundation for exploring BTC as a contagion process in which involvement may propagate across a susceptible group.

Herding and epidemiological models are often considered to be complementary, yet they also exhibit substantial differences. The theory of herd behavior offers an explanation of how the actions, expectations, and information of other market participants influence collective investment decisions. In contrast, SIRS framework explains how participation in the cryptocurrency market spreads, declines and re-emerges over time. However, the current study does not assume that every transition into active BTC participation is driven by herd behavior. Herding is just one of the behavioral instruments influencing the broader contagion process captured by the SIRS model. Another significant distinction relates to the initial phase of the infectious process. The epidemiological perspective, however, also considers the first infected individual (the "index case"), as it is based on the assumption that an infection begins with a single individual. In the BTC case, the enigmatic person Satoshi Nakamoto may be regarded as the index case, from whom participation subsequently spread to other users. Conversely, the herding theory as a concept is typically focused on the behavioral patterns of investors in an already-established market. Consequently, it fails to account for an initial "index case" or "patient zero" from which transmission originates.

The primary focus of social science research is group behavior rather than the actions of a single individual. The domain of individual behavior is traditionally associated with the field of psychology. The disciplines of economics, sociology and political science, alternatively, are concerned with the investigation of behavior development across larger groups. The present study considers the first individual – or the "index case" – to be important, as more widespread behavior can originate from a single source. Therefore, understanding the initial stages of the infection process is crucial to understanding how it subsequently spreads. This logic is not confined only to highly speculative financial instruments. The genesis of political ideologies, religious movements and economic concepts is often attributed to the influence of a single individual or a small group, before their dissemination to a much larger population. Movements like Nazism, fascism, communism and capitalism were influenced by specific thinkers or political figures before evolving into social phenomena. This same rationale can be applied to religion, where the ideas of a single individual have the potential to eventually influence millions of people. In this sense, BTC can be viewed as a process that began with a single individual and subsequently turned into a global pandemic narrative.

2.2. Infectious-Disease Contagion and Epidemiological Parameters

This section discusses selected infectious diseases that serve as a useful benchmark for interpreting BTC contagious characteristics. Infectious diseases are defined as illnesses caused by pathogens that spread among individuals, either directly or indirectly. The transmission of the infection is dependent on various factors, including the rate of infection, infection period, and immunity. Epidemiological studies show considerable heterogeneity in infection and recovery rates across infectious diseases. The basic reproduction number (R_0) constitutes one of the most frequently employed parameters for the measurement

of the transmission rate. However, R_0 cannot be interpreted as a fixed biological parameter as its values depend on population structure, contact patterns, environmental conditions and the assumptions of the epidemiological model (Buckee et al., 2021; Ridenhour et al., 2018; Guerra et al., 2017). This indicator denotes the number of secondary infections generated by an index case within a fully susceptible population. In the presence of $R_0 > 1$, the infection possesses the capacity to propagate within the population. Conversely, a value of $R_0 < 1$ signifies that sustained transmission is not possible.

The value assigned to the reproduction number varies widely among different categories of infectious diseases. Seasonal influenza is generally characterized by a moderate reproduction number. In their study, Biggerstaff et al., (2014) found that the reproduction number for influenza epidemics is around 1.28. Yet estimates for pandemic influenza suggest a higher reproduction number. Conversely, measles and pertussis have historically exhibited notably higher reproduction numbers. The most commonly reported estimates vary between 12–18 and 12–17, respectively, although these figures are subject to variation depending on the population and time period covered (Delamater et al., 2019). These disparities imply that infectious diseases have different transmission patterns, ranging from moderate to extremely rapid. In relation to the novel coronavirus (SARS-CoV-2), there is heterogeneity in the reported values of the reproduction number. Alimohamadi et al., (2020) present estimates ranging between 2 and 4, depending on the location, time period, and methods used. The transmission profiles and reproduction numbers of infectious diseases can be used to draw analogies with BTC's reproduction patterns. This standpoint facilitates the interpretation of adoption dynamics within a well-established infectious disease framework.

The transmission rate alone is insufficient to fully explain the dynamics of infectious diseases. The duration of the infection and the recovery rate are additional vital components. In the standard SIRS framework, the infection rate (β) is defined as the rate at which a susceptible individual becomes infected through contact with an infected one. Conversely, the recovery rate (γ) denotes the rate at which an infected individual transitions out of the infected status. The inverse of this recovery parameter approximates the average infectious period. The earliest evidence for SARS-CoV-2 estimated an infectious period of about 6.25 days (Wang et al., 2021). Nevertheless, considerable heterogeneity was observed among the epidemiological studies. The duration of infectiousness demonstrates significant variation across different diseases. Recent findings on seasonal influenza show that most infected adults shed the virus within about a week of symptoms appearing (Stone et al., 2025). These variations are crucial as a comparatively moderate infection rate, combined with an extended infectious period, may facilitate ongoing transmission even during periods of reduced transmissibility.

Other infectious diseases demonstrate diverse epidemiological features in terms of transmission, recovery and infectious periods. The transmission and recovery rates for mumps are estimated to be 0.41 and 0.125 respectively, with an infectious period of around eight days (Hilton and Keeling, 2019). The combination of these factors has been shown to reduce the duration for which infected individuals are capable of transmitting the disease. Given this, mumps is an example of an infectious disease with a relatively short period of active transmission. Modelling of pertussis indicates an infectious period of approximately 22 days and a reproduction number of 17 (Rozhnova & Nunes, 2012). Pertussis is classified as a highly contagious disease with persistent transmission due to its high reproduction number and prolonged infectiousness. Notable epidemiological variations also occur within varicella and Ebola. Giraldo and Palacio (2008) applied the SIR model to investigate the transmission dynamics of six varicella outbreaks. They determined an infectious period of five days and a removal rate ranging from 1.62 to 5 per week. Their work is particularly relevant, as it reveals how transmission changes across multiple outbreaks of the same disease. Althaus (2014) computed a reproduction number of between 1.51 and 2.53 for the 2014 Ebola outbreak in West Africa. This estimate yielded a transmission rate of between 0.27 and 0.45 per day, as

well as an infectious period of around 5.61 days. Importantly, no single epidemiological parameter describes the complete evolution of an infectious disease unless other factors are also considered.

Immunity is likewise a crucial aspect of epidemiological dynamics. Consequently, alongside viral evolution and the circulation of multiple strains, population mixing is a key element in the ongoing influenza epidemic (Truscott et al., 2011). In diseases where immunity declines, the SIRS framework considers that previously recovered individuals could become susceptible again and contribute to subsequent infection waves. A high R_0 value together with a short infectious period characterizes rapidly spreading infections. On the other hand, a lower reproduction number combined with a longer infectious period signals a less intense yet more sustained transmission pattern. The reproduction number, along with the infection, recovery, re-entry, infectious and immunity rates, are vital in analyzing BTC contagion.

When considered collectively, these studies demonstrate that epidemiological models can provide a unique perspective on the interpretation of speculative instruments. This approach provides a framework for understanding the dynamics of risk, behavior, and participation in financial markets. Specifically, it enables the analysis of how these constructs spread, persist, disappear, and re-emerge through interactions with "infected" individuals. However, there has been limited attention devoted to the potential utilization of epidemiological concepts in the context of BTC participation. To the best of my knowledge, there is no evidence to suggest whether transmission intensity, persistence of participation, recovery and re-entry evolve differently across speculative cycles. Examining such trends over an extended timeframe might offer insights into the evolution of BTC's contagious properties. The present study does not quantify psychological and neurological infection at the individual level, as this falls within the domain of psychology, psychiatry, and behavioral research. Instead, the concept of infection is employed as an epidemiological analogy for the propagation of Bitcoin-related narratives and participation.

3. Data

The present study is based on daily BTC blockchain activity and market data, using R studio. The series covers the period from 1 February 2012 to 2026, based on daily frequencies. The historical series provided by the blockchain database include data on the BTC network, market activity, unique addresses, transactions, and market prices. This creates the framework used to construct the variables in the analysis. The series are initially arranged in order of date and subsequently converted into logarithmic returns.

