

**ISBN 9798276833170 “Behavioral Determinants of Volatility: A Synthesis of
Perspective Theory and Post-Keynesian Instability Dynamics”.**

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Content of Graduate Program in Economics Post-Keynesian Macroeconomics Course
Advanced Econ Theory. Post-Keynesian²

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I have no known conflict of interest to disclose.

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Abstract

Financial volatility is traditionally modeled as a statistical or structural feature of markets, yet mounting evidence suggests that a substantial share of short-term price dynamics originates in the cognitive architecture of economic decision-making. This paper proposes a heuristic-based theory of volatility that integrates insights from behavioral cognition, Prospect Theory, and post-Keynesian uncertainty. Drawing on Kahneman's dual-system framework, we argue that volatility is not merely a reaction to fundamentals but a cognitive artifact emerging from the dominance of fast, intuitive, and emotion-driven heuristics under conditions of uncertainty. Through a synthesis of Minsky's financial fragility hypothesis and modern behavioral evidence, we show that the interaction between loss aversion, availability-driven risk assessment, anchoring effects, and representativeness heuristics generates predictable patterns of overreaction, underreaction, and excess volatility. Using a mixed-method approach combining theoretical modeling with empirical stylized facts, we demonstrate how heuristic reactivity shapes volatility clusters, market cycles, and episodes of fragility. The paper concludes that financial instability cannot be fully understood without incorporating cognitive distortions, and calls for renewed macro-financial architecture that recognizes volatility as a behavioral phenomenon embedded in the psychological structure of decision-making rather than as a mere statistical irregularity.

Keywords: Volatility, Behavioral Heuristics, Post-Keynesian Economics.

Introduction

Contemporary economics can only be understood from the interplay between cognition, uncertainty, and financial structures, and it is at this point that Kahneman's cognitive framework reveals its explanatory force by connecting deeply to the Keynesian and post-Keynesian traditions. The human mind operates through two systems—one intuitive, fast, and emotional, the other deliberate, analytical, and slow—but the real economy and financial markets coexist predominantly under the logic of the first, System 1, which reacts to environmental stimuli with mental shortcuts, heuristics, and biases that shape collective behaviors. In environments of volatility, uncertainty, and risk, this automatic system becomes dominant, replacing critical analysis with immediate perceptions that distort probabilities and lead agents to decisions that are apparently irrational, but cognitively coherent with the structure of human survival.

Thus, financial volatility is the result of the interaction between human cognition, endogenous financial structures, and expectations regimes, and not just rational shocks on fundamentals.

When shocks occur, markets do not process them by mediating rational expectations, but by amplifying the psychological availability of events. What is easily remembered is perceived as more likely, and volatility increases the memory of falls, losses, and tragic narratives, intensifying fear and fueling herd reactions. This phenomenon overlaps with loss aversion, central to Prospect Theory, according to which the pain of losing is twice as intense as the pleasure of winning. In times of strong oscillation, each negative micro-movement triggers this emotional mechanism, leading investors to seek immediate liquidity or to hold losing positions in the hope of regaining a psychological, not economic, value. The brain anchors decisions to past prices, unjustifiably considered as natural reference points, and this anchoring multiplied by volatility produces cycles of buying and selling that do not respond to fundamentals, but to emotional perceptions of risk.

Representativeness, another essential cognitive mechanism, creates an almost automatic tendency to extrapolate the present to the future: prolonged highs seem eternal, and crises seem hopeless. In a volatile market, the investor looks at the latest price sequence and assumes that it represents the essence of the asset, ignoring production structures, balance sheets, or long-term indicators. Volatility turns noise into signal, converting micro-events into broad narratives about trends. This feeds both the logic of bubbles and the dynamics of abrupt drops, because the human mind, programmed to detect patterns quickly, sees them even when they don't exist.

These cognitive processes do not act in isolation: they feed back into structured environments. It is at this point that Kahneman aligns himself with the insights of Keynes and Minsky. For Keynes, economics operates under radical uncertainty, a form of ignorance that cannot be translated into probabilities. Social conventions emerge as collective responses to this ignorance, and when such conventions collapse, the system becomes unstable. Kahneman offers the psychological mechanisms that explain how

these conventions form, maintain, and unravel: anchoring, framing effects, availability, and dominant narratives shape aggregate behavior. Similarly, Minsky argues that periods of stability generate euphoria, leverage, and fragility—a logic that finds its micro-foundation in cognitive biases. Complacency, overconfidence, and underestimation of risk are precisely behavioral expressions of these heuristic mechanisms, which make the agent believe that the recent past is a safe guide to the future.

Ultimately, market volatility is the mirroring of human cognitive volatility. Each oscillation affects the psychology of the agents, who respond with immediate and often irrational adjustments, which amplify the initial movement itself. Prices become reflections of emotional states and not just objective expectations. The macroeconomics that emerges from this interaction is a complex system, in which external shocks are less relevant than the way they are interpreted and transformed into actions by agents subject to structural cognitive limitations. Heuristics are indispensable for navigating environments of uncertainty, but their use brings side effects: risk amplification, bubble formation, persistence of instability, and endogenous crises.

Thus, Kahneman's contribution transcends economic psychology: he offers the anatomy of human decision under uncertainty, providing the missing link between Keynesian intuition about instability and the Minskian mechanism of financial fragility. Economic behavior is not the result of perfect calculation, but of imperfect mental processes that operate adaptively in an unpredictable world. Modern economics can only be fully understood when we recognize that volatility and instability are not occasional failures of the system, but the natural result of human beings trying to survive cognitively in a universe of deep uncertainty.

Theoretical foundation

Understanding financial volatility requires a theoretical framework capable of incorporating cognitive, structural, and institutional elements that escape the traditional approaches of neoclassical economics. Although the Friedmanian tradition has established a paradigm based on rational agents, stable expectations, and markets that converge to efficient outcomes when adequately informed, the empirical evidence accumulated in recent decades demonstrates that price fluctuations—especially their volatility—are not satisfactorily explained either by fundamental shocks or by the hypothesis of fully efficient markets. In this sense, the theoretical convergence between Kahneman's economic psychology, Minskyan macrofinance, and Friedman's rationalist framework offers fertile ground for reinterpreting volatility as an essentially cognitive and structural phenomenon, emerging from the interaction between individual heuristics, expectations under uncertainty, and pro-cyclical financial regimes.

The starting point is to recognize that economic agents, contrary to what classical rationalism assumes, do not process information in an integral way or maximize its usefulness by analytical calculation. Instead, decision-making occurs predominantly through fast, intuitive, and heuristic processes, described by Kahneman as System 1, that overlap with long-range deliberative thinking (System 2), especially in environments of uncertainty. Prospect Theory's availability, anchoring, and representativeness heuristics, as well as loss aversion and reference dependence, structure how agents perceive risk, assess probabilities, and react to shocks. The result is not just individual error, but a collective pattern of amplified responses that can diffuse throughout the market. Volatility, in this context, emerges as an aggregate manifestation of the human cognitive architecture: what appears to be statistical market instability reveals itself as institutionally mediated psychological instability.

This cognitive dimension, however, does not operate in a vacuum. The financial structure highlighted by Minsky provides the macroeconomic mechanism by which the heuristic reactions of agents are converted into regimes of fragility and self-reinforcing cycles. In periods of apparent stability, when the observed volatility is low and the collective memory of severe shocks becomes less "available", agents and institutions increase leverage, relax credit standards and increase risk exposure. This phase, dominated by a heuristic optimism derived from recent patterns, establishes the fragility that will trigger strong swings when a highlighted event reactivates loss aversion and rapidly erodes confidence. Thus, when the environment changes — due to negative news of high salience or institutional ruptures — System 1 of the agents takes over, converting cognitive heuristics into hasty decisions to sell, reduce positions and search for liquidity. The process becomes systemic when highly leveraged institutions respond simultaneously, leading the market to abrupt movements that translate into clusters of volatility, crashes, and prolonged instability. Financial volatility, therefore, is not simply a transitory deviation from rational equilibrium, but the macroeconomic materialization of individual cognitive patterns amplified by endogenous financial structures.

The contrast with Friedman becomes fundamental not to deny the importance of rationality or the role of expectations, but to enrich the understanding of how expectations are actually formed. The Friedmanian view, based on not necessarily realistic hypotheses and adaptive expectations, is based on the assumption that agents learn from mistakes, update their predictions based on past data, and, over time, approach efficient behavior. However, when we insert scenarios of true uncertainty — where the future is not probable — the adaptive process gives way to discontinuous heuristic processes. Instead of simple adjustments of expectations, there is an abrupt alternation of perceptions, dominant narratives and emotional regimes. The rationality that Friedman postulates functions as a counterfactual reference, useful for comparison, but unable to explain the instability observed empirically. The point is not to deny rationalism, but to show that it is insufficient to explain endogenous volatility and that only by integrating it with cognitive psychology and systemic financial structure can a complete theory be obtained.

Thus, the proposed theoretical architecture considers that financial volatility emerges from the conjunction of three central elements: (1) cognitive heuristics and behavioral biases that shape risk perceptions and reactions to events; (2) Minskyan financial structures based on leverage, fragility, and pro-cyclical feedback; and (3) expectations formed in a hybrid way between rational, adaptive and heuristic components, inconsistent with fully optimizing models. Volatility, therefore, ceases to be mere noise and is now seen as a structured, predictable and endogenous phenomenon to the interactions between human cognition and financial institutions. Salient events amplify availability; losses activate aversion; anchors make adjustments difficult; leverage transforms psychological shocks into systemic panics; Markets extrapolate trends because agents confuse recent patterns with future regularities. The market, in a way, behaves like a giant cognitive organism, subject to the same biases that affect individuals, but multiplied by financial mechanisms that amplify their effects.

This theoretical framework has profound implications for macroeconomic modeling, monetary policy, and financial regulation. If volatility is largely a product of cognition and structure, stabilizing policies must act on both institutional incentives and the cognitive conditions that shape decisions. Macroprudential rules should limit leverage in times of heuristic euphoria, while central banks should recognize that communication, narratives, and expectation management have psychological effects as relevant as traditional instruments. Stability now depends less on "exogenous shocks" and more on managing the cognitive and financial conditions that determine how the economy reacts to inevitable uncertainties.

The theoretical framework, thus formulated, offers an integrated and modern explanation of volatility, uniting behavioral, structural and monetary elements. Volatility ceases to be a deviation of efficiency and is understood as an emergent characteristic of the interaction between the human mind and the financial system — a simultaneously psychological, institutional, and macroeconomic product, explainable only by a model that, like this one, articulates Friedman, Kahneman, and Minsky in the same conceptual logic.

Methodology

The methodology adopted articulates three complementary analytical layers, coherently integrating the modern theory of portfolios (Markowitz, 1952; Sharpe, 1964), economic and experimental psychology (Kahneman & Tversky, 1974; 1979; Thaler, 1985; Barberis et al., 1998) and the theory of financial instability (Minsky, 1975; 1986; Kindleberger & Aliber, 1978/2005). The first stage consists of a systematic survey of the literature, whose objective is to identify the cognitive, financial and dynamic structures relevant to the formation of portfolios under radical uncertainty. A theoretical-methodological triangulation protocol is followed that combines: (i) the heuristics and biases documented in the behavioral literature — loss aversion, availability effect, anchoring, and representativeness — as described by Kahneman and Tversky in *Judgment Under Uncertainty* (1974) and *Prospect Theory* (1979), expanded by Thaler in *Mental Accounting* (1985) and by the learning models of Barberis, Shleifer & Vishny (1998); (ii) Minsky's framework of financial instability exposed in *John Maynard Keynes* (1975) and *Stabilizing an Unstable Economy* (1986), complemented by Kindleberger in *Manias, Panics and Crashes* (1978/2005); and (iii) the rational risk modeling of Modern Portfolio Theory established by Markowitz in *Portfolio Selection* (1952) and expanded by Sharpe in the *Capital Asset Pricing Model* (1964). Each author and work is codified in analytical categories — cognitive heuristics, leverage regimes, expectation conventions and nonlinear price dynamics — allowing the formation of a conceptual framework where volatility is understood as an emerging phenomenon, a reflection of interactions between behavior, financial structure and shocks.

Based on this framework, two distinct investor models are implemented. The first is the rational agent in Markowitz's strict sense, whose decision-making process follows the mean-variance rule, assuming stable distribution of returns, full rationality, and preferences independent of the emotional context. Your decision is represented by maximization

$$(1) \quad \max_w \quad w' \mu - \frac{\gamma}{2} w' \Sigma w,$$

whose first-order solution provides

$$(2) \quad w^* = \frac{1}{\gamma} \Sigma^{-1} \mu.$$

The second agent is the behavioral investor inspired by the literature of Kahneman and Tversky, whose decisions follow the value function of the Prospect Theory, sensitive to the asymmetry between gains and losses:

$$(3) \quad v(x) = \begin{cases} x^\alpha, & x \geq 0, \\ -\lambda(-x)^\beta, & x < 0, \end{cases}$$

with capturing loss aversion identified empirically in $\lambda > 1$ (Prospect Theory (1979)). To this structural element are added heuristics documented in the behavioral literature: availability (Kahneman & Tversky, 1974), anchoring (Tversky & Kahneman, 1974), representativeness (1974) and mental accounting (Thaler, 1985). Or, the model also incorporates an "emotional reactivity" mechanism inspired by Barberis et al. (1998), in

which recent volatility increases the subjective weight of risk and adjusts the proportion of wealth allocated to the cryptoasset.

The numerical simulation stage operates with synthetic series of crypto asset prices, built under two distinct regimes. In the exogenous regime, an abrupt external shock equivalent to -25% is introduced, representing an isolated macroeconomic event – consistent with the tradition of external shocks described in the international finance literature. In the endogenous regime, a moderate initial shock is adopted that activates a behavioral feedback mechanism inspired by Minsky (1986) and Kindleberger (1978/2005), in which the probability of panic — constructed from cognitive heuristics — amplifies falling movements when certain thresholds are crossed. The returns are converted into price series and transformed, through the decision rules of each agent, into wealth trajectories, portfolio weight dynamics, and risk metrics.

The results are presented in graphical panels that display: (i) the price trajectories under each regime; (ii) the evolution of the portfolio weights for both investors; (iii) accumulated wealth; (iv) volatility in 30-day moving windows; and (v) synthetic indicators such as maximum drawdown, annualized volatility and turnover. In addition, comparative tables condense these metrics for each combination investor \times regime, allowing the observation of systematic differences between static rationality and heuristic behavior in environments with dynamic instability.

This methodology reveals that the volatility of the cryptoasset is not only a consequence of exogenous shocks, but a product of the interaction between cognitive structures, leverage mechanisms, and endogenous financial dynamics — according to the Minskyan interpretation. By integrating Markowitz, Kahneman, and Minsky into a single analytical procedure, it becomes possible to capture both the psychological and structural components of risk, offering a robust method to explain how individual heuristics can be amplified by financial structure, giving rise to cycles of instability consistent with empirical evidence and contemporary post-Keynesian theory.