Table 1. Descriptive statistics and diagnostic tests

Variable	N	Mean	SD	Skewness	Kurtosis	JB	ARCH	Ljung_Box	Box_Pierce	ADF	KPSS
Beta	2,120	0.005053	5.475589	0.074	3.908	74.736*** (0.000)	902.418*** (0.000)	1061.107*** (0.000)	1058.148*** (0.000)	-25.249** (0.01)	0.003 (0.1)
Gamma	2,120	0.000000	5.445244	-0.070	3.889	71.554*** (0.000)	901.892*** (0.000)	1038.675*** (0.000)	1035.805*** (0.000)	-25.344** (0.01)	0.004 (0.1)
Volume	2,120	0.000737	0.355055	0.066	4.866	309.097*** (0.000)	233.791*** (0.000)	888.722*** (0.000)	885.347*** (0.000)	-16.878** (0.01)	0.008 (0.1)
Interaction	2,120	0.000526	0.080869	-0.231	4.121	129.893*** (0.000)	610.039*** (0.000)	1837.198*** (0.000)	1831.792*** (0.000)	-17.626** (0.01)	0.017 (0.1)
Drawdown	2,120	-0.000226	1.550876	0.159	40.004	120966.219*** (0.000)	395.245*** (0.000)	404.813*** (0.000)	404.028*** (0.000)	-17.511** (0.01)	0.004 (0.1)
Volatility	2,120	0.030573	0.013761	2.108	10.478	6508.428*** (0.000)	2022.933*** (0.000)	17794.206*** (0.000)	17729.707*** (0.000)	-7.064** (0.01)	0.164 (0.1)
Momentum	2,120	0.000693	0.006382	-0.128	4.030	99.477*** (0.000)	1783.386*** (0.000)	13984.41*** (0.000)	13936.919*** (0.000)	-7.135** (0.01)	0.194 (0.1)

Note: N stands for the number of observations and SD for standard deviation. The JB denotes the Jarque–Bera normality test, while the ARCH refers to the conditional heteroskedasticity. The Ljung–Box and Box–Pierce tests are employed to test for serial correlation. Stationarity tests are

Variable	N	Mean	SD	Skewness	Kurtosis	JB	ARCH	Ljung_Box	Box_Pierce	ADF	KPSS
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performed using the Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) methods. The values in brackets refer to the p-values. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

Table 1 presents summary statistics and diagnostic tests for the variables used in the analysis. Each variable contains 2,120 observations, guaranteeing a uniform sample size. The issue of missing values has been addressed using linear interpolation to ensure the continuity of the daily series. The large standard deviations for Beta and Gamma indicate high variability in infection and recovery rates throughout the period. The market-related variables (volume, interaction, drawdown, volatility and momentum) exhibit high positive skewness (2.108) and high kurtosis (10.478). This implies an asymmetric distribution, characterized by high levels of market instability. Conversely, interaction shows the highest skewness level (-0.231). Meanwhile, drawdown shows the largest departure from normal distribution, with a kurtosis of 40, followed by volatility at 10.47. This suggests heavy tails and a notable tendency towards extreme market fluctuations. The remaining variables exhibit lower kurtosis levels, yet remain above the normal distribution threshold.

Additional characteristics regarding time-series properties are revealed by diagnostic tests. The Jarque–Bera test rejects the normal distribution of each variable at a 1% significance level. The ARCH effect reveals conditional heteroskedasticity in all series within the system. The Ljung–Box and Box–Pierce tests demonstrate temporal dependence by rejecting the absence of serial correlation. Alternatively, the ADF and KPSS tests reject the existence of a Unit Roots in the data. These findings emphasize the existence of non-normal distributions, volatility clustering, and temporal dependence in the logarithmic returns.

Table 2. Definition and Interpretation of Variables Used in the Dynamic BTC SIRS Model

Variable	Symbol	Definition / Construction	Economic Interpretation	Role in the SIRS Model	Source
Active BTC Addresses	A_t	Daily number of unique active blockchain addresses.	Measures users actively participating in the BTC network.	Proxy for the Infected (I) compartment.	Blockchain.com API
Total Wallet Users	W_t	Cumulative number of BTC wallet users.	Represents the overall size of the BTC ecosystem and potential user population.	Used to construct the total population N_t .	Blockchain.com API
Transactions	TX_t	Daily number of confirmed BTC transactions.	Reflects blockchain activity intensity and network utilization.	Validation variable describing market activity (not directly included in the SIRS equations).	Blockchain.com API
BTC Price	P_t	Daily closing BTC price (USD).	Captures market valuation and investor sentiment.	Used to derive financial indicators and Bubble Pressure.	Blockchain.com API
Log Return	r_t	$\ln(P_t/P_{t-1})$.	Measures daily percentage price changes.	Input for momentum and volatility estimation.	Author's calculation
Momentum	M_t	30-day rolling mean of log returns.	Captures persistent upward price trends and speculative enthusiasm.	Component of the Bubble Pressure Index.	Author's calculation
Volatility	V_t	30-day rolling standard deviation of log returns.	Measures market uncertainty and speculative intensity.	Component of the Bubble Pressure Index.	Author's calculation
Drawdown	D_t	Relative decline from the	Quantifies the severity of market corrections and crashes.	Component of the Bubble Pressure	Author's calculation

		historical maximum price.		Index and dynamic recovery parameter.	
Bubble Pressure Index	BP_t	Normalized composite index of momentum, volatility, and absolute drawdown.	Measures the degree of speculative pressure in the BTC market.	Dynamically adjusts β and ω and influences γ through drawdowns.	Author's calculation
Susceptible Users	S_t	$S_t = N_t - I_t - R_t$.	Potential market participants who have not yet become active.	Susceptible compartment of the SIRS model.	Author's calculation
Infected Users	I_t	Number of active BTC users.	Represents currently active market participants.	Infected compartment of the SIRS model.	Blockchain.com API / Author's calculation
Recovered Users	R_t	Cumulative inactive users derived from decreases in active addresses.	Represents former participants who have temporarily exited the market.	Recovered compartment of the SIRS model.	Author's calculation
Transmission Rate	β_t	Dynamic adoption rate estimated from observed infections and adjusted by Bubble Pressure.	Measures the speed at which active users stimulate new participation.	Governs transitions from $S \rightarrow I$.	Author's calculation
Recovery Rate	γ_t	Dynamic exit rate estimated from observed recoveries and adjusted by drawdowns.	Measures the probability that active users become inactive.	Governs transitions from $I \rightarrow R$.	Author's calculation
Re-entry Rate	ω_t	Dynamic parameter proportional to Bubble Pressure.	Measures the rate at which inactive users become interested in BTC again.	Governs transitions from $R \rightarrow S$.	Author's calculation

Note: Blockchain variables are obtained from the Blockchain.com API, while the remaining variables are derived by the author from the raw blockchain and market data. The Bubble Pressure Index is constructed from momentum, volatility, and drawdown measures and is used to dynamically adjust the transmission (β), recovery (γ), and re-entry (ω) parameters. Together, these variables provide the empirical foundation for the proposed dynamic BTC SIRS framework.

Table 2 presents an explanation of the dynamic Bitcoin SIRS framework variables used in the present study. The dataset integrates blockchain activity with indicators derived from market-based evidence. This signifies not only the evolution of the user population but also the ecosystem in which participants engage. This distinction is important, as changes in adoption cannot be solely interpreted from network activity. These variables are designed to identify shifts in market sentiment, price instability, and speculative activity. The combined effect between these two mechanisms establishes the underlying principles for understanding BTC adoption as a behavioral contagion process. It is important to emphasize that while certain variables are obtained from original data sources, others are generated within the model itself. The origins of active addresses, wallet holders, transactions and BTC prices are located in blockchain and market-related databases. However, SIRS compartments (for example, the Bubble Pressure Index) and dynamic transition parameters are developed within an empirical framework. This serves to clarify how BTC activity can be incorporated into an epidemiological model. The methodology section provides a detailed explanation of how variables are constructed and used in the SIRS model.

4. Methodology

The methodological framework is divided into three sections. Section 4.1 presents the dynamic SIRS model adapted to the context of BTC. The construction of the relevant epidemiological population is covered in Section 4.2.

4.1. Dynamic SIRS Framework for BTC Adoption

This paper examines the adoption of BTC using the epidemiological SIRS model. The analysis is based on the observation that crypto participants display contagion-like characteristics. In this respect, participants' willingness to invest are influenced by a combination of social interaction, marketplace activity, social media and speculative sentiment. Like infectious diseases, the participants population grows during times of market optimism and shrinks during downturns. Within the SIRS context, the BTC ecosystem is divided into three distinct participant states, based upon the level of market activity. Active addresses are thus classified as "infected" (I_t), representing participants engaged in transactions who are capable of influencing price dynamics. The susceptible participants (S_t) are those who could potentially become active. In our case, this is represented by total open wallets. Their susceptibility suggests capacity for transition into the active category during periods of strong market enthusiasm or sharp declines. Recovered participants (R_t) are defined as those who were previously active but are currently inactive. The recovered compartment represents previously active addresses that become inactive. Thus, recovery is defined as the inactivity of addresses rather than permanent withdrawal from the ecosystem.

The SIRS model is rooted in the seminal compartmental approach pioneered by Kermack and McKendrick (1927). In essence, SIRS can be regarded as an extension of the conventional SIR (Susceptible–Infected–Recovered) model. In contrast to the traditional SIR epidemiological model, the SIRS framework enables individuals who have previously recovered from an infection to eventually rejoin the susceptible population. This is particularly relevant in the context of the crypto industry, where former investors often return to the marketplace. In short, the purpose of the model goes beyond pure prediction. Instead, it is designed to illustrate the dynamics of participants' transitions within the BTC ecosystem, moving from susceptible to infected, then to recovered, and finally back to susceptible. By considering the dynamics of these groups, the model provides a more holistic view of speculative bubbles, market downturns and investor sentiment.

4.2. Construction of the BTC Population

The construction of the dynamic SIRS model is preceded by the necessity of defining the BTC user population and the subsequent classification of participants into susceptible, active (infected), and recovered (inactive) groups. Unlike conventional epidemiological diseases, BTC SIRS states must be obtained from blockchain activity as they cannot be directly detected. The following equations establish the SIRS methodology used to generate these compartments and model the entire dynamic BTC ecosystem.

$$I_t = A_t \quad (1)$$

$$dR_t = \max (I_{t-1} - I_t, 0) \quad (2)$$

$$R_t = \sum_{i=1}^t dR_i \quad (3)$$

I_t denotes the number of active BTC users at time t , whereas A_t signifies the active addresses. Users are deemed 'infected' for as long as they remain actively involved in the BTC ecosystem. Equation (2) represents the stage at which users stop actively participating. If the number of active users falls from $t-1$ to t , this is considered a recovery (removal) or exit. Conversely, when active users in the ecosystem grow, the value is set to zero. This ensures that adoption is not treated as an exit. Meanwhile, R_t in Equation (3) stands as the sum of all former active participants. In epidemiological terms, it represents individuals who were previously active in the system but are no longer. The total population is defined as the overall pool of potential, active, and inactive participants. The equation for the overall BTC ecosystem population is expressed as such:

$$N_t = \max(I_t + R_t, W_t) \quad (4)$$

$$S_t = N_t - I_t - R_t \quad (5)$$

$$dI_t = \max(I_t - I_{t-1}, 0) \quad (6)$$

The symbol W_t in Equation (4) denotes the total number of wallets that have been opened, thus representing the total population of the BTC ecosystem. The model guarantees that the population (total open wallets) remains consistently greater than the sum of active (infected) and inactive (recovered) users. S_t represents potential participants who belong to the ecosystem but are not currently active, and are neither classified as recovered. In other words, they are users who may engage during subsequent adoptions or speculative periods. Equation (6) is indicative of both new adoptions and new infections. An increase in active addresses is indicative of a new infection of users. In contrast, if there is a decrease in active addresses, then the new adoption rate is set to zero. This suggests that dI_t may only capture positive trends in infection rates.

$$dI_t = \beta_t \frac{S_t I_t}{N_t} \quad (7)$$

$$\beta_t = \frac{dI_t N_t}{(S_t + 1000)(I_t + 1000)} \quad (8)$$

$$\gamma_t = \frac{dR_t}{I_t} \quad (9)$$

Equation (7) describes the infection mechanism within the SIRS framework. The model demonstrates that the occurrence of new infections (new adopters) is profoundly influenced by the interaction between susceptible users (S_t) and active users (I_t), as determined by the infection rate (β_t). It is anticipated that the infection rate will rise during periods of network expansion, as these phases attract new users to the ecosystem. During crash phases, the infection rate decreases as active users (infected participants) become recovered or removed. The infection rate (β_t) is added with a +1000 term to stabilize the denominator and prevent spikes when S_t and I_t are very small. Although β_t is crucial for the transition from susceptible to

infected, the gamma rate (γ_t) quantifies the rate of active users who become inactive (recovered). An increase in the γ_t is indicative of heightened exit pressure, frequently observed in the context of crashes, waning interest, or speculative phases.

In addition to the baseline SIRS, the adoption of BTC is also driven by market dynamics. In order to achieve this objective, a number of indicators derived from closed prices have been developed. These indicators are utilized to measure and analyze the dynamics of speculative activities and investors sentiment.

$$M_t = \frac{1}{30} \sum_{i=0}^{29} r_{t-i} \quad (10)$$

$$V_t = \sqrt{\frac{1}{29} \sum_{i=1}^{29} (r_{t-i} - r_t')^2} \quad (11)$$

$$D_t = \frac{P_t - \max(P_1, \dots, P_t)}{\max(P_1, \dots, P_t)} \quad (12)$$

$$BP_t = \text{Rescale} [\max(M_t, 0) + V_t + |D_t|] \quad (13)$$

Equation (11) signifies market momentum (M_t), the calculation of which is derived from the mean logarithmic return¹ (r_t) over the preceding 30 days. Momentum is defined as the persistent upward trend in prices, which is indicated by positive values. Negative values are indicative of a weakening market sentiment. However, a strong positive momentum is characterized by the presence of speculative buying and an increase in investor interest, and vice-versa. The variable V_t in Equation (12) is indicative of the 30-day rolling volatility of returns. Volatility is defined as the measure of price variability and market fluctuations. A high level of V_t is indicative of periods of intense trading, high levels of interest among participants, and significant signals of market intensity. D_t represents the decline from the historical peak of the price. This is indicative of the percentage decline in price relative to the highest recorded value at a given point in time. The variable assumes a value of zero at a recently achieved all-time high and undergoes a progressive negative shift as the price deviates from the preceding peak. From an economic perspective, significant drawdowns are characterized by a decline in market value, a surge in selling activity, and a decline in market confidence. Consequently, the equation that constructs the Bubble Pressure Index is referred to as BP_t . The construction of this index involves the consideration of positive market momentum, market volatility, and absolute drawdown. The results obtained from the index are limited between zero and one ($0 \leq BP_t \leq 1$), where high values indicate high levels of speculation in the ecosystem. The Bubble Pressure Index functions as a behavioral variable in this process, establishing a linkage between infection rate, exit rate, and re-entry dynamics.

¹ The entire analysis was conducted in R using the RStudio development environment. The complete code for constructing the BTC SIRS model, including all estimations and parameters, is available upon request.

$$\beta_t^* = \beta_t (1 + 2BP_t) \quad (14)$$

$$\gamma_t^* = \gamma_t (1 + |D_t|) \quad (15)$$

$$w_t = 0.002 + 0.030BP_t \quad (16)$$

Another key factor is the time-varying transition rate, which is influenced by the infection rate and is represented by the beta coefficient. Equation (14) shows how the static infection rate β_t is transformed into the dynamic infection rate (β_t^*). When bubble pressure is low (BP_t), the dynamic infection rate remains close to the observed infection rate. As bubble pressure increases, the infection rate is amplified. Coefficient 2 determines how sensitive the infection rate is to speculative forces. The transformation of a static exit rate (γ_t) into a dynamic exit rate (γ_t^*) is another important dimension. The dynamic exit rate coefficient rises when drawdowns (D_t) increase. Market corrections lead to an increased probability that active users will abandon active participation. This refers to investors' tendency to leave the BTC ecosystem when they experience substantial losses. In the SIRS model, participants can be active, leave the ecosystem, and return. Equation (16) shows the re-entry rate (w_t) for inactive users, which defines the movement of users from the recovered to the susceptible compartment. Even under normal conditions, a small proportion of previously inactive users can re-enter the susceptible compartment if the baseline re-entry rate is set at 0.002. The calibration value of 0.030 indicates the extent to which the Bubble Pressure Index (BP_t) influences the re-entry rate.