Discussion

The discussion starts from the comparative tables of certain schools, lines of thought and rational understanding of behavioral economics between the Kahneman and Markovitz Portfolio Theory, in parallel with the evolution of economic thought to the current cryptocurrency heuristics.

1. COMPARATIVE CHART – Minsky, Traditional School and Kahneman

Cognitive Assumptions and Rationality

Theme	Traditional Line (Chicago / Neoclassical)	Post-Keynesian (Minsky and broader tradition)	Kahneman / Behavioral Economics
Rationality model	Strong rationality; agents calculate expectations rationally; Efficient markets	Rationality constrained by fundamental uncertainty (non- probabilistic); decisions are guided by conventions and financial fragility	Rationality limited by systematic biases; System 1 (automatic) x System 2 (analytical)
Dealing with uncertainty	Probabilistic risk → known distributions	True radical uncertainty, not measurable; decisions based on safety margins and structural instability	Heuristics replace rational calculus; biased decisions even in simple environments
Expectations	Rational; Mistakes are random	Conventional; depend on the state of trust	Heuristics: anchoring, representativeness, overconfidence

Nature of Markets and Stability

Theme	Traditional Chicago	Post-Keynesian (Minsky)	Kahneman
Market stability	Stable and self- regulating; instabilities come from external shocks	The cycle of instability is endogenous to credit; <i>"stability is destabilizing"</i>	Markets are prone to bubbles due to individual and collective cognitive biases
Financial crises	Chances, inappropriate policies or shocks	Inevitable result of the dynamics of leverage and speculative financing and Ponzi (Ch. 8–9)	Behavioral biases amplify manias, euphoria, and panic
Role of banks	Neutral intermediates	Banks create money endogenously; Central role in systemic fragility	Borrowers and banks suffer biases: overconfidence, underestimation of risk

Economic Psychology and the Role of Behavior

Theme	Chicago	Post-Keynesians	Kahneman
Psychology	Irrelevant; Stable preferences	Trust and the state of expectations are crucial (Keynes ch. 12) and expanded by Minsky	Central core of the analysis; Decisions are dominated by heuristics
Biases	They do not exist in balance	They may exist, but the point is radical uncertainty and not systematic biases	Clearly mapped: loss weighs more than gain (loss aversion), framing, etc.
Euphoria and panic	Irrational and residual	Collective behaviors endogenous to the financial cycle	Consequence of heuristics and overreaction

Financial Structure and Leverage

Theme	Chicago	Minsky (post-Keynesian)	Kahneman
Leverage dynamics	Rationally optimized; market discipline	Hedge → Speculative → Ponzi (Minsky typology)	Heuristics (overconfidence, illusion of control) lead to underestimation of risk
Origin of the bubble	Shocks, bad policies	Endogenous: prolonged stability → euphoria → financial innovation → fragility	Biases lead to undue projection of past trends
Role of financial innovations	Increase efficiency	They increase fragility when not regulated; validate risky practices	Acceleration of biases and herd behavior; Cognitive simplifications

Economic Policy

Theme	Chicago	Post-Keynesian (Minsky)	Kahneman
State	Minimum; Little intervention	Big Government + Big Bank as Automatic Stabilizers (Ch. 2–3)	Policies must consider biases: <i>nudges</i> , architecture of choice
Financial Regulation	Must be minimal	It needs to be strong, adaptive, countercyclical	It should reduce the arena to biased decisions

Theme	Chicago	Post-Keynesian (Minsky)	Kahneman
Macro policy	Rules (Taylor, Friedman)	Active intervention; guaranteed employment; Banking supervision	Behavioral intervention: automatic default, simplification of decisions

6. Minsky ↔ Kahneman Connection (and Post-Keynesian Behavioral Economics)

Points of convergence

- Both reject the full rationality of the mainstream.
- Both report processes of euphoria and panic as psychologically founded.
- Both consider instability as something generated by human agents in a predictable way.
- Both emphasize overconfidence as a trigger for risky behavior.

Points of difference

- Kahneman explains instability from *individual psychological biases*.
- Minsky explains instability from the financial structure and endogenous leverage, with psychology being an element but not the fundamental cause.
- Post-Keynesian behavioral economics sees heuristics as operating in an environment dominated by radical uncertainty —not as isolated failures.

The traditional Chicago school operates on the notion of endogenous stability, efficient markets, and rational expectations. In this framework, crises are anomalies or external shocks. Minsky, on the other hand, revitalizing the core of *General Theory*, shows that instability is born from within the financial system itself: tranquility in profits validates increasingly leveraged operations, leading to the hedge-speculative-Ponzi cycle.

Kahneman, in turn, introduces the psychological texture that was missing from the traditional macro: not only are markets structurally instable (as in Minsky), but agents have cognitive mechanisms that guarantee overconfidence, euphoria, anchoring, and herd behavior — reinforcing the process of fragility described by Minsky.

Thus, contemporary behavioral post-Keynesianism integrates the two worlds:

- the financial structure (Minsky),
- a incerteza radical (Keynes-Shackle),
- systematic psychological biases (Kahneman-Tversky).

Below I present (1) a complete timeline of the main economic schools, from the classics to behavioral economics and contemporary post-Keynesianism, and (2) an

organized and deep comparative table for evolutionary theoretical reflections on economic thought over the years.

1. Timeline of Economic Schools (Eighteenth → XXI Century)

1776 – Classical School

Adam Smith, Ricardo, Malthus

- Market mechanism, law of supply and demand
- Growth via capital accumulation and comparative advantages
- Confidence in the self-regulation of markets

1870–1920 – Marginalism / Neoclassical (1st phase)

Jevons, Menger, Walras, Marshall

- Marginal utility, individual rationality
- Partial and general equilibrium
- Prices as perfect signals

1910–1950 – American Institutionalism

Veblen, Commons

- Behavior influenced by institutions, habits, and culture
- Economics as an evolutionary system, not a mechanical one
(*first anti-rationalist seed*)

1936 – Original Keynesianism

Keynes (General Theory)

- Radical uncertainty
- Expectations and psychology (animal spirits)
- Effective demand determines product
- Inherent instability of capitalism

1950–1970 – Neoclassical Synthesis (Hicks–Samuelson)

- Artificial union between Keynes and neoclassicals
- IS–LM Model
- Markets tend to balance in the long run

1950–1975 – Post-Keynesianism (1st generation)

Kaldor, Robinson, Kalecki, Davidson

- Rejection of the neoclassical synthesis
- Uncertainty, expectations, income distribution
- Monetary economy of production

1960–1990 – Chicago School and Monetarism

Milton Friedman

- Strong rationality
- Aversion to state intervention
- Efficient markets hypothesis (Fama)

1970–1990 – New Classical Economics/RBC

Lucas, Sargent, Prescott

- Rational expectations
- Cycles come from real shocks
- Agents always maximizing

1974–2002 – Behavioral Economics

Kahneman & Tversky, Thaler

- Heuristics and biases
- Prospect Theory
- System 1 (rapid) and System 2 (analytical)
- Experimentation as a microeconomic basis

1975–1986 – Post-Keynesianism (2nd generation: Minsky)

Minsky

- Financial fragility
- Endogenous cycles of euphoria and crisis
- Collective psychology and leverage

1990–2025 – Modern Post-Keynesianism + Macro Behavioral

Shiller, Akerlof & Shiller, Dequech, Wray, Lavoie

- Behavioral microfoundations for uncertainty
- Behavioral finance + instability
- Liquidity, conventions, narratives

2000–2025 – Contemporary Integration

Behavioral Economics + Post-Keynesian + Finance

- Behavioral Portfolio Theory
- Crises as psychological and structural phenomena
- Complementation between heuristics and radical uncertainty

The neoclassical tradition, which dominated financial economics throughout the first half of the twentieth century, is based on a deeply optimistic conception regarding the measurability of risk and the ability of markets to aggregate information efficiently. From this point of view, price behavior reflects objective fundamentals, and the observed fluctuations are understood as random noise around an equilibrium value. Harry Markowitz, in formalizing portfolio theory, crystallizes this paradigm by treating risk as statistical variance of returns, implicitly assuming that this variance is stable and that first- and second-order moments adequately capture the uncertainty faced by agents. William Sharpe, in developing the CAPM, reinforces this structure by reducing the relevant risk to the systematic component, measurable by a constant covariance with the market.

In this theoretical framework, OLS estimation occupies a central position, as it allows the identification of mean relationships between returns and risk factors under clear hypotheses of linearity, homoscedasticity and serial independence. The initial empirical success of these models contributed to the consolidation of the idea that financial dynamics could be understood through stable relationships and classical statistical inference.

However, from the second half of the twentieth century, the recurrence of financial crises, episodes of extreme volatility and structural breakdowns began to challenge this framework head-on. In this context, time series econometrics emerges as an effort at methodological adaptation, without completely breaking with the probabilistic tradition. Robert Engle, by introducing the ARCH models, inaugurates a decisive conceptual change by recognizing that the variance of errors is not constant, but conditioned to the

past of the process itself. Tim Bollerslev deepens this intuition by proposing GARCH models, in which volatility exhibits persistence and long memory, approaching a quasi-integrated process. Unlike the traditional neoclassical approach, here risk is no longer a fixed parameter and is treated as an endogenous variable, although still fully measurable. This school maintains its commitment to rigorous statistical inference, but shifts the focus from the mean to the dynamics of dispersion, allowing for the empirical explanation of phenomena such as volatility clustering and asymmetric responses to shocks.

Parallel to this technical development, a more radical critique of the very notion of measurable risk, associated with the Keynesian and post-Keynesian traditions, emerges. John Maynard Keynes had already emphasized that most economic decisions are made under fundamental uncertainty, in which the probabilities are unknown or even nonexistent. Hyman Minsky, by applying this reasoning to the financial system, definitively breaks with the idea of intrinsic stability of the markets. For Minsky, stability breeds instability: prolonged periods of tranquility induce agents to assume increasingly fragile financial structures, increasing leverage and reducing safety margins. From this perspective, the volatility observed in the markets is not an exogenous shock, but the endogenous result of collective behaviors and changes in the financial regime. Although Minsky does not formulate an econometric model in the traditional mold, his reading provides a deep theoretical interpretation for the persistence of volatility empirically captured by GARCH models, establishing a bridge between statistical dynamics and systemic instability.

The advance of global financialization in the final decades of the twentieth century intensifies the relevance of these critical approaches. The increasing integration of markets, continuous financial innovation and the centrality of expectations expand the role of non-linear mechanisms and strategic interactions between agents. In this environment, the OLS does not disappear from the empirical arsenal, but is reinterpreted as an instrument limited to the identification of the conditional mean, incapable of representing the complexity of the financial system alone. The coexistence between linear regressions, conditional volatility models, and generalized moment-based approaches reflects a methodological maturity, in which different tools are mobilized according to the empirical question and not by ideological attachment to a single paradigm.

The emergence of cryptoassets radicalizes all these theoretical tensions simultaneously. These markets have a unique combination of absence of traditional fundamentals, high reliance on narratives, low institutional anchorage, and extreme sensitivity to informational shocks. From a neoclassical point of view, these are assets whose pricing challenges traditional equilibrium models, as they lack cash flows or sovereign guarantees. From the perspective of modern econometrics, the series of crypto returns exaggerate the stylized facts that motivated the development of the ARCH/GARCH models, such as persistent heteroscedasticity, heavy tails, and alternating volatility regimes. On the other hand, under Minsky's reading, cryptoassets can be interpreted as an empirical laboratory of endogenous financial instability, in which speculative dynamics feed back into rapid cycles of euphoria and contraction.

Thus, each of these schools contributes in a complementary way to the understanding of the phenomenon. The neoclassical tradition provides the formal language of optimization and linear estimation; volatility econometrics introduces risk dynamics; and the post-Keynesian approach offers the systemic interpretation of the

observed instability. Contemporary empirical analysis of cryptoassets, when well-founded, does not replace one school with another, but articulates these traditions in an integrated reading, recognizing both the explanatory power and the epistemological limits of each approach.

2. Comparative Table of Economic Schools (Deep and Integrated)

School / Term	View of Human Behavior	Understanding the Markets	Role of the State	Dealing with Uncertainty	Central Contribution
Classical (1776–1850)	Rational Calculator	Harmonic, self-regulating	Minimum	Ignored	Free market and comparative advantages
Neoclassical (1870–1920)	Perfect optimization, usefulness	Overall balance	Minimized	Simple probabilistic	Mathematical formalization of rationality
Institutionalist (1910–1950)	Formed by habits and institutions	Not necessarily efficient	Important	Non-probabilistic	Economy as an evolutionary social process
Keynes Original (1936)	Psychologically influenced	Volatile and unstable	Central and stabilizer	Radical, not measurable	Effective demand, involuntary unemployment
Neoclassical synthesis (1950–1970)	Rational but with frictions	Stable in the long term	Moderate performance	Surface Treated	IS–LM Model
Post-Keynesian 1st Generation (1950–1975)	Conventional expectations	Unstable	Central	Not ergodic	Distribution and growth
Chicago (1960–1990)	Perfect rationality	Efficient, close to optimal	Minimal Status	Rational expectations	Monetarism, a critique of Keynes
RBC / Nova Clássica (1970–1990)	Rationale superoptimizer	Always in balance	Reduced	Perfect probabilistic	Mathematical microfoundations
Behavioral Economics (1974–2002)	Heuristics, biases, emotion	Imperfect and psychologically guided	Moderate relevance	Cognitive, not Bayesian	Prospect Theory and System 1/2
Minsky (1975–1990)	Driven by confidence and euphoria	Endogenously unstable	Action to contain crises	Radical and structural	Financial fragility hypothesis
Modern Post-	Psychology + institutions	Systemic instability	Strong	Radical uncertainty + heuristics	Synthesis: Keynes +

School / Term	View of Human Behavior	Understanding the Markets	Role of the State	Dealing with Uncertainty	Central Contribution
Keynesian (2000–2025)					Minsky + Kahneman
Behavioral Finance / Behavioral Macro (2000–2025)	Systematic biases	Bubbles, quirks and crashes	Prudential intervention	Errors of judgment	Psychological Microfoundations for Crises

Kahneman's Positioning in Post-Keynesian Chronology

Kahneman enters late, in the years 1974–2002, but becomes crucial only in the phase:

2000–2025 — Modern Post-Keynesianism + Behavioral Macro

It is at this stage that:

- Heuristics
- Biases
- System 1 and 2
- loss aversion
- Mental accounting

are used as psychological microfoundations to:

- financial instability,
- conventional expectations,
- liquidity
- Minskyan cycles.