After defining the SIRS compartments and incorporating baseline transition estimates, the final step is to formulate the dynamic mathematical framework. The following equation describes how the number of susceptible, active and recovered participants evolves over time, taking into account the dynamic processes of infection, exit and re-entry.

$$NI_t = \beta_t^* \frac{S_t I_t}{N_t} \quad (17)$$

$$NR_t = \gamma_t^* I_t \quad (18)$$

$$RU_t = w_t R_t \quad (19)$$

Equation (17) is the first to integrate all components into a dynamic mechanism. The variable NI_t denotes the quantity of new adopters (or new infections) at time t . The variables S_t and I_t indicate the probability of susceptible users contacting active users, thereby forming the dynamic infection rate β_t^* , which varies over time. Unlike standard epidemiological models, this study incorporates a dynamic infection rate that varies from 2012 to 2026. Additionally, the model enables the daily adjustment of transmission rates in response to evolving market conditions. NR_t indicates the proportion of users who stop actively participating. This rate depends on the size of the active compartment and the exit rate dynamic (γ_t^*). Large drawdowns produce high γ_t^* values, resulting in higher exit rates. Finally, RU_t in Equation (19) represents

the number of recovered users who are rejoining the BTC ecosystem. Consequently, periods of rising prices and market bubbles might encourage inactive users to become potential active participants (S_t).

$$S_{t+1} = S_t - NI_t + RU_t \quad (20)$$

$$I_{t+1} = I_t + NI_t - NR_t \quad (21)$$

$$R_{t+1} = R_t + NR_t - RU_t \quad (22)$$

Equations (21)– (23) illustrate how the SIRS compartments evolve over time. Collectively, they describe the dynamic state of the susceptible, active and recovered compartments. This process incorporates the dynamic infection, exit, and re-entry rates. The proposed model describes cyclical movements in the BTC ecosystem between different market engagements. S_{t+1} refers to the susceptible compartment in subsequent periods. Meanwhile, I_{t+1} signifies active participants in the following period, and R_{t+1} indicates the recovered compartment in the next time frame.

The proposed approach in the present study is based on the standard SIRS model but incorporates methodological modifications adapted to the BTC network. The standard SIRS model defines the susceptible, infected and recovered compartments in advance, with the total population transmission, recovery and re-entry parameters being held constant throughout the simulation. In contrast, the newly proposed model allows the infection rate (adoption ratio) and the recovery rate (exit ratio) to fluctuate over time. The infection rate is derived from active addresses, while the recovery rate is analyzed from the number of users who leave active participation. The size of the total population (number of open wallets) varies over time, reflecting the growth or decline of the BTC network rather assuming a constant population size. Another feature of the updated model is the incorporation of cryptocurrency market trends within the SIRS model. The infection rate, recovery rate and re-entry are directly influenced by the Bubble Pressure Index, returns, momentum, volatility and drawdown. Consequently, the current framework considers the impact of speculative market activity on user behavior.

The modified SIRS mathematical model is simulated using a discrete-time recursive algorithm. The susceptible, active and recovered compartments are computed on a daily basis using differential equations and time-varying transition rates. At any given iteration, the system calculates new infections and recoveries while ensuring that no negative values are permitted. This means that all compartments contain non-negative values, improving the numerical stability of the system while enabling its epidemiological interpretation. Figure A.1, located in the appendix, illustrates the comprehensive structure of the dynamic SIRS model adapted to the specific case of BTC. Blockchain inputs (e.g., user numbers, addresses, transactions, and BTC prices) have been converted into epidemiological categories comprising susceptible, infected, and recovered participants. The construction of the Bubble Pressure Index involves the application of rolling measures of momentum, volatility, and drawdown, with the objective of quantifying market sentiment and the prevailing level of speculation. In distinction to the conventional SIRS model, this index enables the infection, recovery, and re-entry rates to vary dynamically throughout the study period. This modification allows the system to respond autonomously to market fluctuations, eliminating the need for constant coefficients. The updated parameters facilitate the transition between new adoptions, market exits, and investor re-entry. Concurrently, continuous updates to the system are facilitated by recursive SIRS equations, ensuring the framework constantly recalibrated to reflect evolving changes. This design captures

speculative aspects, market corrections, price crashes and adoption cycles. In short, it brings together blockchain activity and behavioral contagion in a single dynamic model.

5. Results and discussions

The results and discussion section are divided into three parts. Section 5.1 presents the characteristics of BTC contagion during major speculative cycles. Section 5.2 extends the analysis by examining peak contagion, the distribution of participants across the SIRS states, and the dynamics of entry, exit, and re-entry. Finally, Section 5.3 compares BTC's SIRS dynamics with those of analogous infectious diseases to provide an epidemiological interpretation of the results.

5.1. BTC Contagion Dynamics Across Speculative Cycles

This section employs an analytical approach to investigate how BTC users behave during speculative episodes. Specific attention is paid to changes in user activity within the ecosystem as it transitions into a more established financial instrument. Like infectious diseases, users move from a susceptible state to an infected (active) state, then to a recovered state, and eventually back to a susceptible state (re-entry). The analysis compares major bubble periods to understand how the SIRS model performs at various stages of BTC's evolution.

Table 3. Dynamic SIRS calibration during BTC speculative periods

Bubble	β - 5th	β - Mean	β - 95th	γ - 5th	γ - Mean	γ - 95th	ω - 5th	ω - Mean	ω - 95th	Reproduction Number ($R_t = \beta/\gamma$)	Average Infectious Period ($1/\gamma$)	Average Immunity Period ($1/\omega$)
2013–2014	0.63	1.46	2.06	0.01	0.10	0.19	0.003	0.011	0.019	14.6	10.0 days	90.9 days
2017–2018	0.02	0.14	0.35	0.00	0.08	0.22	0.003	0.007	0.015	1.75	12.5 days	142.9 days
2020–2021	0.01	0.10	0.26	0.00	0.06	0.12	0.003	0.010	0.019	1.67	16.7 days	100.0 days
2024–2025	0.00	0.06	0.14	0.00	0.03	0.08	0.002	0.006	0.013	2.00	33.3 days	166.7 days

Note: This table summarizes the dynamic SIRS calibration across selected BTC bubble periods. The transmission rate (β), recovery rate (γ), and re-entry rate (ω) are reported using only positive parameter values. For each parameter, the table reports the 5th percentile, mean, and 95th percentile, reducing the influence of zero values and extreme observations. The columns report the simulated compartment ranges, generated by the calibrated SIRS model. These estimates represent the evolution of BTC users across the three epidemiological states.

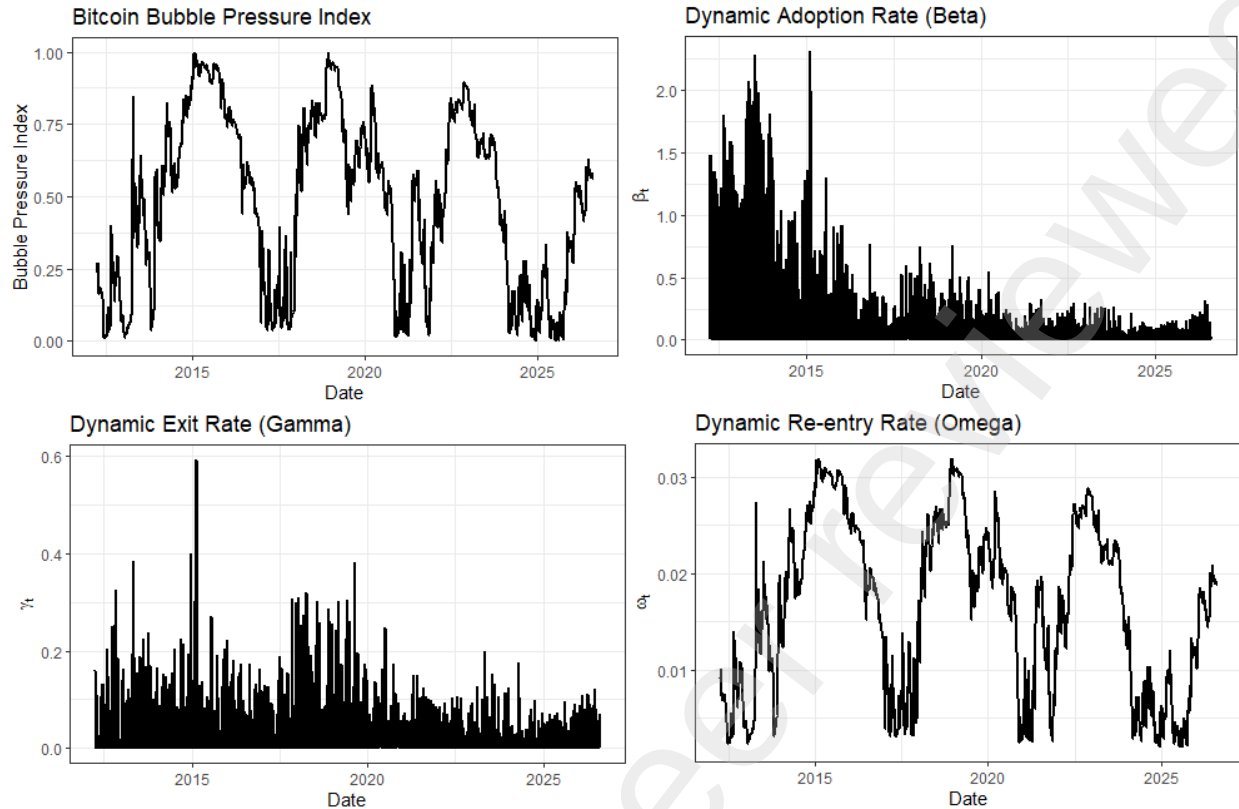
Table 3 presents dynamic SIRS calibration across diverse BTC bubble episodes. The table presents estimations related to infection, recovery, and re-entry rate. These are the parameters used to derive reproduction, active participation and inactivity duration. The reproduction number ($R_t = \text{Mean } \beta / \text{Mean } \gamma$) is indicative of the rate at which active participation is spreading within the BTC ecosystem. The presence of values greater than one is telling of an increase in the number of active participants, thereby suggesting a stronger adoption rate. The mean infectious period ($1/\text{Mean } \gamma$) is defined as the average number of days a user remains active prior to entering a state of inactivity. The average immunity (inactive) period ($1/\text{Mean } \omega$) is defined as the average number of days that an inactive user stays outside the active market until they become susceptible to re-entry.

The results indicate substantial variations in participation dynamics across distinct bubble episodes. In epidemiological terms, the reproduction number is indicative of the degree to which participation is transmitted from active users to potential newcomers. The 2013-2014 bubble had the largest reproduction number (14.6) and the lowest average infectious period (10 days). These results suggest that users became

active relatively quickly but remained active for only a short period. This situation may be attributed to the early stage of BTC's existence, during which its recognition was primarily confined to technology experts (Catalini and Tucker, 2017). It is evident that over time, cryptocurrencies have transformed from entirely unfamiliar financial instruments to reach a substantially broader population of users (Steinmetz et al., 2021). Concurrently, the number of participants during that period was comparatively limited, while the inflow of new users represented a substantial increase in comparison to the existing users. In subsequent bubbles, the reproduction numbers were considerably lower (1.75, 1.67, and 2.00), indicative of an expanded user population and a more established BTC infrastructure. Concurrently, the average active period becomes longer, reaching 33.3 days in the 2024–2025 bubble episode. This suggests that participation is increasingly becoming a long-term commitment.

Significant changes are also observed in the average immunity period, representing the time users remain inactive before becoming susceptible to re-entering the market. This figure increased from 90.9 days in the 2013–2014 reporting period to 166.7 days in the 2024–2025. In epidemiological terms, immunity period lengthens the time it takes for recovered individuals to become susceptible again. This suggests that it may require a longer period of time for previously active users to once again become potential participants. The results obtained show substantial changes in the nature of participation over time. The earlier bubble was defined by the rapid spread of "infection" and high rates of participation. However, later bubbles reveal a more gradual spread of infection, yet persistently high levels of active participation. This shift could suggest that the BTC ecosystem is transitioning from being a highly speculative instrument to a more stable and well-established market. In summary, early bubbles were identified by a faster spread of infection and a shorter participation period. Later bubbles, however, showed a slower rate of infection, yet a more sustained level of active participation. Figure A.2, located in the appendix, provides a visual representation of the developments that have occurred within the BTC ecosystem over the sample period. Over time, the total number of wallets, active addresses and transactions tends to increase. The figure indicates that the most important market fluctuations occurred during periods of highly limited ecosystems. In contrast, subsequent market cycles were characterized by a substantially larger user base, encompassing active wallets and users, and a considerable surge in transaction activity.

Figure 2. BTC Bubble Pressure Index and dynamic SIRS transition rates



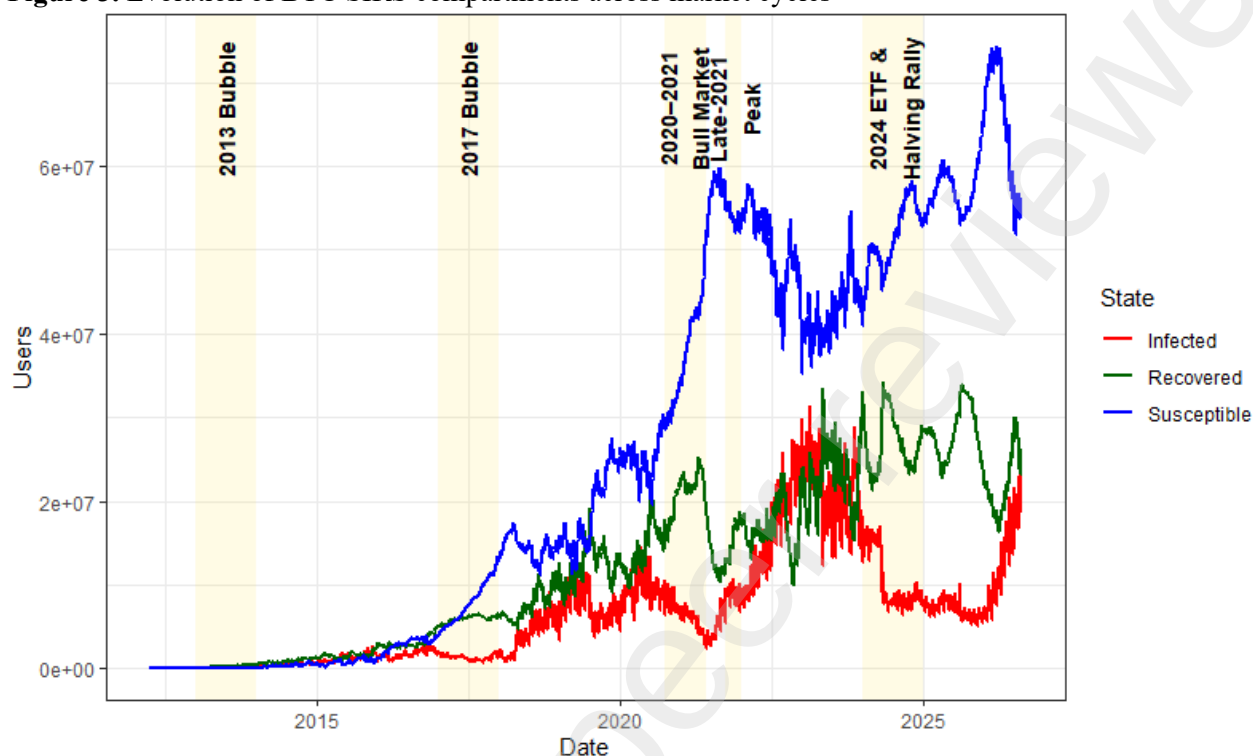
Note: The figure shows how the Bitcoin Bubble Pressure Index (BPI) has changed over time, alongside the adoption rate (β_t), the exit rate (γ_t) and the re-entry rate (ω_t). The series stand on daily basis and cover the period from 1 January 2012 to 31 July 2026. The BPI reflects market speculation, while β_t , γ_t and ω_t illustrate changes between susceptible, infected and recovered compartments. A higher β_t indicates a strong shift from the susceptible state to the active (infected) state. Conversely, a higher γ_t value suggests a quicker transition from active to inactive state, while a higher ω_t value highlights a faster return from recovered to susceptible status.

Figure 2 shows how participation dynamics have evolved within the BTC ecosystem over the years. The transmission rate (β_t) was initially high, but declined as the market expanded. Initially, BTC was primarily known within the tech community, but from 2016 onwards it became popular among risk-seeking investors. However, as BTC became more widely accepted and its user numbers increased, new users accounted for a smaller proportion of the population, resulting in lower transmission rates. The recovery rate (γ_t) showed regular spikes, being very high in the early periods and dropping in the later ones. This phenomenon can be attributed to the fact that, in the early stages of BTC's existence, participants would enter the market and rapidly exit by liquidating their positions. This was mainly because it was widely unknown and highly unpredictable. However, it withstood numerous successive shocks over the years and established itself as a reliable instrument, which resulted in lower exit rates. This suggests that, after a certain period, participants started to hold onto their units rather than rapidly liquidating them.

The re-entry rate (ω_t) exhibits different behavior, tracking movements in the Bubble Pressure Index. Higher re-entry rates are observed during periods of high bubble pressure, while lower rates are seen when speculative pressures decline. In the context of the SIRS model, high speculative pressure prompts many inactive users to re-engage with the market. This pattern aligns with economic logic, as rapid price growth and renewed market attention attract former BTC participants back to the marketplace. Ultimately, the high

infection and exit rates observed in BTC's initial stages transitioned to lower rates as the ecosystem matured. Meanwhile, the re-entry rate remains closely associated with speculative market conditions.