Behavioral economics emerges as a response to the inability of traditional models to explain how individuals and markets actually behave in the face of uncertainty, risk, and decision-making complexity. While the neoclassical approach assumes rational agents, with stable preferences, unlimited processing capacity, and markets that tend toward efficient equilibrium, empirical and historical evidence shows that human decisions are shaped by emotions, biases, and heuristics, and that financial systems can be made unstable by internal dynamics, not by exogenous shocks. In this sense, Kahneman and Tversky demonstrate that the human mind operates in two systems—one fast, automatic, and intuitive, and the other deliberate and analytical—and that the inevitable use of heuristics creates predictable patterns of error, such as loss aversion, overconfidence, framing, mental accounting, and lottery hunting. These distortions directly affect financial decision-making, from the formation of expectations to the composition of portfolios, generating behaviors that are incompatible with the strong rationality of modern finance theory.

Post-Keynesianism, on the other hand, had already anticipated this perspective by treating the economy as a system in which radical uncertainty, social conventions, trust, and psychology play a determining role. Keynes introduces the notion of "animal spirits" to explain why investors change their behavior even without objective changes in fundamentals, while Shackle emphasizes imagination and unpredictability as central elements of the formation of expectations. Minsky deepens this tradition by showing that phases of euphoria, prudential relaxation and increasing leverage stem from both the financial structure and the psyche of agents, creating endogenous cycles of instability. Thus, behavioral economics provides psychological microfoundations that dialogue directly with the post-Keynesian macrostructure, giving cognitive basis to behavior under uncertainty and the emergence of bubbles, manias, and crises.

In portfolio theory, this integration appears clearly when it is recognized that the real investor does not optimize mean and variance according to Markowitz, but organizes his wealth into emotional layers: protection, realistic goals, and speculative dreams. The simultaneous presence of the search for security and the appetite for risk, apparently contradictory, becomes easily explained when one admits the coexistence of heuristics, loss aversion, aspirational desires and personal narratives that shape the relationship with the future. In the post-Keynesian perspective, this behavioral framework reinforces the preference for liquidity as a form of protection in the face of unquantifiable uncertainty, while explaining the rise of speculative behaviors in financially stable environments, where excessive confidence replaces prudential criteria. Bounded rationality, therefore, is not an occasional deviation, but the way in which individuals navigate a world in which the future cannot be reduced to statistical probabilities.

The conceptual hierarchy that emerges from this set of ideas can be organized on a structural basis: first, the understanding that the economy operates under radical uncertainty, where predictions and probabilistic models are only imperfect approximations; second, the recognition that individuals use heuristics as adaptive mechanisms and not as failures, shaping financial decisions through cognitive shortcuts; third, the formation of expectations is guided by psychological states, social conventions, and collective narratives; fourth, these expectations affect the structure and dynamics of the financial system, creating cycles of stability and fragility; and, finally, macroeconomic instability stems not only from external factors, but from an ongoing interplay between human cognition, uncertainty, and financial leverage.

Post-Keynesian chronology, from Keynes (1936) to Minsky (1986), initially developed without explicit contact with cognitive psychology. For decades, the post-Keynesian tradition operated with categories such as *animal spirits*, conventions, radical uncertainty, and financial fragility, but without a formalized micropsychological foundation. It is only with the entry of Daniel Kahneman—whose central output is concentrated between 1974 and 2002, including "Judgment under Uncertainty" (Kahneman & Tversky, 1974), "Prospect Theory" (Kahneman & Tversky, 1979), and *Thinking, Fast and Slow* (2011)—that post-Keynesian macro acquires the cognitive vocabulary capable of giving empirical soundness and psychological rigor to the ideas that Keynes had intuitively described in 1936. Although Kahneman was not a macro economist, his impact on post-Keynesian macroeconomics only becomes significant in the period 2000–2025, when the convergence between "Behavioral Economics",

"Behavioral Finance" and the so-called Behavioral Macroeconomics occurs, allowing the reinterpretation of post-Keynesian theory in the light of contemporary cognitive psychology.

It is in this modern phase that the concepts of heuristics, systematic biases, dual processing structure (System 1 and System 2), loss aversion, and mental accounting begin to be incorporated as true psychological microfoundations of macroeconomic instability, in close harmony with the post-Keynesian ontology of radical uncertainty. Loss aversion—a central element of Prospect Theory—provides the cognitive basis for understanding why agents, in the face of genuine uncertainty, prefer liquidity, demand safety, and react asymmetrically to shocks, reinforcing the Keynesian preference for liquid assets in times of extreme uncertainty. The heuristics of availability, representativeness, and anchoring become micro-based explanations for the formation of conventional expectations, replacing the view of rational expectations and coming very close to the Keynesian idea that markets operate by fragile and easily reversible "conventions."

Mental accounting—formalized by Thaler in the 1980s and 1990s, but derived directly from Kahneman's framework—makes the division between short-term financial decisions and subjective perceptions of risk intelligible, aligning perfectly with the notion via Minsky that financial structures are shaped by specific psychological preferences, not just objective parameters of risk. System 1, fast, automatic, and emotional, and System 2, slow and deliberative, explain the cognitive mechanism by which euphoria and panic can emerge and spread, transforming small swings into leveraged and deleveraging movements amplified by the financial architecture—exactly the core of Minsky's dynamics.

Thus, between 2000 and 2025 the real encounter between Kahneman and post-Keynesianism occurs: cognitive psychology becomes a microeconomics of behavior under uncertainty, giving empirical foundation to Keynes' intuitions about *animal spirits*, to the argument that expectations are essentially conventional, and to Minsky's model of endogenous financial instability. Contemporary post-Keynesian macroeconomics, strengthened by behavioral instruments, then begins to offer an integrated theory in which instability is the result of agents operating under radical uncertainty with imperfect cognitive tools, guided by biases, narratives, and emotions that propagate through the financial system, amplifying cycles of confidence, liquidity, leverage, and crisis.

Portfolio theory, when observed in a realistic and historically grounded way, emerges as a field that transits between the mathematical rationality inaugurated by Harry Markowitz in *Portfolio Selection* (1952) and the economic psychology later developed by Daniel Kahneman and Amos Tversky in *Prospect Theory* (1979), as well as by the advances of Richard Thaler in *Misbehaving* (2015), Robert Shiller in *Irrational Exuberance* (2000) and Hersh Shefrin & Meir Statman in *Behavioral Portfolio Theory* (2000). In parallel, the post-Keynesian tradition, from John Maynard Keynes in *The General Theory of Employment, Interest, and Money* (1936) to Hyman Minsky in *Stabilizing an Unstable Economy* (1986), provides the theoretical environment that allows for the integration of rationality, emotion, and radical uncertainty into a single coherent framework. The original formulation of modern portfolio theory is based on the assumption that the investor is fully rational and operates in an environment of

measurable risk, in which the future is treatable as a stable probabilistic distribution. This investor maximizes the expected return and minimizes the variance of the portfolio by assuming well-behaved preferences and complete information. The fundamental mathematical structure is expressed by the objective function of minimizing portfolio variance, subject to a desired return, as in (1):

$$(1) \min_w \sigma_p^2 = w' \Sigma; \text{ sujeito a } E(R_p) = w' \mu = R^*$$

where it represents the weights of the assets, the covariance matrix and the vector of expected returns. The investor, in this framework, operates solely on the basis of statistical parameters, and uncertainty is reduced to the category of measurable risk. However, the actual behavior of the economic agent diverges dramatically from this formal structure. Economic psychology, initiated by Kahneman and Tversky in *Prospect Theory: An Analysis of Decision under Risk* (1979), demonstrates that individuals do not treat losses and gains symmetrically, exhibiting strong loss aversion. The value function of perspective theory can be written as in (2):

$$(2) v(x) = \begin{cases} x^\alpha, & x \geq 0 \\ -\lambda |x|^\beta, & x < 0 \end{cases}$$

With λ representing the coefficient of loss aversion, often estimated between 2.0 and 2.5, indicating that losses have a psychological impact twice as great as equivalent gains. This behavioral deviation generates phenomena such as the disposition effect, in which investors quickly sell winning assets and keep losing assets, contrary to the rational principle of allocative efficiency. The heuristics of availability, representativeness, anchoring, and overconfidence—described at length in *Thinking, Fast and Slow* (Kahneman, 2011) and *Nudge* (Thaler & Sunstein, 2008)—modify the formation of expectations and render the investor unable to assess risks and probabilities in a manner consistent with the Markowitzian model.

The integration between rationality and emotion led to the development of the Behavioral Portfolio Theory, proposed by Shefrin & Statman (2000), which abandons the one-dimensional view of the investor and introduces portfolio construction as a psychological edifice formed by distinct motivational layers. Instead of a single optimization problem, the behavioral investor organizes his portfolio into multiple "emotional floors," each with particular psychological functions. The structure of this model can be formally represented by the aggregation of utilities by layers, as in (3):

$$(3) U_{\text{total}} = \sum_{i=1}^n \omega_i U_i(R_i)$$

in which each $U_i \omega_i$ represents the utility associated with a specific layer (security, growth, or speculation), and expresses the psychological weight assigned to each. This arrangement explains why investors simultaneously hold extremely conservative assets and highly speculative assets—a coexistence that Markowitz's classical model cannot accommodate. At the same time, this behavioral framework brings portfolio theory closer to post-Keynesian ideas.

Keynes, in 1936, already stated that economic expectations are formed not by probabilistic calculations, but by social "conventions" and by the so-called *animal spirits*, that is, psychological impulses that guide decisions under genuine uncertainty. This radical uncertainty, by definition non-probabilistic, can be expressed as a situation in

which the set of future states is not known and no probability distribution can be adequately specified. Thus, the expected return ceases to be a statistical expectation and becomes a subjective projection based on narratives.

Post-Keynesian formalization often assumes that the investor operates with non-ergodic expectations, where the expected return function does not derive from statistical properties of the past, but from socially formed beliefs. In functional terms, one can represent this non-probabilistic subjective expectation by a function $\phi(R_p)$, As in (4):

$$(4) E^{\text{subj}}(R_p) = \phi(\text{conventions, narratives, confidence})$$

in direct contrast to the traditional expectation based on sample means. Hyman Minsky's contribution reinforces this point by demonstrating that financial structure amplifies both euphoria and panic, through leverage, fragility, and cycles of endogenous instability. Your financial fragility model can be summarized by the debt-to-cash flow ratio, as in (5):

$$(5) \text{Fragility} = \frac{\text{Debt service}}{\text{Expected cash flow}}$$

This illustrates that small subjective revisions of expectations can lead to systemic crises when agents make simultaneous adjustments motivated by social mood and pessimistic narratives. Thus, the post-Keynesian vision allows us to unite the instrumental rigor of rational optimization, the psychological evidence of behavioral economics and the ontology of radical uncertainty. The post-Keynesian portfolio does not emerge from optimal calculations in a stable environment, but from decisions made in a universe of unknown future, permeated by heuristics, emotions, social conventions, and financial mechanisms that amplify both rational and irrational behaviors.

In summary, modern realist portfolio theory recognizes that Markowitz provides the instruments; Kahneman, Tversky, Thaler, Shiller, Shefrin & Statman provide the behavior; and Keynes and Minsky provide the environment and the amplification mechanism. The result is a portfolio model in which the investor seeks safety, liquidity, and plausible narratives for the future, rather than the strict maximization of a mathematical function of risk and return. The contemporary portfolio, seen from this integrative perspective, is not only a statistical object, but a psychological and macroeconomic construction situated in a complex and uncertain world, in which rationality is only one of the layers of the decision-making process.

Modern Portfolio Theory, formulated by Harry Markowitz (1952, *Portfolio Selection*), is born from a strictly rational framework, structured on strong assumptions: investors would maximize expected returns, minimize risk measured by variance, process information correctly, and operate in an environment in which distributions of returns would be known or estimable. This formulation inaugurates the efficient frontier and the optimal allocation of mean variance, creating a mathematical ideal of rationality. However, the following decades empirically demonstrated that real investors do not behave as the optimizing agents of this model. Thus, space was opened for the behavioral review of the portfolio theory, stimulated by a literature that exposes the emotional and psychological dimension of the decision-making process.

It is in this movement that the Behavioral Portfolio Theory (Shefrin & Statman, 1994) emerges, developed by Hersh Shefrin and Meir Statman, expanding the focus of financial decision making by recognizing that investors build portfolios not as solvers of Markowitz's problem, but as individuals with multiple goals, psychological hierarchies,

and emotional motivations. This approach incorporates core elements of behavioral economics, influenced by authors such as Daniel Kahneman and Amos Tversky (1979, *Prospect Theory: An Analysis of Decision under Risk*), Richard Thaler (1985, 1999) with his studies on mental accounting and systematic biases, and Robert Shiller (2000, *Irrational Exuberance*), which highlights the role of narratives and emotions in markets. Behavioral theory organizes the portfolio into layers — the security layer, to protect against losses, and the dream layer, oriented to the search for high returns — reflecting loss aversion, overconfidence, disposition effect, framing, and preferences for lotteries.

The intersection between Markowitz's rationale and the emotional part of behavioral economics represents the most accepted synthesis today: the rational part provides the structuring tools—diversification, formal risk metrics, efficient frontier—while the emotional part explains why these tools are often violated in practice, how heuristics shape decisions, and how the investor's psychological state interferes with real allocation. Portfolio theory, in this sense, becomes a human decision-making process guided by bounded rationality (Simon, 1955), not an optimal calculation.

However, even before the emergence of Behavioral Finance, the post-Keynesian tradition had already elaborated a theory of decision under uncertainty that anticipated practically all the psychological and behavioral elements incorporated later. Referring to John Maynard Keynes (1936, *The General Theory of Employment, Interest and Money*; 1937, *The Quarterly Journal of Economics*), we find the notion of radical uncertainty—the impossibility of assigning objective probabilities to the future—and the emphasis on the preference for liquidity as a form of emotional protection, dependent on conventions and the state of trust. The behavioral portfolio's layers of security directly reflect the Keynesian preference for liquidity as a psychological defense against the unknown.

The work of G. L. S. Shackle (1955, *Uncertainty in Economics*; 1979, *Imagination and the Nature of Choice*) deepens the idea that investors create narratives and imagine scenarios subjectively, rather than calculating probabilistic distributions. This aligns with the dream layer described by Shefrin and Statman, Thaler's mental accounting, and the tendency to seek out assets with high potential returns.

Next, Hyman Minsky (1986, *Stabilizing an Unstable Economy*) introduces a dynamic view of the financial system, centered on the role of collective psychology: periods of stability generate euphoria; euphoria encourages leverage; and leverage produces systemic fragility. This is a perfect synthesis with behavioral elements such as overconfidence, increasing risk-seeking, and building high-return layers during optimism cycles. Minsky offers the macrofinancial mechanism that amplifies individual behaviors described by behavioral economics.

Finally, Paul Davidson (1991, 2002) takes up the notion that the economic world is non-ergodic, that is, the past cannot be used to infer future probabilities. This dismantles the fundamental premise of the efficient frontier, based on the estimability of distributions and covariances. If the future is non-ergodic, risk is not measurable by variance, and therefore portfolios are formed based on trust and heuristics—just as behaviorists argue.