Figure 3. Evolution of BTC SIRS compartments across market cycles



Note: This figure visualizes the alterations to the three user categories within the BTC SIRS framework. These compartments consist of the Susceptible (S), Infected (I) and Recovered (R) groups. The series covers the period from 1 January 2012 to 31 July 2026, based on daily frequencies. The susceptible users represent individuals who have the potential to participate in the ecosystem. Infected users are active participants who directly influence the price, while recovered users are inactive participants who could become active again at any time. The shaded area highlights the major BTC speculative episodes.

Figure 3 shows the complete implementation of the dynamic SIRS model within the context of BTC bubble episodes. During the 2013–2014 bubble, the 'infected' population increased relatively within a small base, reflecting the early stages of adoption. The 2017–2018 bubble was characterized by a much faster increase in the size of the 'infected' population, coupled with a substantial expansion of the participant base. Notably, the largest growth took place during the 2020–2021 bull market, when the infected group expanded sharply as more users became active. Concurrently, the 'recovered' population (exit rate) increased at a similar rate. The combination of a lack of intrinsic value and a limited regulatory framework resulted in high infection and recovery rates, meaning that BTC offered the potential for both substantial gains and severe losses. The period was also characterized by numerous scandals and Ponzi schemes. During times of decreasing market activity or when a bubble bursts, there are rapid shifts between active and inactive users.

The 2024–2025 period shows a further increase in the number of infected users, which is consistent with strong interest in the crypto industry. Unlike the initial bubbles, the population of susceptible and recovered individuals is much larger. This reflects BTC's sustained growth over time. In the aftermath of market peaks, there is a decline in the number of infected users, accompanied by an increase in recovered users. This is indicative of a shift in which many previously active users become inactive when market conditions

deteriorate. Within the SIRS model, this denotes evident transitions from the infected (active) phase to the recovered (inactive) status as market activity decreases. To summarize, the predominant waves of active participation, inactivity, and re-entry occur during major speculative cycles.

Another interesting observation is that each successive bubble emerges within a significantly larger user population. Despite the fact that the infection rate (β) declines over time, the absolute number of infected users increases exponentially, particularly during speculative periods. This observation indicates that a low infection rate in the initial stage does not signify weak activity. Instead, new infections occur within a substantially larger and more developed BTC ecosystem, resulting in a considerably expanded bubble growth. In this context, even a lower rate can be linked to a large number of active users. In 2017, the infection rate was high, but the population was significantly smaller. Later, despite a lower β , the susceptible population is considerably larger, thus involving a greater number of users and a more substantial bubble explosion.

5.2. BTC Contagion, Participation, and Re-entry

This section provides a detailed examination of when contagion reaches its peak and how participation is distributed across SIRS states. The analysis focuses on peak intensity, timing, and alterations within the compartments. A particular focus is placed on the dynamics of entry, exit and re-entry, which offer further insight into the development of participation as the ecosystem expanded. This distinction is important for the SIRS model, as re-entry through the transition from $R \rightarrow S$ constitutes the main difference from the traditional SIR model.

Table 4. Peak BTC contagion across speculative episodes

Bubble	Peak β	Date of Peak β	Peak Infected Users	Date of Peak Infected	Peak BPI	Date of Peak BPI	Peak γ	Date of Peak γ
2013–2014	2.283	2013-07-09	433,349	2014-01-07	0.847	2013-04-16	0.385	2013-05-02
2017–2018	0.595	2017-11-13	2,351,282	2018-01-08	0.595	2018-01-24	0.311	2018-01-14
2020–2021	0.321	2021-09-27	10,728,734	2021-11-10	0.591	2021-07-19	0.150	2021-06-06
2024–2025	0.217	2024-01-24	17,055,698	2024-04-31	0.455	2024-01-25	0.176	2024-04-23

Note: This table reports the peak contagion characteristics during the four major speculative periods. Peak Beta represents the maximum infection rate, while Peak Infected Users represents the maximum number of active participants during each period. Peak BPI represents the maximum value of the BTC Bubble Pressure Index, while Peak Gamma represents the maximum recovery or exit rate. The corresponding dates identify when each peak occurred within the respective speculative cycle. Peak infection (β) and recovery rates (γ) measure the maximum daily values during each speculative episode. The peak infection and recovery rate are calculated as follows: $\beta_j^{Peak} = \max_{tej}(\beta_t)$ while $\gamma_j^{Peak} = \max_{tej}(\gamma_t)$. The dynamic infection rate is defined as $\beta_t = \beta_{obs,t}(1 + 2BPI_t)$ while dynamic recovery rate stands as $\gamma_t = \gamma_{obs,t}(1 + |Drawdown_t|)$.

Table 4 provides supplementary evidence with regard to changes in BTC contagion attributes during speculative phases. The intensity of peak infection underwent considerable decline over the observed period, with the β value decreasing from 2.283 in 2013–2014 to 0.217 in 2024–2025. Conversely, the number of peak infected users exhibited an increase, rising from 433,349 active addresses on January 7, 2014, to 17,055,698 on April 30, 2024. The timing of these peaks suggests that the intensity of infection, participation and recovery do not all reach their maximum values at the same time. This distinction is particularly pronounced in the 2017–2018 period, where β peaked on 13 November 2017, followed by the peak in infected users on 8 January 2018, and the peak in γ on 14 January 2018. Such sequencing shows that intensity of transition into active participation may decline before the stock of infected participants reaches its maximum. This pattern, however, is not consistent across all speculative periods, indicating that the dynamics of entry, active participation, and exit vary between cycles. It is important to note that the

infected users presented by the active addresses, does not exclusively refer to new buyers. Accordingly, high levels of infected may occur during both market expansions and downturns, as participants continue to engage in buying, selling, transferring, or interacting with the network.

Table 5. BTC SIRS compartments across speculative episodes and their participation flow

Panel A: Bubble	Mean Population	Susceptible (%)	Infected (%)	Recovered (%)
2013–2014	534,574	6.39	26.54	67.06
2017–2018	15,813,401	51.36	9.48	39.17
2020–2021	70,663,721	64.37	9.69	25.94
2024–2025	90,835,598	59.64	9.94	30.42
Panel B: Bubble	Avg. Daily Entries	Avg. Daily Exits	Avg. Daily Re-entries	Re-entry/Exit Ratio
2013–2014	7,256	6,148	4,138	0.673
2017–2018	47,658	50,626	43,859	0.866
2020–2021	165,700	161,931	160,921	0.994
2024–2025	143,711	158,131	170,286	1.077

Note: In Panel A, the compartment shares are expressed as percentages of the total simulated SIRS population in each period. In Panel B, entries represent daily transitions from the susceptible to the infected state ($S \rightarrow I$), exits represent daily transitions from the infected to the recovered state ($I \rightarrow R$), and re-entries represent transitions from the recovered to the susceptible state ($R \rightarrow S$). The re-entry/exit ratio measures the number of returning participants relative to exiting active participation. Daily re-entry is calculated as $Re - entry = \omega_t R_t$, where $\omega_t = 0.002 + 0.030BPI_t$. Average daily re-entry is the mean of the daily $R \rightarrow S$ flows within each speculative period. The re-entry/exit ratio is calculated by dividing average daily re-entries by average daily exits.

As demonstrated in Table 5, there are significant changes in the structure and flow of BTC participation during speculative cycles. Panel A shows that the SIRS population increased markedly, growing from 534,574 in 2013–14 to 15.81 million in 2017–18, 70.66 million in 2020–21 and 90.84 million in 2024–25. The infected share exhibits a decline, from 26.54% in the initial cycles to between 9% and 10% in all subsequent periods. The susceptible share increases from 6.39% in 2013–14 to 59.64% in 2024–25. This suggests that a fall in the proportion of infected users does not necessarily indicate a decline in market participation. Initially, the vast majority of susceptible individuals traded BTC because it was a highly volatile and unknown financial instrument. However, in later periods, it withstood numerous shocks and began to be held as a long-term investment, which explains the increase in the number of susceptible individuals.

In Panel B, the average daily entries increased from 7,256 in 2013–2014 to 47,658 in 2017–2018 and 165,700 in 2020–2021, before remaining high at 143,711 in 2024–2025. Concurrently, average daily exits escalate from 6,148 in 2013–2014 to 158,131 in 2024–2025. This rise is coupled with an even more pronounced increase in re-entry flows, which surge from 4,138 to 170,286 participants per day. Thus, earlier speculative periods contain a smaller infected share but a much larger number of participants flow, which reflects the larger BTC ecosystem. A notable finding is the re-entry/exit ratio, which exhibits a steady increase from 0.673 to 0.866, 0.994, and ultimately 1.077. This finding suggests that the re-entry rate was initially lower than the flow of participants leaving the active state. However, in the final cycles (e.g., 2020–2021 and 2024–2025), the re-entry rate eventually surpassed that flow.

These results suggest that the pool of previously inactive participants is increasingly returning to a susceptible state. While 67 participants re-entered the susceptible pool for every 100 participants in 2013–2014, this ratio increased to 99 in 2020–2021 and 108 in 2024–2025. This finding suggests that, over time, withdrawal became less frequent within the ecosystem. Consequently, subsequent cycles were

characterized by a stronger return of formerly active participants to the susceptible state. The findings presented here provide compelling arguments for using the SIRS framework instead of the conventional SIR framework. In this context, by allowing recovered participants to return to the susceptible state, the SIRS model more effectively captures the dynamics of exit and re-entry trends.

5.3. Comparing BTC SIRS Dynamics with Infectious Diseases

This section compares the dynamics of BTC SIRS model with those of representative infectious diseases. This comparison involves the analysis of various epidemiological parameters, including infection rate, recovery, reproduction, incubation period, and the duration of the infectious disease. The parameters are used as benchmarks in the analysis of the BTC contagion characteristics.

Table 6. Representative SIRS/SIR parameters reported in epidemiological studies

Disease / System	β	γ	R_0	Incubation Period	Average Infectious Period	Supporting studies
Seasonal Influenza	0.20–0.60	0.14–0.33	1.2–1.8	1–4 days	5–14 days	Biggerstaff et al., (2014); Stone et al., (2025)
COVID-19 (Original strain)	0.30–0.90	0.07–0.20	2.0–3.5	2–14 days	7–10 days	Alimohamadi et al., (2020); Wang et al., (2021)
Measles	1.50–3.50	0.10–0.20	12–18	10–14 days	7–14 days	Guerra et al., (2017); Delamater et al., (2019)
Mumps	≈ 0.41	≈ 0.125	4–7	12–25 days	7–9 days	Hilton and Keeling, 2019
Pertussis (Whooping Cough)	≈ 0.71	≈ 0.048	≈ 17	4–22 days	≈ 22 days	Rozhnova and Nunes, 2012
Chickenpox (Varicella)	0.40–1.20	0.07–0.14	8–12	10–21 days	10–20 days	Giraldo and Palacio (2008)
Ebola	0.27–0.45	0.05–0.18	1.5–2.5	2–21 days	5–14 days	Althaus (2014)

Note: The values are epidemiological benchmarks derived from SIR/SIRS models and should not be interpreted constant. The parameter estimates vary across populations, outbreak periods, model specifications and time units. The transmission rate is denoted by β , the recovery rate by γ , and R_0 is the basic reproduction number. In standard SIR/SIRS formulations, the average infectious period is approximated by $1/\gamma$. In the context of pertussis, the β value is an estimated coefficient derived from the following equation: $\beta = R_0\gamma$.

Table 6 compares the characteristics of infectious diseases with those of BTC, using an epidemiological framework. The findings suggest that BTC's epidemiological profile does not align with a particular infectious disease. Instead, it exhibits a shift in its epidemiological characteristics as the ecosystem evolves. During the 2013-2014 BTC bubble period, the reproductive rate was 14.6, and the infectious period 10 days. In terms of the reproduction number, BTC is comparable to highly contagious diseases such as measles ($R_0=12-18$) and pertussis ($R_0 \approx 15$). This finding suggests that in its early stages, BTC may exhibit characteristics of highly transmissible diseases. However, in later periods, the transmission rate is lower, but the persistence of infected individuals is prolonged.

The epidemiological profile of BTC underwent substantial changes during successive speculative periods. The reproduction number decreased to 1.75 during the 2017–2018, 1.67 during the 2020–2021, and 2.00 during the 2024–2025. This made BTC analogous to moderately infectious diseases like seasonal influenza and COVID-19. These results align with those of Aliu (2024), who compares the BTC narrative to that of COVID-19 omicron strain. His findings originate from a static SIR model, in which the parameters of infection and recovery are derived from a regression of BTC closing prices. In contrast, Shiller (2017) draws parallels between the BTC narrative and the Ebola outbreak, which is confined to specific regions of sub-Saharan Africa. However, BTC's distribution is global, and its characteristics are more akin to those of global pandemics than to those of localized epidemics.

On the other hand, BTC's average infectious period increased from 10 days in 2013–2014 to 12.5 days in 2017–2018, 16.7 days in 2020–2021, and 33.3 days in 2024–2025. This indicates a significant shift in the dynamics of the infection rate, which became less intense. However, once users become infected (active),

they tend to remain in that state for a prolonged period. The 2024–2025 infectious period is of particular interest as it exceeds the typical infectious periods documented in the speculative cycles. The average duration for which BTC users remain in the infected (active) state was 33.3 days, which is longer than the infectious period of most diseases reported in Table 4. However, longer-lasting infections, such as tuberculosis, demonstrate that infectious states can persist considerably longer depending on the nature of the disease.

Overall, the early developmental stages of BTC are similar to those of highly infectious diseases such as measles and whooping cough. Later bubble periods are comparatively similar to diseases like seasonal influenza or SARS-CoV-2. This shows that BTC moves from highly infectious diseases to more persistent ones. The evolving nature of BTC might be analyzed by considering its propagating influence. During the early period, BTC demonstrated characteristics consistent with an epidemic, as it rapidly spread within a small population of participants. As the ecosystem expanded internationally, later cycles had a broader, pandemic-like reach, spreading across a larger population despite a lower infection rate. The findings of the present study are in support of, and in some ways contradictory to, those reported by Aliu (2025). Utilizing the SIR framework and monthly data, he documented variations in infection and recovery rates during two successive bubbles. In contrast, the present study employs daily data and the dynamic SIRS model to reveal more pronounced epidemiological parameters for BTC. In comparison with the findings of Aliu (2025), the present study demonstrates that the reproduction number decreased from 14.6 in 2013–2014 to between 1.67 and 2.00 in subsequent cycles. The current findings reinforce earlier evidence of BTC's pandemic-like reach by showing that its epidemiological patterns have changed alongside the development of the ecosystem.

6. Conclusions

This study analyses BTC marketplace participation using the SIRS epidemiological model. By categorizing users as susceptible, infected (active) and recovered (inactive), this study provides an alternative view of how BTC activity evolves during speculative cycles. The contagion does not remain constant over time, rather it changes as the ecosystem grows and matures. There are important differences between early and later bubbles. Specifically, the 2013–2014 period was characterized by a high reproduction number and a relatively short infectious period. In the early years, even small increases in the number of active users can lead to large proportional changes within the ecosystem. This suggests that the infection spreads quickly within a small population of users who remain active for a short time. In the 2017–18, 2020–21 and 2024–25 speculative cycles, the reproduction number falls substantially, while the infectious period gradually rises. As the population grows in later periods, a lower infection rate is associated with a significantly higher number of active infected users. This suggests that users were active for longer periods of time, demonstrating greater persistence. Meanwhile, the BPI and the dynamic re-entry mechanism suggest that speculative conditions are important in attracting previously inactive participants back to the marketplace.