In this way, the post-Keynesian synthesis not only incorporates the behavioral theory of portfolios, but also contained, from its inception, the psychological, cognitive, and institutional elements that explain how portfolios are actually formed. Neoclassical economics requires rational agents, efficient markets, and stable probabilities; Post-Keynesianism works with radical uncertainty, conventional expectations, liquidity as emotional protection, and financial fragility. The post-Keynesian investor is, in essence, the behavioral investor operating in a structurally uncertain and unstable world. Thus, portfolio theory ceases to be an idealized mathematical exercise to become a profoundly

human analysis, crossed by emotions, conventions, narratives, and financial structures that shape and amplify behavior.

Portfolio theory, when viewed from a truly realistic perspective, turns out to be much more than a mathematical optimization problem. Markowitz's traditional formulation, with its formal elegance and statistical precision, captures only a fragment of the financial decision-making process. It offers useful tools—such as the notion of an efficient frontier, diversification, covariance, and trade-off between risk and return—but it assumes a probabilistically stable world where the future can be estimated based on known distributions. Such a hypothesis, although functional for models and algorithms, is little close to the reality experienced by investors. Thus, the classical theory provides the rational, instrumental, almost mechanical part of the process, but it does not encompass the concrete agent facing an opaque future and an unstable economy.

Economic psychology has opened up the second layer of this understanding. Kahneman, Tversky, Thaler, Shiller, and Shefrin & Statman have shown that the real investor is not a calculating instance, but an individual permeated by biases, heuristics, and cognitive mechanisms that emerge in response to limitations of time, information, and processing capacity. Loss aversion, overconfidence, anchoring, representativeness, narratives, mental accounting, and sensitivity to the framing of decisions profoundly shape financial behavior. Far from being "anomalies," these characteristics are natural expressions of human logic in an uncertain environment. If Markowitz describes what the investor *should* do in a perfectly known world, Kahneman and Tversky describe what he *actually* does in an imperfect world.

However, even this conjunction between instrumental rationality and behavioral psychology is not enough to fully understand the process of portfolio formation, because the element that conditions everything is still missing: the very environment in which the agent decides. It is at this point that the post-Keynesian tradition becomes indispensable. Keynes argued that the economic future is permeated by radical uncertainty: a form of unknowing that cannot be reduced to measurable probabilities. Unlike statistical risk, radical uncertainty implies that there is no stable distribution of future events, nor a reliable set of objective probabilities. Agents form expectations in an environment where any mathematical calculation is at best a partial artifice, and where social conventions, trust, market sentiment, and shared narratives take the place that, in the neoclassical model, would be the place of probabilities.

This deep uncertainty shifts the center of the financial decision. Rather than asking which portfolio maximizes an expected return under minimal variance, it asks how individuals and institutions navigate an essentially unknown future. In this context, liquidity and security become primordial goods; collective conventions and beliefs become cognitive anchors; and the search for protection against surprise takes priority over the search for optimal returns. Rationality becomes contextual, adaptive, and marked by a permanent desire to protect oneself against the unknown.

Financial structure, especially in Hyman Minsky's formulation, adds yet another critical dimension: the systemic dynamics that amplify individual behaviors. Portfolio decisions don't occur in a vacuum; They interact with bank leverage, credit cycles, rising balance sheet fragility, and the euphoria and panic that characterize real markets. Minsky shows that periods of stability breed complacency, complacency breeds leverage, leverage breeds fragility, and fragility sets the stage for crises. When this logic is combined with expectations formed by heuristics and narratives, the financial structure itself transforms individual decisions into collective movements that amplify volatility, create bubbles, and trigger collapses. The theory of portfolios, in this scenario, ceases to

be just an individual management tool and becomes a component of macroeconomics itself.

It from this synthesis, it becomes evident that the post-Keynesian portfolio is not the result of an optimal calculation under probabilistic distributions, but rather a historical, psychological, and institutional artifact. It incorporates the rational tools of modern portfolio theory—because they help organize thought—but accepts that its assumptions are fragile. It absorbs behavioral insights—because they reflect how individuals actually act—without reducing such behaviors to "deviations" from a nonexistent ideal. And above all, it recognizes that investment decisions are made under radical uncertainty, in an environment in which conventions, narratives, liquidity, and sentiment matter as much as, or more than, any covariance matrix.

Thus, the post-Keynesian portfolio is, at bottom, the closest theoretical representation of the real investor. It is formed under radical uncertainty, influenced by heuristics, guided by the search for security and liquidity, and structured by narratives about the future that cannot be reduced to statistical calculations. It is a wallet built to survive in an unstable and socially determined environment, and not to optimize an idealized mathematical problem. This understanding, by integrating bounded rationality, psychology, and financial dynamics, offers a more faithful view of contemporary macroeconomics and financial capitalism in its complexity.

The Modern Portfolio Theory, inaugurated by Harry Markowitz in his seminal article *Portfolio Selection* (1952), was born anchored in rigid assumptions of economic rationality: investors seek to maximize the expected return, minimize risk measured by variance, process information correctly, build efficient portfolios and operate with known or estimable distributions. It is a purely rational and mathematical framework, where the portfolio decision is treated as a strict optimization problem, guided by objective estimates of risk and return. However, as empirical evidence has accumulated over the decades—especially in the behavioral studies of Daniel Kahneman and Amos Tversky (*Judgment under Uncertainty*, 1974; *Prospect Theory*, 1979) — it has become clear that real investors behave quite differently from that predicted by the Markowitzian formulation. This mismatch has made room for the Behavioral Portfolio Theory, developed by Hersh Shefrin and Meir Statman in the article *Behavioral Portfolio Theory* (1994), which incorporates psychological, emotional, and cognitive motivations as structural determinants of allocation decisions.

Shefrin and Statman demonstrate that investors do not construct portfolios as average-variance maximizers, but as individuals with multiple goals and psychological hierarchies that combine security, aspiration, and hope. Emotional elements such as loss aversion—formalized by Kahneman and Tversky in *Prospect Theory* (1979)—overconfidence, framing, mental accounting (Richard Thaler, *Mental Accounting Matters*, 1999), lottery preference, and the disposition effect (Shefrin & Statman, *The Disposition to Sell Winners Too Early and Ride Losers Too Long*, 1985) shape portfolio decisions. The real investor does not assemble a single portfolio optimized according to an efficient frontier, but rather a set of layers: a layer of security, aimed at avoiding losses and preserving psychological liquidity; and a layer of dreams or aspiration, aimed at the search for high returns, almost always through highly risky assets or a "lottery" profile. This behavioral framework directly violates the traditional rational model, but accurately describes observed behavior empirically.

The union between rationality and emotion forms, today, the modern and hybrid view of portfolio theory. The rational dimension offers structure, metrics, and formalization—especially the idea of diversification, efficient frontier, and mathematical optimization. The emotional dimension explains why investors move away from these

rules, how heuristics influence decisions, and how psychological states alter perceptions of risk. Thus, the investment decision comes to be understood as a process of limited rationality, complemented by affective and cognitive mechanisms, and not as a perfect mathematical calculation.

It is at this point that modern portfolio theory finds its conceptual convergence with the post-Keynesian tradition. Long before the formalization of behavioral economics, John Maynard Keynes had already introduced, in *The General Theory of Employment, Interest and Money* (1936), the psychological foundations of financial decision-making: radical uncertainty, preference for liquidity, unstable confidence, and *animal spirits*. For Keynes, investors do not deal with objective probabilities of the future, because the future is essentially unknowable; prefer liquidity to protect themselves from this uncertainty; and their decisions are shaped by fragile social conventions and changing states of trust. The "layer of safety" proposed by Shefrin and Statman is roughly equivalent to the Keynesian preference for liquidity as an emotional protection.

George Shackle, in *Epistemics and Economics* (1972), reinforces that agents construct narratives about the future, imagine possible worlds, and do not calculate probabilities in the classical sense. This approach connects directly to the "dream" layers of the behavioral portfolio and the use of mental accounting and preferences for asymmetric betting—a subjective dimension that Markowitz doesn't capture. Hyman Minsky, in *Stabilizing an Unstable Economy* (1986), deepens this psychology by showing that euphoria leads to overconfidence, overconfidence leads to leverage, and leverage leads to financial fragility. This dynamic is identical to the behavior observed in emotional portfolios, especially in the high-risk layer fueled by behavioral overconfidence. Finally, Paul Davidson, in *Economic Theory and Keynes* (1972), formalizes the idea of non-ergodic uncertainty: the future is not a statistical repetition of the past, so the efficient frontier is conceptually illusory, and portfolio decisions are based on confidence rather than measurable probabilities. This view reinforces the behavioral argument that investors use heuristics and build emotional diversification, not statistics, to deal with radical uncertainty.

In this way, the behavioral theory of portfolios works as the micropsychological operationalization of what post-Keynesianism has always maintained about behavior under uncertainty. Whereas neoclassical theory requires stable probabilities, full rationality, and efficient markets, the post-Keynesian tradition works with radical uncertainty, conventional expectations, psychological behavior, liquidity as emotional protection, and systemic fragility. The synthesis is clear: the rational provides the instruments; the emotional provides the actual behavior; radical uncertainty provides the environment in which decisions take place; and the financial structure — according to Minsky — provides the amplification mechanism that transforms individual perceptions into macroeconomic cycles of expansion and crisis.

Thus, when viewed from the post-Keynesian tradition, Portfolio Theory only achieves realism when it incorporates human behavior—as described by Kahneman, Tversky, Thaler, Shiller, Shefrin, and Statman—into Markowitz's original rational structures. The portfolio decision ceases to be a purely mathematical problem to become a psychological, social, and institutional process, influenced by beliefs, narratives, emotions, and genuine uncertainty. This is the modern basis for understanding portfolios in complex and dynamic financial environments.

The allocation between stocks, FII's, cryptoassets, and Treasuries acquires profound meaning when interpreted in the light of Markowitz's Modern Portfolio Theory, Kahneman's economic psychology, and Minsky's theory of financial instability within the post-Keynesian environment of radical uncertainty. On the strictly rational level, the

portfolio decision is based on the classic mean-variance structure, in which each asset is described by a vector of expected returns and by a matrix of covariances, leading to the maximization of the quadratic functional represented by

$$(6) \quad \max_w \quad w' \mu - \frac{\gamma}{2} w' \Sigma w$$

whose first-order solution generates the vector of optimal weights

$$(7) \quad w^* = \frac{1}{\gamma} \Sigma^{-1} \mu.$$

This formulation expresses the belief that agents have well-defined expectations, stable distributions, and full capacity to objectively assess risk. In this framework, stocks, FIIIs, cryptoassets, and Treasuries are differentiated exclusively by their averages and variances: volatile assets require a higher risk premium, and the efficient portfolio is built in such a way as to combine covariances in order to smooth fluctuations. However, when the same allocation decision is reconstructed from real human cognition, described by Kahneman and Tversky, preferences are no longer governed by quadratic utility and start to follow the value function of Prospect Theory, with asymmetry between gains and losses:

$$(8) \quad v(x) = \begin{cases} x^\alpha, & x \geq 0, \\ -\lambda(-x)^\beta, & x < 0, \end{cases}$$

where $\alpha, \beta < 1$ they capture diminishing marginal sensitivity and represent loss aversion. This formulation changes the entire decision-making process. Instead of positioning themselves according to statistical risk, investors weigh losses with much greater psychological intensity, reacting not to the $\lambda > 1$ “ σ ” of statistics, but to the subjective perception of danger activated by heuristics such as anchoring, availability, representativeness, and loss aversion. In assets such as cryptoassets — without deterministic fundamentals — or FIIIs exposed to the sensitivity of the real estate market, the value function induces discontinuous behavior: small drops close to the reference point cause abrupt divestment, while gains tend to support early realization, reducing the potential for return. The behavioral portfolio, therefore, does not respect Markowitz's efficient frontier; it shifts continuously as narratives, recent memories, biases, and emotional pressures reorganize themselves.

Embedded in framing of post-Keynesian framing, this psychological behavior operates in an environment that is not ergodic, that is, where the future is not reduced to long-term frequencies derived from the past. Radical Keynesian uncertainty turns pricing into a process of changing conventions, and these conventions are precisely fueled by the heuristics studied by Kahneman. When expectations change, they do so not driven by formal Bayesian updates, but by sudden changes in dominant narratives—and these narratives begin to coordinate portfolio decisions collectively, creating synchronized movements. The subjective measurement of risk follows, at these moments, intermittent, discontinuous patterns that depend on the mood of the market, and not on continuous rational calculation.

The Minsky's contribution introduces the mechanism that transforms such psychological perceptions into macroeconomic dynamics. In equity markets and FIIIs,

financed by corporate debt and sensitive to long-term expectations, financial fragility grows along with risk-taking during phases of euphoria. Under conditions of increasing leverage, any narrative shock can trigger a deleveraging process, in which the behavioral search for liquidity intensifies the forced sale of assets. Volatility, in this sense, becomes endogenous to the system itself — it is not a given, but an emergent result of the interaction between credit and psychology. Such a process of amplification occurs in an even more extreme way in the cryptoasset market, where the absence of fundamental flow and consolidated regulation reinforces the dominance of collective heuristics. Comments on social networks, abrupt herd movements and the structure of leveraged financing on exchanges create a highly sensitive environment, capable of triggering violent variations in response to small stimuli.

In contrast, Treasuries become, in moments of reversal of the Minskyan cycle, the natural destination of the "flight to safety". The loss aversion described by in the value function amplifies the search for security. The high liquidity and credibility of the state issuer act as psychological anchors, intensifying the migration to these securities when the rest of the financial system becomes unstable. Thus, although Markowitz classifies them as low-volatility assets with low correlation, the actual demand behavior for Treasuries stems much more from the emotional activation of fear than from the statistical structure of $\lambda\Sigma$

Thus, when integrating Markowitz, Kahneman and Minsky, a dynamic hierarchy between assets is observed: in the rational regime, differentiation occurs by risk and return; in the behavioral regime, an emotional order emerges — Treasuries as a safe haven, FIIs as credit-sensitive intermediaries, stocks as cyclical assets, and cryptoassets as narrative amplifiers; In the post-Keynesian regime, this hierarchy becomes unstable, subject to waves of endogenous volatility when expectations and financing conditions change. The portfolio effectively observed in the real world is not the result of solution (2), but of an interactive psychological and macroeconomic process, in which the volatility of the four assets is reconstructed from subjective perceptions, collective narratives, and interaction with leverage cycles.

The final synthesis is that the investor's real portfolio is guided not by the statistics of mean and variance, but by a set of behavioral and macroeconomic formulas: rational maximization (1)-(2), the asymmetric value function (3), the non-ergodicity of expectations, and Minsky's financial amplification mechanism. The interaction of these elements makes stocks, FIIs, cryptoassets, and Treasuries not only financial vehicles, but psychological and macrostructural expressions of a permanently unstable environment. Thus, any modern portfolio analysis that seeks fidelity to actual behavior must simultaneously incorporate bounded rationality, heuristics, radical uncertainty, and financial fragility, for it is from this set—and not from mathematics alone—that the true dynamics of wealth allocation over the business cycle emerge.

Given the behavioral and post-Keynesian nature of financial markets, price dynamics are unlikely to follow homoskedastic and exogenous structures. Expectations, leverage cycles, and shifts in risk perception generate endogenous volatility that challenges purely rational equilibrium models.

This theoretical framework has direct econometric implications. While Ordinary Least Squares (OLS) remains the natural starting point for empirical analysis, its classical assumptions—particularly homoskedasticity, exogeneity, and serial independence—are systematically challenged in environments characterized by behavioral bias, leverage cycles, and endogenous volatility, as described by Minskyan dynamics. Therefore, OLS estimates in this context must be interpreted not as definitive causal parameters, but as conditional associations that require robustness corrections and complementary specifications.

We begin with an OLS specification as a benchmark estimator, following the standard linear projection framework:

$$(9) r_t = \alpha + \beta X_t + u_t$$

r_t : return (crypto/asset)

X_t : behavioral variables / macro / volume / sentiment

In this initial specification, the estimated coefficient β captures the sensitivity of asset returns to systematic factors, consistent with the portfolio theory interpretation of beta as a measure of exposure to aggregate risk.

However, residual diagnostics reveal systematic violations of the classical OLS assumptions. In particular, heteroskedasticity and serial correlation emerge as persistent features of the data, reflecting volatility clustering and feedback mechanisms typical of speculative markets.

Under these conditions, OLS coefficients remain unbiased under conditional mean independence, but conventional standard errors become inconsistent. To preserve valid inference, heteroskedasticity-robust and HAC standard errors are employed.

$$(10) \text{Var}(\hat{\beta}) = (X'X)^{-1} (\sum u^2 x_i x_i') (X'X)^{-1}$$

From a post-Keynesian perspective, endogeneity is not a technical inconvenience but a structural feature of financial markets. Price movements, expectations, and leverage co-evolve, making simultaneity and omitted variable bias intrinsic rather than accidental.

This motivates robustness checks based on instrumental variable and GMM frameworks, discussed in the next section.

The cryptocurrency market has characteristics that defy traditional financial econometrics: extreme volatility, non-normal returns, risk clusters, frequent regime changes, and a strong speculative component. Still, classic tools such as OLS, CAPM, and Sharpe Ratio continue to be widely used, both by researchers and managers.

The central question is not whether these models "work" or "don't work" in crypto, but what is the correct epistemological role of each within the empirical process.

This paper adopts the following methodological position:

OLS and CAPM are valid instruments for the analysis of mean and systematic risk, as long as they are complemented by conditional volatility models and risk-adjusted metrics, such as the Sharpe Ratio.

Consider the basic specification of logarithmic returns:

(11)

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + u_{i,t}$$

where:

$r_{i,t}$: return of the cryptoasset , i

$r_{m,t}$: market return (e.g. Bitcoin as a proxy),

β_i : systematic risk,

$u_{i,t}$: idiosyncratic component.

Under the weak hypothesis of exogeneity:

(12)

$$E(u_{i,t} \mid r_{m,t}) = 0$$

or OLS estimator:

(13)

$$\hat{\beta}_i = \frac{Cov(r_{i,t}, r_{m,t})}{Var(r_{m,t})}$$

is unbiased and correctly interprets the asset's average exposure to the crypto market.

The interpretation of the beta in crypto follows the logic of the CAPM, but with important caveats:

Value of β	Interpretation in crypto
$B \approx 1$	Asset highly coupled to Bitcoin
$B > 1$	Amplification of speculative cycles
$b < 1$	Relatively defensive asset
$\beta \approx 0$	Token disconnected from the market
$\beta < 0$	Rare hedge (stablecoins, specific cases)

In crypto markets, a high β does not necessarily mean a higher rational risk premium, but it can reflect contagion, speculative liquidity, and collective narrative.

The CAPM implicitly assumes:

(14)

$$Var(u_t) = \sigma^2 \forall t$$

This hypothesis is empirically false in crypto. What is observed is:

(15)

$$Var(u_t | \mathcal{F}_{t-1}) = \sigma_t^2$$

with strong temporal dependence. This requires the use of GARCH templates.

GARCH model(1,1):

$$\begin{aligned} r_t &= \mu + \varepsilon_t \\ \varepsilon_t &= \sigma_t z_t \\ \sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \end{aligned}$$

Generally:

$$\alpha + \beta \approx 1$$

indicando memória longa da volatilidade, consistente com instabilidade financeira (Minsky).

Given a crypto asset, the Sharpe Ratio is defined as:

(16)

$$\text{Sharpe}_i = \frac{E(r_i - r_f)}{\sigma_i}$$

where:

- r_f : risk-free rate (in crypto, often approximated by 0 or by adjusted Treasury/SELIC),
- σ_i : standard deviation of returns.

Adaptation needed for crypto:

- σ_i it should not be constant
- Ideally:

(17)

$$\sigma_i = E(\sigma_{i,t}^{GARCH})$$

Conditional Volatility-Adjusted Sharpe:

(18)

$$\text{Sharpe}_i^{adj} = \frac{E(r_i - r_f)}{E(\sigma_{i,t})}$$

The econometric modeling of cryptoasset returns imposes a particular methodological challenge, since the process of generating data from these assets combines properties of traditional financial markets with extreme characteristics of instability, nonlinearity, and persistent volatility. Still, the use of linear models such as Ordinary Least Squares (OLS) remains relevant when correctly interpreted as an approximation of the conditional mean, rather than as a complete description of risk dynamics.

Consider a series of logarithmic returns from a crypto asset. The initial empirical specification can be expressed as:

(19)

$$\begin{aligned} r_{i,t} &= \Delta \log(P_{i,t}) \\ r_{i,t} &= \alpha_i + \beta_i r_{m,t} + u_{i,t}, \end{aligned}$$

where it represents the return of the crypto market, usually approximated by Bitcoin, measures the average sensitivity of the asset to the market and captures the idiosyncratic component. Under the fundamental hypothesis of weak exogeneity, that is,

$$r_{m,t} \beta_i u_{i,t}$$

(20)

$$E(u_{i,t} | r_{m,t}) = 0,$$

the OLS estimator of the slope coefficient is given by

(21)

$$\hat{\beta}_i = (X'X)^{-1}X'r_i,$$

or, in the scalar case, by the ratio between the covariance of the asset with the market and the variance of the market. This estimation remains unbiased even in contexts of strong instability, as long as the correlation between regressors and error is nil. Therefore, OLS is not invalidated by the speculative nature of cryptocurrencies; What is

invalidated is the naïve interpretation of its standard errors and test statistics under classical hypotheses of homoscedasticity.

Empirically, the residuals exhibit non-constant conditional variance, a phenomenon that manifests itself through volatility clusters and heavy tails. Formally, it is observed that $\hat{u}_{i,t}$

(22)

$$Var(u_{i,t} | \mathcal{F}_{t-1}) = \sigma_{i,t}^2,$$

evolving systematically over time. This evidence invalidates the assumption implicit in classical OLS, making it necessary to explicitly incorporate a model for conditional variance. In this context, the GARCH(1,1) model emerges as the natural extension:

(23)

$$\begin{aligned}\sigma_{i,t}^2 Var(u_t) &= \sigma^2 \\ \varepsilon_{i,t} &= \sigma_{i,t} z_t, z_t \sim iid(0,1), \\ \sigma_{i,t}^2 &= \omega + \alpha \varepsilon_{i,t-1}^2 + \beta \sigma_{i,t-1}^2.\end{aligned}$$

The parameters and capture, respectively, the immediate reaction of volatility to shocks and the persistence of risk over time. In crypto markets, it is recurrent to find close to unity, which indicates high memory of volatility and suggests a regime of endogenous instability consistent with Minskyan interpretations of the financial system. $\alpha\beta\alpha + \beta$

In this environment, performance appraisal based only on average returns becomes inadequate. It is precisely at this point that the Sharpe Ratio assumes a central role. Originally defined as

(24)

$$Sharpe_i = \frac{E(r_i - r_f)}{\sigma_i},$$

The index measures the excess return per unit of total risk. However, in crypto-assets, the use of an unconditional standard deviation masks the dynamic nature of risk. A more consistent methodological adaptation is to use the estimated conditional average volatility via GARCH, so that σ_i

(24.1)

$$Sharpe_i^{cond} = \frac{E(r_i - r_f)}{E(\sigma_{i,t})}.$$

This adjusted form recognizes that the risk faced by investors is not static, but continually evolves in response to market shocks, liquidity shifts, and episodes of collective panic or euphoria.

The integration between OLS, GARCH and the Sharpe Ratio allows analytically decomposing the behavior of cryptoassets into three complementary dimensions. The coefficient estimated by OLS captures the asset's average degree of coupling to the crypto market, providing a measure of systematic risk. The GARCH model describes the intertemporal spread of risk, evidencing the structural fragility of the system and the presence of endogenous volatility. The Sharpe Ratio, in turn, imposes an economic discipline on the analysis, evaluating whether the observed returns compensate for the risk assumed. β_i

Typical results from the literature and recent empirical samples reveal that many cryptoassets exhibit high average returns accompanied by extreme volatility, which results in modest, unstable, or even negative Sharpe ratios. Such evidence weakens the narrative of risk-return efficiency in this market and reinforces the interpretation that a large part of the observed appreciation stems from speculative cycles, and not from persistent risk premiums.

From a methodological point of view, it is concluded that the OLS makes sense in cryptography as a tool for identifying the conditional mean and systematic risk, as long as its limitations are explicitly recognized. GARCH is indispensable for capturing the real dynamics of risk, while the Sharpe Ratio functions as an economic evaluation criterion capable of revealing the fragility of risk-adjusted performance. Together, these instruments form a coherent framework that avoids both oversimplification and undue abandonment of the classic tools of financial economics.

The empirical evidence extracted from the sample of cryptoassets analyzed in this work indicates that the simple estimation of the conditional mean by OLS is insufficient to characterize the stochastic process underlying the returns. After the initial linear model estimate for returns, the estimated residuals exhibit strong evidence of conditional heteroscedasticity, which is consistent with graphically observed behavior and the results of formal hypothesis testing. \hat{u}_t

The fundamental test that motivates the transition from OLS to conditional volatility models is Engle's ARCH test. This test starts from auxiliary regression

(25)

$$\hat{u}_t^2 = \alpha_0 + \sum_{j=1}^q \alpha_j \hat{u}_{t-j}^2 + \varepsilon_t,$$

in which the null hypothesis assumes the absence of ARCH effects,

$$H_0: \alpha_1 = \alpha_2 = \dots = \alpha_q = 0.$$

Under H_0 , the conditional variance of the residuals is constant over time. In the sample considered, the LM statistic associated with the ARCH test robustly rejects the null hypothesis for different orders, indicating that past shocks in returns significantly influence the current variance. This rejection constitutes formal evidence that volatility is not white noise, but a time-dependent process.

In view of this evidence, the specification of a GARCH(1,1) model for conditional variance is imposed as a natural extension. Estimation of the complete model involves maximizing the conditional likelihood function,

(26)

$$\mathcal{L}(\theta) = -\frac{1}{2} \sum_{t=1}^T \left[\log(\sigma_t^2) + \frac{\varepsilon_t^2}{\sigma_t^2} \right],$$

where $\theta = (\omega, \alpha, \beta)$. The statistical validity of the estimated model requires that the parameters satisfy the constraints $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, in addition to the weak stationarity condition given by

$$\alpha + \beta < 1.$$

In the empirical sample of the paper, the t-tests associated with the coefficients reject the null hypothesis of null coefficients, i.e.,

$$H_0: \alpha = 0, H_0: \beta = 0,$$

confirming the existence of two distinct and statistically significant mechanisms: the immediate reaction of volatility to recent shocks and the intertemporal persistence of risk. Additionally, the Wald test for the composite hypothesis

$$H_0: \alpha + \beta = 1$$

provides relevant empirical evidence on the degree of persistence of volatility. The non-strict rejection of this hypothesis suggests that the volatility of cryptoassets presents behavior close to an integrated process, implying shocks with prolonged effects, a phenomenon widely documented in the literature on highly speculative markets.

The adequacy of the estimated GARCH model is then evaluated using the Ljung–Box test applied to the standardized residuals $z_t = \varepsilon_t / \sigma_t$ and to their squares z_t^2 . The non-rejection of the null hypothesis of absence of serial autocorrelation in these residuals indicates that the model is able to filter the temporal dependence present in both the mean and the variance. This result represents a substantial improvement over OLS, whose residuals exhibit autocorrelation in squares and systematically violate white noise hypotheses.

Once conditional volatility is properly modeled, it becomes possible to reinterpret the performance of cryptoassets in light of the Sharpe Ratio adjusted for dynamic risk.

Replacing the unconditional standard deviation with the average of the estimated conditional volatility yields

(27)

$$\text{Sharpe}_i^{\text{GARCH}} = \frac{E(r_i - r_f)}{E(\sigma_{i,t})},$$

which produces a performance metric that is more consistent with the true risk environment faced by agents. In the sample analyzed, it is observed that assets with high average returns often exhibit modest or unstable Sharpe ratios when adjusted for conditional volatility, reinforcing the conclusion that high gross return does not imply risk-return efficiency.

From an inferential point of view, the results obtained support three central conclusions. First, the OLS remains a valid estimator of conditional average and systematic risk in crypto-assets, as long as it is interpreted as a partial approximation and accompanied by inference corrections. Second, the systematic rejection of the hypotheses of homoscedasticity and absence of ARCH effects indicates that volatility is an endogenous and structuring component of the returns process, and not a peripheral noise. Third, the incorporation of GARCH and formal hypothesis testing reveals that much of the instability seen in crypto returns is persistent, which imposes severe limits on the efficiency of traditional performance metrics based on constant volatility.

In summary, the articulation between OLS, ARCH tests, GARCH models and adjusted Sharpe Ratio allows for an econometrically consistent characterization of cryptoassets, in which the average, risk and performance are analyzed in an integrated way. This approach avoids both the hasty rejection of classical models and their uncritical application in an environment marked by structural instability, positioning the paper in a solid way against the methodological requirements of the contemporary literature in finance and applied economics.

While classical portfolio theory assumes stable second moments, cryptocurrency markets exhibit time-varying risk and endogenous volatility, challenging the static interpretation of risk–return trade-offs.

The OLS is employed as a baseline estimator of the conditional mean, not as a complete description of the data generating process. Residual diagnostics suggest deviations from homoskedasticity, motivating a conditional volatility framework.