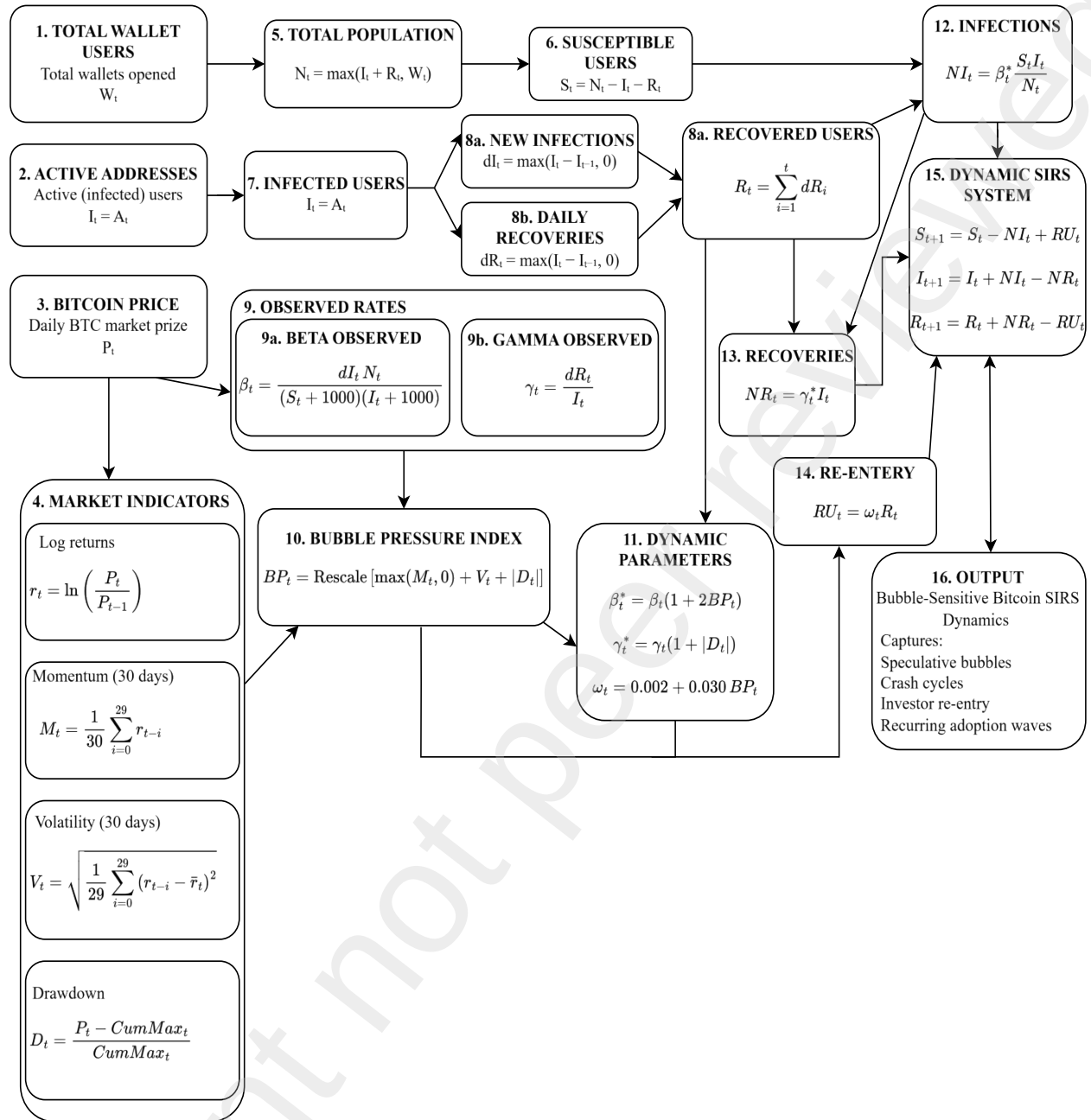
A comparison with infectious diseases offers further insight into the speculative nature of BTC over time. The early speculative cycles present a high reproduction rate, which is similar to that of highly contagious infectious diseases such as measles and pertussis. However, in later cycles, it is more comparable to diseases such as influenza and the original strain of SARS-CoV-2. In this sense, the initial stages can be viewed as epidemic-like, characterized by high infection rates but confined to a small population. Conversely, later cycles exhibit features of a widespread pandemic, with lower infection rates but spreading to a much larger

population. This may be because BTC was initially mainly known among technology-oriented users. However, in later periods, it gained much wider recognition and adoption across different countries and user groups worldwide. Rather than being taken as strict epidemiological classifications, these terms should be considered as analogies for describing the scale and patterns of diffusion.

Altogether, the results indicate that the epidemiological nature of BTC has evolved alongside the market itself. More specifically, it has shifted from a small ecosystem of rapid contagion to a larger system of repeated infection, recovery, re-entry and persistent active participation. Therefore, the SIRS model presents a novel perspective not only on how participation spreads, but also on how users leave and subsequently return during new speculative cycles. Additionally, these findings demonstrate the potential application of epidemiological models beyond the field of finance, to areas such as politics and religion.

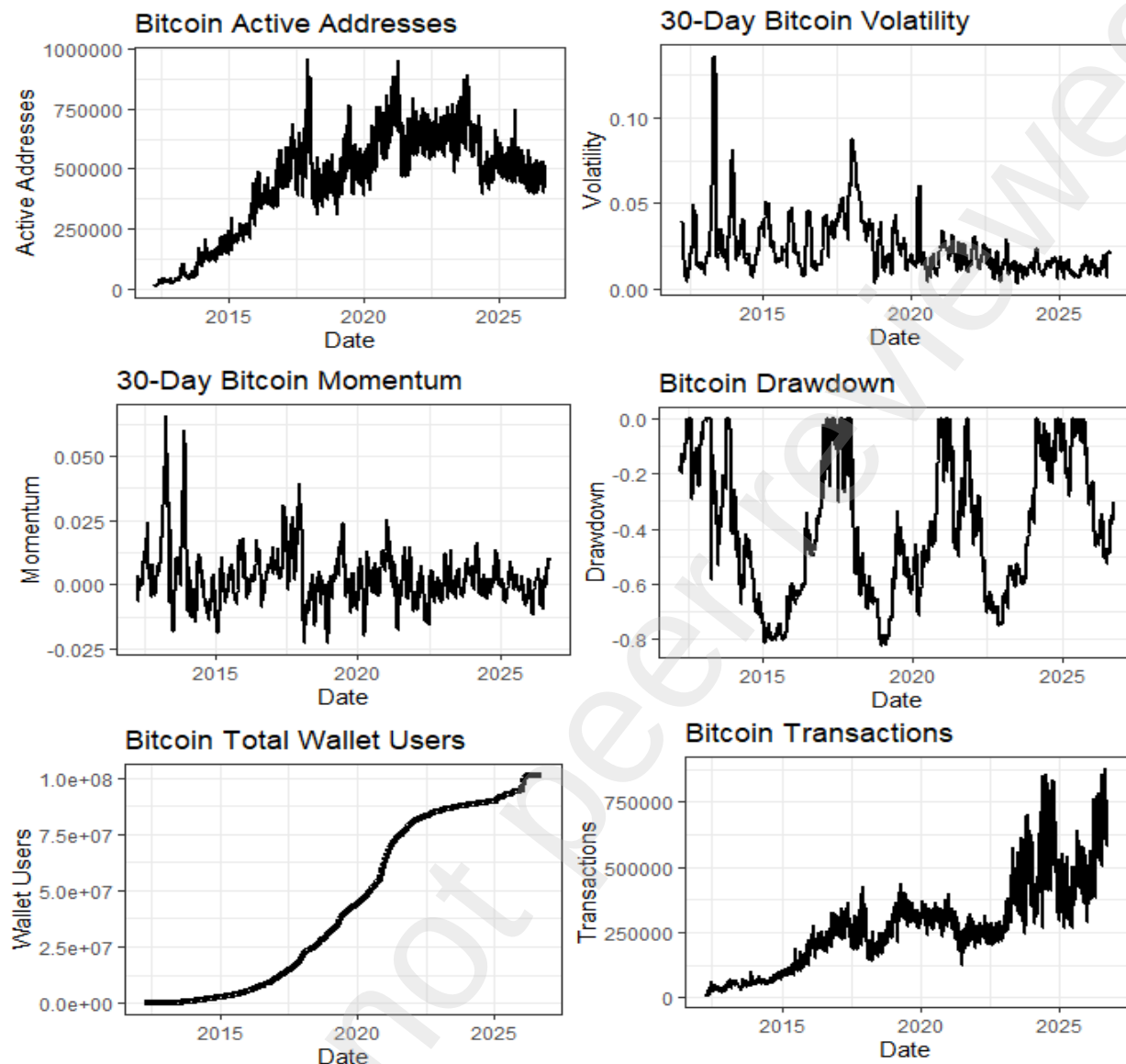
Appendix:

Figure A.1. Conceptual Framework of the Dynamic Bubble-Sensitive SIRS Model for BTC Adoption and Market Dynamics



Note: The figure provides a schematic representation of the methodological process of the BTC dynamic SIRS mathematical model. The framework uses blockchain variables to construct the susceptible (S), infected (I), and recovered (R) user populations. The BPI, calculated from drawdown, momentum, and volatility, serves to adjust the dynamic nature of the infection rate (β), recovery rate (γ), and re-entry rate (ω).

Figure A.2. Evolution of BTC market activity, user adoption, and speculative conditions



Note: This figure illustrates BTC market and network indicators. The series covers the period from 1 February 2012 to 31 July 2026, with daily frequencies. Total wallet users represent the size of the BTC ecosystem while active addresses capture blockchain activity. These indicators include 30-day momentum, 30-day volatility, and absolute drawdown. Momentum is calculated as the 30-day rolling mean of BTC log returns. Ultimately, volatility stands as the 30-day rolling standard deviation while drawdown is the percentage decline from the historical price.

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