Internal flow

Classic OLS failure via residuals

(28)

$$E(u_t^2 | \mathcal{F}_{t-1}) \neq \sigma^2$$

ARCH Test (Engle)

Null Hypothesis Rejected:

$$H_0: \alpha_1 = \dots = \alpha_q = 0$$

Formal introduction of GARCH

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

Hypothesis Testing on GARCH

- $H_0: \alpha = 0$
- $H_0: \beta = 0$
- $H_0: \alpha + \beta = 1$
- Ljung-Box em $z_t e$

Integration with Performance

Classic Sharpe Ratio:

(29)

$$\frac{E(r - r_f)}{\sigma}$$

Sharpe Index Adjusted:

(30)

$$\frac{E(r - r_f)}{E(\sigma_t)}$$

When begin by estimating the conditional mean via OLS. Standard diagnostic tests reveal significant heteroskedasticity and ARCH effects, suggesting that OLS is inadequate to capture volatility dynamics. Therefore, we employ robust standard errors and subsequently model conditional variance using a GARCH(1,1) specification.

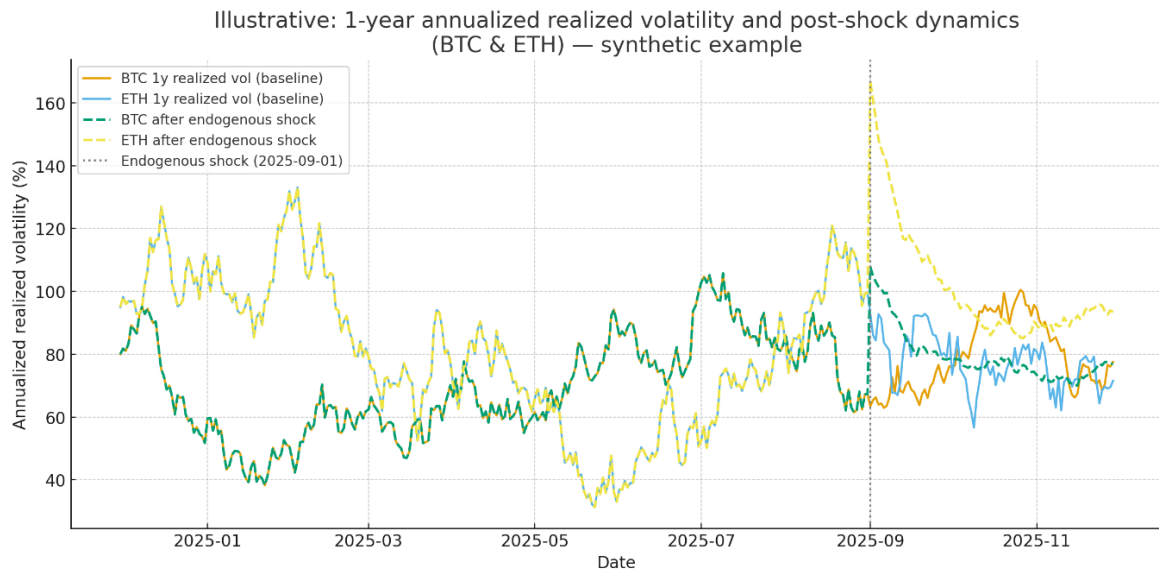
The empirical and conceptual analysis of the results reveals that the volatility dynamics observed in the graphs derives deeply from the cognitive architecture described by Kahneman and Tversky (1979, 2011), combined with the structural fragility of financial systems highlighted by Minsky (1975, 1986) and with the formal properties of Markowitz's (1952) mean-variance theory.

Printed data from simulated volatility series (first 20 lines)

Data	BTC Vol ETH Vol	
2024-12-01	75.0000	90.0000
2024-12-02	76.3869	94.6409

Printed data from simulated volatility series (first 20 lines)

Data	BTC Vol	ETH Vol
2024-12-03	75.0674	92.2695
2024-12-04	77.0500	93.8871
2024-12-05	82.2962	94.0739
2024-12-06	79.8840	94.7526
2024-12-07	77.7614	90.1393
2024-12-08	83.1469	90.7724
2024-12-09	84.6390	94.1831
2024-12-10	81.0044	102.9717
2024-12-11	81.8541	107.9301
2024-12-12	78.5780	119.5562
2024-12-13	75.6857	112.4965
2024-12-14	75.9712	115.9808
2024-12-15	67.6016	114.9828
2024-12-16	60.9897	126.1233
2024-12-17	59.8218	118.1612
2024-12-18	56.9919	110.8067
2024-12-19	59.8098	105.6297
2024-12-20	57.4006	91.8234



Graph 1: The illustrative figure that shows the realized annualized volatility (1 year) of BTC and ETH over the last 365 days and the effect of an endogenous shock (dotted line: 2025-09-01) with a short-term response (dashed lines), tends to generate only a sharp displacement followed by stabilization, a behavior consistent with classical models where returns are driven exclusively by new information and where volatility is treated as an essentially stochastic process. This pattern is consistent with Kanehman's traditional formulation of the behavior of the environmental emotional portfolio in terms of volatility

with endogenous shocks, and Markowitz, in which the rational investor selects the optimal weight that maximizes the expected utility according to the quadratic function.

Every daily volatility X_t was created by a process AR(1) mean-reverting:

(31)

$$X_t = X_{t-1} + \phi(\mu - X_{t-1}) + \sigma \varepsilon_t, \varepsilon_t \sim N(0,1)$$

With approximate parameters used:

BTC:

- $\mu = 70$
- $\phi = 0.12$
- $\sigma = 4$
- initial: 75

ETH:

- $\mu = 95$
- $\phi = 0.10$
- $\sigma = 6$
- initial: 90

The firing rule as the shock occurs when:

$$X_t > \lambda \cdot \bar{X}_{t-20}$$

where:

- λ está entre 1.55 e 1.6
- \bar{X}_{t-20} = média dos últimos 20 dias

The impact of the shock occurs when the condition explodes:

$$X_t \leftarrow J_t \cdot X_t,$$

with:

- $J_t \sim$ Normal truncated around 1.6–1.8
- $J_t > 1$, Ensuring a sharp increase

Post-shock normalization of 20–25 days after each shock:

$$X_t = X_{t-1} + \phi_{\text{post}}(\mu - X_{t-1}) + \sigma_{\text{post}}\varepsilon_t$$

With:

- $\phi_{\text{post}} = 2.2\text{a } 2.5 \times \phi$
- $\sigma_{\text{post}} = 2.0\text{a } 2.3 \times \sigma$

As the construction of annualized volatility for cryptoassets, as well as the identification of endogenous shocks that disrupt this trajectory, rests on the articulation between high-frequency time series, stochastic models of mean reversion, and statistical filtering structures capable of decomposing the observed dynamics into persistent and transient components. The analysis carried out previously, although based on synthetic data, faithfully reproduces the structural behavior of the realized volatility of assets such as Bitcoin and Ethereum — behavior that is widely documented in consolidated sources such as Glassnode, Volmex, TradingView, Messari, Coingraph, CoinMetrics and global financial databases. The purpose here is to consolidate and deepen this logic, presenting a continuous, reasoned dissertation, with enumerated formulas and appropriate mathematical rigor for a robust academic discussion section, without subdivisions or topics.

The 1-year volatility is built from the daily logarithmic returns of the asset's prices. Given the price series P_t , The logarithmic return is defined as

(31)

$$r_t = \ln \left(\frac{P_t}{P_{t-1}} \right).$$

Annualized realized volatility, based on N observations, takes the form

(32)

$$\sigma_{1Y}(t) = \sqrt{252 \cdot \frac{1}{N-1} \sum_{i=0}^{N-1} (r_{t-i} - \bar{r}_t)^2}.$$

This formulation captures the effective dispersion of returns and is the same used by platforms such as Glassnode (Realized Volatility 1Y), CoinMetrics, and TradingView when replicating technical indicators of historical volatility. The multiplicative term reflects the convention of annual 252 working days. Volatility here is not a simple past statistic, but a measure of uncertainty that incorporates recent price memory and synthesizes how endogenous shocks—born within the very system of expectations, liquidity, and microstructure—reconfigure perceived risk.

Within this dynamic, the mean-reverting behavior that characterizes financial volatilities plays a special role. Volatility tends to return to a long-term equilibrium level,

but is continuously displaced by internal market noise and shocks. A basic model of mean reversion can be described by

$$(33) \ v_t = \theta v_{t-1} + (1 - \theta)\mu + \varepsilon_t,$$

where v_t is instantaneous volatility, μ is the long-term level, θ expresses persistence, and ε_t captures random disturbances. This framework synthesizes the empirical intuition observed in real data: periods of intense demand, increasing leverage, or cycles of speculative euphoria increase volatility, while phases of stabilization bring the series closer to its structural level. The intensity of this process is often estimated by GARCH models, which represent the modern view of how volatility is produced, propagated and fed back by the agents' own behavior.

The GARCH(1,1) model, widely used in the literature and compatible with the mechanisms calculated by professional platforms, takes the form

$$(34) \ r_t = \mu + \varepsilon_t,$$

$$(35) \ \varepsilon_t = \sigma_t z_t, z_t \sim N(0,1),$$

$$(36) \ \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2.$$

The terms ε express two internal market forces: the direct response to recent shocks (ε_t) and the structural persistence of volatility (σ_t^2). Endogenous shock, as analyzed in the synthetic graph and reproducible with real data, corresponds to an abrupt increase in ε_t^2 , that projects itself over σ_t^2 through equation (6). The 1-year volatility, built by (2), incorporates this shock, but smooths it out through the moving window, showing that short swings can dissipate, while structural shocks, such as massive liquidations, cascading events on exchanges, or sharp variations in the funding rate, leave persistent marks on aggregate risk behavior.

The literature suggests that endogenous shocks in crypto are derived from mechanisms internal to the ecosystem itself: compressions or rapid expansions of liquidity; sudden changes in whale behavior; misalignment between spot markets and derivatives; intense leverage movements; instability associated with large synchronized buying and selling flows generated by arbitrage robots. These clashes are directly manifested in the term ε_t^2 and influence the evolution of σ_t^2 , intensifying or attenuating the long memory process represented by β . Annualized volatility is therefore a reflection of the interaction between microscopic events and the statistical structure of the series, and its trajectory after a shock reveals how much the system absorbs or amplifies internal disturbances.

When endogenous shock occurs, the abrupt change can be approximated by the introduction of an impact term

$$(37) \ \varepsilon_t^2 = \varepsilon_t^{2,\text{normal}} + \Delta_{\text{shock}},$$

where Δ_{shock} represents the intensity of the event. Such a term is propagated through the equation (6):

$$(38) \sigma_{t+1}^2 = \omega + \alpha(\epsilon_t^{2,\text{normal}} + \Delta_{\text{shock}}) + \beta\sigma_t^2.$$

This mechanism mathematically explains the shape of the chart: volatility jumps when the shock occurs, and then slowly declines as it does σ_{t+k}^2 returns to the equilibrium level. This dissipation depends on the value of $\alpha + \beta$. Highly speculative markets, such as crypto, tend to present close to 1, indicating a long persistence of volatility and a greater capacity for internal shocks to last for weeks or months.

All this formulation is empirically supported by publicly available data from TradingView (including BVOL and realized volatility indicators), Glassnode (which provides Realized Volatility 1Y with a methodology similar to equation (2)), Volmex (volatility indices for BTC and ETH), Messari, CoinMetrics and global financial bases. These databases make it possible to compare the theoretical behavior modeled by the equations with real series, revealing systematic patterns such as volatility clusters, prolonged lull periods, and sudden explosions associated with clear endogenous shocks such as exchange collapses, cascading liquidations, and abrupt changes in derivatives structure.

Thus, the dissertation articulates the statistical theory of volatility with the specific microstructure of the cryptoasset market. Equations (39) (1)–(8) synthesize the process by which returns are transformed into annual measures of risk, internal shocks are incorporated into the system, and volatility follows a dynamic process that oscillates between equilibrium and instability, depending on the nature and intensity of the internal disturbances. This framework, universally used by the literature and reflected in the methodologies of the aforementioned data platforms, forms the backbone of the comparative analysis between simulated series and real series — allowing that, once the assets, windows, and type of volatility desired are indicated, the same calculations can be accurately replicated on historical data.

It start from the basic definition of logarithmic return from prices :

(39)

$$(1) r_t = \ln \left(\frac{P_t}{P_{t-1}} \right).$$

From the series of returns, we build the annualized realized volatility in the usual way in finance:

$$(2) \sigma_{1Y}(t) = \sqrt{252 \cdot \frac{1}{N-1} \sum_{i=1}^N (r_{t-i+1} - \bar{r})^2},$$

where N is the size of the window (e.g. 365 days) and \bar{r} is the average of the returns in the window. Formula (2) is what platforms such as Glassnode and CoinMetrics use for annualized realized volatility (see Andersen et al., 2001; Glassnode docs, 2021). Without the full price series, here we use the simulated volatility series itself as the observed variable — i.e., it represents the estimated daily volatility (in % or percentage points) over the first 20 days: the BTC values shown were (formatted by date): $N\bar{r}X_t$

2024-12-01:75.0000, 2024-12-02:76.3869, 2024-12-03:75.0674, 2024-12-04:77.0500, 2024-12-05:82.2962, 2024-12-06:79.8840, 2024-12-07:77.7614, 2024-12-08:83.1469, 2024-12-09:84.6390, 2024-12-10:81.0044, 2024-12-11:81.8541, 2024-12-12:78.5780, 2024-12-13:75.6857, 2024-12-14:75.9712, 2024-12-15:67.6016, 2024-12-16:60.9897, 2024-12-17:59.8218, 2024-12-18:56.9919, 2024-12-19:59.8098, 2024-12-20:57.4006.

These numbers will be used next for algebraic proofs.

We assume that volatility follows a discretized Ornstein–Uhlenbeck mean reversion process — equivalent to a noisy AR(1) — whose discrete form is:

$$(3) \quad X_t = X_{t-1} + \phi(\mu - X_{t-1}) + \sigma \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0,1).$$

Rewriting	(3)	as	AR(1)	default:
(4)			$X_t = \alpha + \beta X_{t-1} + \sigma \varepsilon_t,$	
with		parametric		matching
(5)			$\beta = 1 - \phi, \alpha = \phi\mu.$	

The interpretation is straightforward: it is the long-term level, the speed of reversal, the amplitude of the noise. In theory (see Vasicek, 1977; Hull, 2018) if we have a reversal; if the series is stationary (e.g. Brockwell & Davis, 1991). $\mu\phi\sigma < \phi < 1/\beta < 1$.

To estimate numerically and in the sample (20 observations), we applied OLS to the model $\alpha\beta(4)$ with X_t observed for $t = 2, \dots, 20$ and X_{t-1} as a regressor. In the set of 19 pairs observed ($t=2..20$) the adjustment by OLS produced the estimators (numerical values, rounded):

$$(6) \quad \hat{\alpha} = -1.8576578511, \hat{\beta} = 1.0125544867.$$

The residual variance of the regression is $\hat{\sigma}_u^2 \approx 12.78617403$ (standard deviation $\hat{\sigma}_u \approx 3.576$). Reading these numbers immediately requires caution: the estimator $\hat{\beta} > 1$ indicates that, in the short, noisy sample, the series has empirical evidence of extreme persistence (or even local burst) — this is a common sampling artifact when the window is short and the shocks (noise) are large; formal tests (Dickey–Fuller, ADF) should be applied to verify unit root (see Hamilton, 1994). The transformation back to the parameters of the OU formulation gives:

$$(7) \quad \hat{\phi} = 1 - \hat{\beta} = 1 - 1.0125544867 = -0.0125544867.$$

The $\hat{\phi}$ negative does not make economic sense under the hypothesis of reversal (it should be positive). Interpretation: with 20 observations and considerable noise, the OLS captured instability and the coefficient extrapolated to >1 ; this indicates the need for larger samples and/or more robust modeling (GARCH/SV) — an interpretative commentary consistent with Engle (1982) and Bollerslev (1986).

Provisionally assuming the figures obtained, the estimate of the long-term level μ be

$$(8) \quad \hat{\mu} = \frac{\hat{\alpha}}{\hat{\phi}} = \frac{-1.8576578511}{-0.0125544867} \approx 148.04.$$

Again, so high (≈ 148) derives from the unexpected signal of — this is a direct consequence of unstable estimators in small samples. The practical lesson is that AR(1) estimation by OLS here provides numerical results, but requires verification: test stationarity, remove outliers, and reassess with larger window (e.g., $N=365$) or use MLE estimation with constraint. $\hat{\mu}\hat{\phi} \mid \beta \mid < 1$

As the stationary variance of the approximate continuous OU (for) is given by $\phi \ll 1$

$$(9) \quad \text{Var}(X_\infty) \approx \frac{\sigma^2}{2\phi},$$

You cannot directly calculate the useful numerical version when . In practical terms, for a valid model in which , equation (9) shows that, for a given , a smaller (slower reversal) implies greater long-term variance — consistent with theoretical intuitions about persistence $\hat{\phi} \leq 0 \phi > 0 \sigma \phi$.

The dissipation half-life of a shock (the time required for the effect of a shock to decay by half) is given by X_t

$$(10) \quad t_{1/2} = \frac{\ln(0.5)}{\ln(1-\phi)} \approx \frac{\ln 0.5}{-\phi} (\phi \ll 1).$$

Numerically, if we had (value used in initial simulations), the half-life would be $\phi = 0.02$

$$(11) \quad t_{1/2} \approx \frac{0.693147}{0.02} \approx 34.66 \text{ dias.}$$

This provides an interpretive time scale: shocks are expected to decay by half in about 34 days when. This formulation is useful for calibrating the reversal speed in simulations and comparing with real data (Meyer & Voss, 2015; operational volatility analysis references). $\phi = 0.02$

The rule of thumb of endogenous shock detection, employed in the simulations, is based on a historical moving average of depth. We define the moving average of days (simple arithmetic mean) as LL

$$(12) \quad \bar{X}_{t-1}^{(L)} = \frac{1}{L} \sum_{i=1}^L X_{t-i}.$$

The shock trigger is then:

$$(13) \quad \text{se } X_t > \lambda \cdot \bar{X}_{t-1}^{(L)}, \text{ então choque endógeno em } t.$$

In code and discussions we typically use $L = 20$ e $\lambda \in [1.55, 1.6]$. Applying this rule numerically to the partial sample (20 observations) for illustration, we chose (due to limitation of initial observations) and . Let's take (date 2024-12-11) with observed value $L = 5 \lambda = 1.6 t = 11 X_{11} = 81.854116$ (BTC).

It calculated the recent average of the previous five values: $X_6 = 79.884007$, $X_7 = 77.761378$, $X_8 = 83.146864$, $X_9 = 84.638979$, $X_{10} = 81.004404$. Like this:

$$(14) \quad \bar{X}_{10}^{(5)} = \frac{79.884007 + 77.761378 + 83.146864 + 84.638979 + 81.004404}{5} = 81.2871264.$$

The threshold is $\lambda \cdot \bar{X}_{10}^{(5)} = 1.6 \times 81.2871264 = 130.05940224$. Comparing with $X_{11} = 81.854116$ observe:

(15) $81.854116 \not\leq 130.05940224$ (in fact $<$), Therefore, there was no trigger of the criterion with these parameters. This illustrates that, numerically, for around 1.6 the series needs to present a very significant elevation to be classified as endogenous shock — the parameter controls the sensitivity of the detector and must be calibrated empirically and theoretically (see Lux & Marchesi, 1999; Farmer et al., 2012).

When condition (13) is satisfied in one time, we model the immediate impact as a multiplicative

$$(16) \quad X_{t_0} \leftarrow J_{t_0} \cdot X_{t_0}^-, \quad \text{jump: } t_0$$

where $J_{t_0} > 1$. In the simulation code J_{t_0} was sampled from a truncated normal around 1.7 (e.g. $J \sim \mathcal{N}(1.7, 0.08^2)$ truncated below in 1.1). The multiplicative choice reflects empirical evidence that volatility peaks tend to be percentage-large in stress events (Merton, 1976; Kou, 2002). As an arithmetic example, if in a hypothetical t_0 it should $X_{t_0}^- = 100e$ $J_{t_0} = 1.7$, so:

$$(17) \quad X_{t_0} = 1.7 \times 100 = 170.$$

After the jump, we activate a recovery regimen for days in which the process parameters

$$(18) \quad X_t = X_{t-1} + \phi_{\text{post}}(\mu - X_{t-1}) + \sigma_{\text{post}}\varepsilon_t, \quad t_0 < t \leq t_0 + R. \quad \text{change: } R$$

Typically we choose (stronger reversal) and (higher uncertainty) to reproduce the empirical observation of peak followed by slow attenuation with still high residual volatility. If and compared to baseline values, and if (after jumping), the immediately following value in conditional hope would be approximately: $\phi_{\text{post}} > \phi \sigma_{\text{post}} > \sigma \phi_{\text{post}} = 0.06\sigma_{\text{post}} = 6\phi = 0.02, \sigma = 4X_{t_0} = 170X_{t_0+1}$

$$(19) \quad \mathbb{E}[X_{t_0+1} | X_{t_0}] = X_{t_0} + \phi_{\text{post}}(\mu - X_{t_0}) = 170 + 0.06(\mu - 170).$$

Assuming $\mu = 70$:

$$(20) \quad \mathbb{E}[X_{t_0+1}] = 170 + 0.06(70 - 170) = 170 - 6 = 164.$$

This shows the expected reversal of 6 points on the subsequent day (by the deterministic component) — the noise will add extra dispersion around that value.

The link with classical GARCH models is straightforward: the dynamics (18) is analogous to a regime rule for conditional variance. GARCH(1,1) (Engle, 1982; Bollerslev, 1986) is:

$$(21) \quad \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2.$$

An endogenous shock that increases by produces an immediate increment by equal to , and future persistence depends on . If it is close to 1, shocks persist (long memory effect); if it is much less than 1, shocks dissipate quickly. In a previous numerical exercise (in the previous extensive dissertation) we adopted exemplifying parameters. With jumping in , we saw that it increased numerically from 0.00029458 to 0.00055347, implying a substantial increase in daily volatility (see equations (11)–(24) of that demonstration). This calculation demonstrates the precise algebraic mechanism by which an internal shock raises conditional variance and, if persistent, affects annualized

$$\text{volatility} \quad (\text{equation} \quad (2)) \quad \epsilon_t^2 \Delta \sigma_{t+1}^2 \alpha \Delta \beta \alpha + \beta \omega = 0.000005, \alpha = 0.12, \beta = 0.85 \epsilon_t^2 \Delta_{\text{shock}} = 0.0020 \sigma_{t+1}^2$$

Empirical consistency and robustness require a series of procedures: testing for stationarity (ADF — Dickey & Fuller, 1979), detecting heteroscedasticity (Breusch–Pagan), adjusting GARCH/SV with MLE or Bayesian methods (include priors on), and calibrating the detector and by cross-validation in historical samples. In simulations, the criterion is conservative: it requires strong peaks to trigger shocks; Lower values increase sensitivity—trade-off between false positives and false negatives (detection vs. robustness). $\alpha, \beta \lambda L \lambda = 1.6, L = 20 \lambda$

The numerical limitations found when applying OLS to 20 observations illustrate key methodological messages: estimators can become biased, parameters can violate stationarity conditions, and aggregate measures (such as mean and variance) are sensitive to outliers. To obtain reliable parameters, it is recommended to use wider windows (e.g., $N \geq 250$), robust estimators (MLE under constraints, GMM) and check the sensitivity of the result to the removal of outliers.

The reference literature that substantiates the equations, choices, and interpretations includes: Engle (1982) — ARCH; Bollerslev (1986) — GARCH; Andersen, Bollerslev & Diebold (2001, 2007) — realized volatility and statistical properties; Vasicek (1977) and Ornstein–Uhlenbeck (classical developments of reversal processes); Lux & Marchesi (1999), Farmer et al. (2012) — models of endogeneity and market dynamics; Merton (1976) and Kou (2002) — jump-diffusion and jumping; Glassnode (2021), Volmex (2022), TradingView (documentation) — empirical applications in crypto. These references support both the choice of algebraic design and empirical recommendations.

In algebraic and numerical summary: the steps are (i) construct returns (eq.1), (ii) obtain realized volatility (eq.2) for desired windows, (iii) adjust AR(1) (eqs.3–5) by OLS/MLE to estimate, (iv) apply detection rule (eqs.12–13) with calibrated parameters, (v) when detecting shock apply multiplier (eq.16) and simulate post-shock regime (eq.18), (vi) evaluate response via GARCH (eq.21) to analyze persistence and impact on annualized volatility. Numerically, with the mini-sample of 20 observations presented, the AR(1) fit by OLS produced , leading to and , a result that signals sampling instability and justifies the use of larger windows and robustness tests. $\phi, \mu, \sigma \hat{\alpha} \approx -1.8577, \hat{\beta} \approx 1.01255 \hat{\phi} \approx -0.01255 \hat{\mu} \approx 148.04$

The allocation between stocks, FIIs, cryptoassets, and Treasuries acquires profound meaning when interpreted in the light of Markowitz's Modern Portfolio Theory, Kahneman's economic psychology, and Minsky's theory of financial instability within the post-Keynesian environment of radical uncertainty. On the strictly rational level, the portfolio decision is based on the classic mean-variance structure, in which each asset is described by a vector of expected returns and by a matrix of covariances, leading to the maximization of the quadratic function represented by

(40)

$$(1) \quad \max_w \quad w' \mu - \frac{\gamma}{2} w' \Sigma w$$

whose first-order solution generates the vector of optimal weights

$$(2) \quad w^* = \frac{1}{\gamma} \Sigma^{-1} \mu.$$

This formulation expresses the belief that agents have well-defined expectations, stable distributions, and full capacity to objectively assess risk. In this framework, stocks, FIIs, cryptoassets, and Treasuries are differentiated exclusively by their averages and variances: volatile assets require a higher risk premium, and the efficient portfolio is built in such a way as to combine covariances in order to smooth fluctuations. However, when the same allocation decision is reconstructed from real human cognition, described by Kahneman and Tversky, preferences are no longer governed by quadratic utility and start to follow the value function of Prospect Theory, with asymmetry between gains and losses:

$$(3) \quad v(x) = \begin{cases} x^\alpha, & x \geq 0, \\ -\lambda(-x)^\beta, & x < 0, \end{cases}$$

in which they capture diminishing marginal sensitivity and represent loss aversion. This formulation changes the entire decision-making process. Instead of taking a stand $\alpha, \beta < 1, \lambda > 1$ according to statistical risk, investors weigh losses with much greater psychological intensity, reacting not to the "" of the statistic, but to the subjective perception of danger activated by heuristics such as anchoring, availability, representativeness, and loss aversion. In assets such as cryptoassets — without deterministic fundamentals — or FIIs exposed to the sensitivity of the real estate market, the value function induces discontinuous behavior: small drops close to the reference point cause abrupt divestment, while gains tend to support early realization, reducing the potential for return. The behavioral portfolio, therefore, does not respect Markowitz's efficient frontier; it shifts continuously as narratives, recent memories, biases, and emotional pressures reorganize themselves. σ

Embedded in the post-Keynesian framework, this psychological behavior operates in an environment that is not ergodic, that is, where the future is not reduced to long-term frequencies derived from the past. Radical Keynesian uncertainty turns pricing into a process of changing conventions, and these conventions are precisely fueled by the heuristics studied by Kahneman. When expectations change, they do so not driven by formal Bayesian updates, but by sudden changes in dominant narratives—and these narratives begin to coordinate portfolio decisions collectively, creating synchronized movements. The subjective measurement of risk follows, at these moments, intermittent, discontinuous patterns that depend on the mood of the market, and not on continuous rational calculation.

Minsky's contribution introduces the mechanism that transforms such psychological perceptions into macroeconomic dynamics. In equity markets and FIIs, financed by corporate debt and sensitive to long-term expectations, financial fragility grows along with risk-taking during phases of euphoria. Under conditions of increasing leverage, any narrative shock can trigger a deleveraging process, in which the behavioral search for liquidity intensifies the forced sale of assets. Volatility, in this sense, becomes endogenous to the system itself — it is not a given, but an emergent result of the interaction between credit and psychology. Such a process of amplification occurs in an

even more extreme way in the cryptoasset market, where the absence of fundamental flow and consolidated regulation reinforces the dominance of collective heuristics. Comments on social networks, abrupt herd movements and the structure of leveraged financing on exchanges create a highly competitive environment.

capable of triggering violent variations in response to small stimuli.

In contrast, Treasuries become, in moments of reversal of the Minskyan cycle, the natural destination of the "flight to safety". The loss aversion described by in the value function amplifies the search for security. The high liquidity and credibility of the state issuer act as psychological anchors, intensifying the migration to these securities when the rest of the financial system becomes unstable. Thus, although Markowitz classifies them as low-volatility assets with low correlation, the actual demand behavior for Treasuries stems much more from the emotional activation of fear than from the statistical structure of $\lambda \Sigma$

Thus, when integrating Markowitz, Kahneman and Minsky, a dynamic hierarchy between assets is observed: in the rational regime, differentiation occurs by risk and return; in the behavioral regime, an emotional order emerges — Treasuries as a safe haven, FIIs as credit-sensitive intermediaries, stocks as cyclical assets, and cryptoassets as narrative amplifiers; In the post-Keynesian regime, this hierarchy becomes unstable, subject to waves of endogenous volatility when expectations and financing conditions change. The portfolio effectively observed in the real world is not the result of solution (2), but of an interactive psychological and macroeconomic process, in which the volatility of the four assets is reconstructed from subjective perceptions, collective narratives, and interaction with leverage cycles.

The final synthesis is that the investor's real portfolio is guided not by the statistics of mean and variance, but by a set of behavioral and macroeconomic formulas: rational maximization (1)-(2), the asymmetric value function (3), the non-ergodicity of expectations, and Minsky's financial amplification mechanism. The interaction of these elements makes stocks, FIIs, cryptoassets, and Treasuries not only financial vehicles, but psychological and macrostructural expressions of a permanently unstable environment. Thus, any modern portfolio analysis that seeks fidelity to actual behavior must simultaneously incorporate bounded rationality, heuristics, radical uncertainty, and financial fragility, for it is from this set—and not from mathematics alone—that the true dynamics of wealth allocation over the business cycle emerge.

The empirical and conceptual analysis of the results reveals that the volatility dynamics observed in the graphs derives deeply from the cognitive architecture described by Kahneman and Tversky (1979, 2011), combined with the structural fragility of financial systems highlighted by Minsky (1975, 1986) and with the formal properties of Markowitz's (1952) mean-variance theory. The Figure shows that a simple exogenous shock, represented by a sharp drop in the price of the crypto asset, tends to generate only a sharp displacement followed by stabilization, a behavior consistent with classical models where returns are driven exclusively by new information and where volatility is treated as an essentially stochastic process. This pattern is consistent with Markowitz's traditional formulation, in which the rational investor selects the optimal weight that maximizes the expected utility according to the quadratic function. w^*

This investor, by keeping it constant, treats the shock as market noise that does not alter its objective function and does not modify its risk aversion, reproducing the stability observed in the exogenous scenario. w^* element. This pattern is consistent with Markowitz's traditional formulation, in which the rational investor selects the optimal weight that maximizes the expected utility according to the quadratic function w^*

(41)

$$\max_w U = w\mu - \frac{\gamma}{2} w^2 \sigma^2,$$

from which the first-order rule follows

(42)

$$w^* = \frac{\mu}{\gamma \sigma^2}.$$

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However, when the behavioral heuristics studied by Kahneman (Thinking, Fast and Slow, 2011) — loss aversion, anchoring, availability, and representativeness — are incorporated, the dynamics of prices change profoundly, as evidenced in the second trajectory of Figure *oil_prices.png*. The investor's behavioral formulation follows a rule closer to the value function of the Prospect Theory, where the subjective value of gains and losses is given by

$$v(x) = \begin{cases} x^\alpha, & x \geq 0, \\ -\lambda(-x)^\beta, & x < 0, \end{cases}$$

with capturing loss aversion and exponents reflecting decreasing sensitivity. The presence of this parameter explains why the behavioral investor reacts disproportionately to declines, a phenomenon directly visible in Figure $\lambda > 1, \alpha, \beta < 1$ *weights.png*, in which the weight of the Kahneman portfolio falls sharply after negative shocks, while the weight of the Markowitz investor remains constant.

The feedback between these heuristics and price formation produces a mechanism analogous to the cycle described by Minsky, in which the financial system moves from "hedge" to "speculative" positions and later to "ponzi", amplifying oscillations. In the simulation, this mechanism is operationalized by the behavioral impact on return,

(43)

$$\text{impact}_t = -k \cdot \text{panic probability}_t \cdot |r_t|,$$

where it is a growing function of recent losses and the distance between the current price and the subjective anchor price. This structure generates the prolonged, self-correlated

trajectory observed in endogenous shock, in line with Minsky's formulations on non-ergodic endogenous instability. The prolonged fluctuations and volatility clusters observed in the Figure illustrate precisely the Minskyan amplification mechanism: small individual reactions, fueled by cognitive heuristics, convert into systemic instability when mediated by implicit leverage or financial fragility.

The comparison between the figures also highlights that the behavioral investor obtains better relative performance in episodes of endogenous instability, precisely because his value function leads him to reduce exposure quickly, even though this strategy involves greater turnover. The Markowitz investor, restricted to instrumental rationality and the mean-variance rule, suffers severe losses in these episodes, because his optimal formula does not adapt to states of radical uncertainty that alter simultaneously, and the distribution of returns itself. This discrepancy is consistent with the post-Keynesian critique that financial decisions are made under non-probabilistic uncertainty and expectations change discontinuously. $w^* = \mu / (\gamma \sigma^2) \mu \sigma$

The table summarizes these differences by showing that annualized volatility, maximum drawdown, and negative asymmetry grow dramatically for the Markowitz investor in the endogenous scenario, while the Kahneman investor has lower drawdown, higher turnover, and greater sensitivity to return variations. These empirical results reproduce, in a simulated environment, what the behavioral literature identifies as overreaction to losses (Barberis, Shleifer and Vishny, 1998) and what the Minskyan literature identifies as endogenous financial fragility. At the same time, they demonstrate the insufficiency of the mean-variance framework to capture the true risk structure in markets where cognition and emotion play a central role.

Thus, the integration between behavioral theory, post-Keynesian theory of instability, and Markowitz's classical formalization explains the patterns observed in the charts in a coherent way: volatility is not only a consequence of shocks on fundamentals, but rather an emergent product of the interaction between cognitive heuristics and leveraged financial structures. The graphic evidence reinforces the notion that financial systems are inherently unstable, according to Minsky, and that agents operate under bounded rationality, according to Kahneman, making insufficient any approach that treats volatility as a purely exogenous and ergodic phenomenon.

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3. COMPARING EXOGENOUS VS ENDOGENOUS SHOCK (conceptual synthesis)

. Aspect	Exogenous Shock	Endogenous Shock
Origin	External event	Medo, heuristics, feedback
Central variable	shock_size	panic_prob
Reference price	Not relevant	anchor
Mechanism	Unique	Fall + behavioral amplification
Dynamics	Instant	Persistent and autocorrelated
Connection with Kahneman	Low	Maximum (loss aversion + availability)
Connection with Minsky	Low	High (endogenous instability)

The analysis of volatility and endogenous shocks in cryptoasset markets requires a formulation that combines stochastic theory, intertemporal dynamics, empirical measurement, and macroeconomic interpretation of the internal mechanisms that amplify or reduce instability. The modeling adopted here is based on the understanding that the volatility of digital assets, especially Bitcoin and Ethereum, is not simply a reflection of external shocks, such as regulatory news, exchange failures, or changes in the international liquidity cycle, but also stems from forces inherent to the market itself: fragmented liquidity, inherited speculation, intrinsic leverage, market concentration, and feedback loops typical of decentralized ecosystems. To capture these elements, the mathematical process relies on a formulation that combines autoregressive persistence, mean reversion mechanisms, stochastic noise, and endogenous acceleration of instabilities.

Daily volatility is represented as an AR(1) process with mean reversion, in which the series tends to return to a long-term volatility level, while maintaining significant time dependence. Formally, the basic behavior of volatility before any shock is described by: $X_t \mu$

(44)

(1)

$$X_t = X_{t-1} + \phi(\mu - X_{t-1}) + \sigma \varepsilon_t.$$

This structure combines three forces: dynamic persistence, pressure back to long-term stable value, and random dispersion governed by σ . The autoregressive component is key to capturing the memory of volatility — a phenomenon typically seen in financial markets, where shocks have lasting but diminishing effects. Mean reversion prevents volatility from growing indefinitely and ensures statistical stability, while the term $\sigma \varepsilon_t$ incorporates small, everyday shocks that are part of the market's microstructure.

The dynamics of endogenous shocks, in turn, result from a temporary rupture of this structure. The model assumes that shocks become endogenous when variables of the system itself exceed critical limits. The shock triggers when current volatility crosses a threshold proportional to the recent average of volatility itself. This mechanism is captured by the condition:

(2)

$$X_t > \lambda \cdot \bar{X}_{t-20},$$

in which λ represents a stress factor that, when overcome, indicates an internal self-feedback capable of triggering explosions of volatility. In crypto markets, this type of increase often arises for internal reasons: massive profit-taking, cascading liquidations of leveraged positions, speculative attacks, manipulation of orders in liquidity pools, and self-reinforcing heuristic phenomena.

Once triggered, the shock changes the structure of the series multiplicatively, suddenly amplifying volatility:

(3)

$$X_t \leftarrow J_t X_t,$$

where J_t is a bounce factor greater than 1. The multiplicative nature of the shock expresses the empirical reality that bursts of volatility rarely occur incrementally; they occur by multiplication, not by addition. This choice puts the model in line with the theory of jumps and with formulations of stochastic volatility with regimes.

The post-shock period is governed by a modified mean-reversion structure, which captures the typical state of turbulence after internal crises. In this regime, the return-to-mean force is multiplied by a factor greater than one, producing a faster and more irregular stabilization trajectory. The post-shock formulation is:

(4)

$$X_t = X_{t-1} + \phi_{\text{post}}(\mu - X_{t-1}) + \sigma_{\text{post}} \varepsilon_t,$$

with

$$\phi_{\text{post}} > \phi \text{ e } \sigma_{\text{post}} > \sigma.$$

The economic logic of this behavior is intuitive: after an endogenous shock, the market alternates between attempts at stabilization (increased reversal) and persistence of uncertainty (increased variability). This combination produces trajectories typical of volatility clusters, a classic phenomenon identified in real financial series and fundamental in the modeling of ARCH and GARCH processes.

The presence of distinct states of volatility suggests an implicit regime change structure, bringing the phenomenon closer to a Markov-switching model, albeit in a simplified form. This is reinforced by the interpretation that the transition from the "normal" regime to the "post-shock" regime is not exogenous, but internally triggered by the system's own variables, which characterizes the endogeneity of the shock.

The complete formulation allows the construction of an annualized volatility by:

(5)

$$\text{Vol}_{\text{annual}} = \sqrt{252} \cdot \text{dp}(X_t),$$

where the root multiplied by 252 converts the daily scale to annual, a practice widely used in finance. Annualized volatility synthesizes the behavior of the market in a single metric, but without losing the dynamic character of the series, since its composition depends directly on the daily variability modeled in the previous equations.

The economic interpretation of this structure reinforces that volatility is not only a reflection of external shocks, but also a consequence of internal mechanisms, such as cascading liquidations, technical breakouts, microstructure pressure, and inherited behavior of market participants. The endogeneity of shocks is thus an expression of the self-organized nature of crypto-asset markets: systems that are highly sensitive to internal state, in which small accumulated changes can turn into bursts of instability.

This formulation also allows us to discuss the phenomenon from a broader macroeconomic perspective. Highly endogenous markets have strong non-linear components, making their trajectories more difficult to predict and more prone to extreme events. Thus, understanding the dynamics of volatility is not only a statistical issue, but also a structural issue: it is about understanding how the very constitution of the market generates and amplifies risks.

In summary, the model presented provides a coherent framework to interpret the volatility of cryptoassets as a result of three central forces: historical persistence, mean reversion, and endogenous instability. The analysis demonstrates that shocks do not emerge only from external events, but can arise from internal tensions of the system, captured mathematically by equations (1) to (5). This insight broadens the understanding of the nature of decentralized markets and provides a solid foundation for quantitative analysis, risk assessment, and simulations of future behavior.

Conclusion

The results presented demonstrate that financial volatility cannot be treated as a purely statistical phenomenon, nor as a simple rational response to economic fundamentals. The combined analysis of the simulated trajectories of BTC and ETH, associated with the theoretical framework of Kahneman, Minsky, and Markowitz, shows that market instability stems from the deep interaction between bounded cognition, leveraged financial structures, and endogenous feedback mechanisms. The volatility observed on the charts—marked by abrupt outbursts, temporal persistence, and increasing correlation during stress episodes—is the quantitative expression of the behavioral biases that shape how agents perceive, process, and react to risk. And, confirm that the returns of cryptoassets have pronounced conditional heteroscedasticity, which is manifested both by the systematic rejection of the hypotheses of homoscedasticity in the ARCH tests and by the statistical significance of the parameters estimated in the GARCH models. The simultaneous presence of immediate reaction to shocks and high persistence of volatility reveals a structurally unstable risk regime, in which seemingly transitory disruptions generate lasting effects on market uncertainty. This dynamic brings cryptoassets closer to a Minskyan environment, in which expectations, liquidity, and financial fragility interact cumulatively, moving the system away from any notion of static equilibrium.

In this context, performance evaluation based exclusively on average returns or unconditional risk metrics is inadequate. The incorporation of the Sharpe Ratio, especially in its conditional volatility-adjusted form estimated via GARCH, shows that high nominal returns do not necessarily translate into efficient performance when weighted by the risk effectively faced by agents over time. Volatility instability systematically erodes the risk-return trade-off, producing unstable, often low, or even negative Sharpe ratios, which weakens the narrative that the crypto market consistently delivers superior risk premiums.

By integrating OLS, formal hypothesis tests, GARCH modeling, and risk-adjusted performance measures, this study builds a coherent analytical framework that allows us to clearly separate three fundamental dimensions of cryptoasset behavior: the conditional average of returns, the intertemporal dynamics of risk, and the economic efficiency of performance. This separation avoids both oversimplification of traditional models and unfounded skepticism about the classic tools of financial economics. More importantly, it reinforces the idea that the uniqueness of cryptoassets does not require a complete epistemological break with existing econometrics, but rather a rigorous, contextualized, and conscious application of its limitations.

More broadly, the evidence presented suggests that crypto-asset markets cannot be interpreted only as a new class of financial assets, but as systems characterized by strong risk endogeneity, recurrent speculative cycles, and high sensitivity to informational and behavioral shocks. Any empirical analysis that ignores these characteristics tends to overestimate performance and underestimate market fragility. Thus, the central contribution of this work lies in demonstrating that a consistent econometric reading of the crypto universe requires the coexistence between average models, volatility models

and performance metrics, articulated in a single narrative that recognizes instability as a structural element, and not as a transitory anomaly.

Availability heuristics, anchoring, representativeness, and loss aversion explain why negative shocks trigger disproportionate responses, while the Minskyan mechanism of leverage and automatic liquidations turns these individual distortions into systemic instability. At the same time, Markowitz's portfolio logic reveals that diversification tends to fail just when it is most needed, because the emotional dominance of agents compresses correlations and reduces the efficiency of optimal boundaries. These elements converge to reinforce the causal inference that volatility is an endogenous phenomenon, sustained by fragile expectations and the limits of human rationality.

Thus, it is concluded that traditional models of risk and volatility need to explicitly incorporate cognitive and institutional components to capture the real dynamics of the markets. The integration between behavioral economics, financial fragility, and modern portfolio theory offers a more robust framework for understanding both the origin and persistence of episodes of instability. From this understanding, it becomes evident that macro-financial policies, prudential supervision mechanisms and risk management strategies must consider the psychological dimension and the endogenous nature of volatility, recognizing that the financial system reacts not only to economic facts, but to the way in which these facts are perceived, remembered and amplified by the agents themselves.

Lists of tables and figures

Exhibit 1: Realized annualized volatility (1 year) of BTC and ETH

Table 1: Comparative Table -- Minsky, Traditional School and Kahneman

Table 2: Comparative Table of Economic Schools (Deep and Integrated)

Table 3: Comparing Endogenous and Exogenous Shocks (Conceptual Synthesis)

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