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Bounded Rationality and Price Adjustment: A Cognitive Load Perspective on Investor Overreaction and Underreaction

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Abstract: This paper, inspired by the psychological mechanisms of human cognition and microstructure economics, proposed and tested the theory of Cognitive Load-Based Price Adjustment (CLBPA), where equity-market overreactions and underreactions are united to explain better market behaviour. Utilising abnormally intense intraday tick-by-tick TAQ data for 2,847 stocks traded in NYSE, NASDAQ, LSE, NSE (India), and B3 (Brazil) during the months of January 2018–December 2023 (approximately 15.4 million distinct intraday observations), the researchers assessed cognitive load toward a composite index formed as the behavioural proxy for reaction time, VPIN, and order-to-trade ratios. Thus, instead of some esoteric constellations of regime-switching models, panel threshold estimators, and modified GMM steamrolled by fishing for "just-in-time data," this study formally and experimentally applied these and several other methodologies—most notably, real-time dimensions of cognitive-load-influenced market regulation: (1) on the very essence of the matter, both proofs of the impact of System-1 vs. System-2 on prices; and (3) sub-allenance. Not surprisingly, under the circumstances, the empirical-regression techniques converting instantaneous reactions into relevant reaction times allowed for evaluating trading dynamics with respect to cognitive processing and for rigorously analysing the effects of CG on more than one iteration over the downturn. Conclusions include designing dynamic, empirical-regression-driven circuit breakers, enabling them to install further temporal information architecture on their exchange circuits, and encouraging them to use cognitive-aware execution algorithms for fair and efficient price discovery. Future work would test the same metrics.

Keywords: cognitive load, bounded rationality, price adjustment speed, market microstructure, overreaction and underreaction, dual-process theory, CLBPA model, VPIN (order-flow toxicity), investor sentiment, regime-switching models, high-frequency trading, emerging vs developed markets, circuit breakers, price discovery, behavioral finance

1. INTRODUCTION

A foundational paradox has come to rest upon the architecture of modern financial markets that has been living with economists for the last 50 years. This dilemma is the tension between the theoretical perfection of price formation and empirical reality. The heart of this paradox is the Efficient Market Hypothesis (EMH), which was formalised by Eugene Fama in his seminal 1970 paper titled "Efficient Capital Markets: A Review of Theory and Empirical Work" and published in the Journal of Finance. Fama's tripartite classification of efficiency—weak, semi-strong, and strong—asserts that security prices fully reflect all available information, from which no consistent excess returns may arise through methods like fundamental and technical analyses. Yet the brilliant logic of market efficiency, based on the edifice of Homo Economicus information, information, Economicus, the perfectly rational, utility-maximising agent with unlimited computational capacity, faces a peculiar adversary: the behavioural complexities of real human decision-making. The 2017 Nobel Memorial Prize in Economic Sciences, awarded to Richard H. Thaler of the University of Chicago Booth School of Business, offers a dynamic description of this very confrontation, honouring him for "incorporating psychologically realistic assumptions of limited rationality, social preferences, and lack of self-control into analyses of economic decision-making" (Royal

Swedish Academy of Sciences, 2017). As the Academy pointed out, Thaler's findings and the evolution of his theory represent significant milestones in the development of the new and rapidly expanding field of behavioural economics. The literature serves to connote how human traits systematically interplay in individual decisions and market outcomes.

Thaler's Nobel-winning ideas can be traced back to Simon's critical notion of bounded rationality, as discussed in his Quarterly Journal of Economics essay "A Behavioural Model of Rational Choice" (Simon, 1955). Simon, who was honoured with the Nobel Prize in Economic Sciences in 1978 for his pioneering work on this theme, denounced the conventional economic assumption that decision-makers are perfectly enlightened beings capable of optimising across all imaginable choices with perfect foresight and computational abilities. Certainly, Simon (1955) nearly proposed a big intellectual challenge by proposing that human behaviour optimising optimising behaviour is limited by severe cognitive restrictions: "rationality... implies a perfect foresight about the consequences of an act, given the state of the world. Actually, the knowledge of consequences is always fragmentary and too meagre for the kind of rationality that orthodox economics presupposes. Because the consequences lie in the future, imagination must help to fill in the lack of actual felt experience of possessing values for them; but imaginings, too, must always be well short of actual knowledge of consequences" (pp. 103-104). To portray this actual behaviour, Simon introduced the keyhole term of "satisficing", which is a contraction of "satisfying" and "sufficient"—a call to the decision-maker to set aspiration levels and opt for the first choice that thereby meets these basically created instrumental aspirations, in short, in lieu of the physically and computationally impossible task of global optimisation (Simon 1956; 1957). Or optimisation optimisation Or, like he put it in Models of Man afterwards, "The most important consideration of administrative theory concerns the boundary between the rational and the non-rational aspects of social behaviour...and the behaviour...and the behaviour...and the behaviour of human beings who satisfice because they have not the wits to maximise" (p. xxiv).

Unfortunately, the last two decades have also shown a series of repeated empirical challenges to market efficiency theories, along with some of the initial theoretical findings and subsequent analyses in behavioural finance. A few of these challenges include long-term persisting irrationality, i.e., overreaction-underreaction, overconfidence, under-confidence, the disproportionate effect of extreme probabilities and the impact of funds that invest distantly from where they derive their resources, just to name some key findings signified by empirical evidence highlighting the absence of behavioural market strategies from empirical findings. For instance, when numerous investors interpret national economic conditions concurrently, their conspicuous unity ensures the presence and function of markets! Owing to this logic, inefficient market strategies were withdrawn from any real consideration in the realm of analysis. The venture capital model is simply an application of the expression. Note that, before the model can become operational, enterprises and indices that are financed by venture capital must be reviewed separately before they can be qualified. Meanwhile, the disintegration of enforcement mechanisms does not improve the flawed CAPM.

As much as behavioural venture-capital-financed behaviouraleconomy has been improving, it is still struggling to interpret overreaction and underreaction as different illustrations of a single, general mechanism. De Bondt and Thaler (1985) associated overreaction with psychological biases such as representativeness heuristics, while Hong and Stein (1999) linked underreaction to limits in information diffusion, presenting two separate theoretical perspectives that cannot be reconciled. The significance of this disjointed explanation is particularly noteworthy, especially considering the fundamental insights from cognitive psychology presented in Daniel Kahneman and Amos Tversky's influential 1979 paper, "Prospect Theory: An Analysis of Decision under Risk," published in Econometrica. Prospect theory has achieved classic status and receives the most citations in the economic community, providing a framework for understanding that decision-making involves evaluating choices based on reference points rather than final wealth states; it includes concepts such as loss aversion, where losses are perceived as more significant than equivalent gains, and probability weighting, which overweights small probabilities while underweighting moderate-to-high probabilities. These cognitive patterns, validated by a worldwide study conducted in 2020 across 19 countries and 13 languages published in Nature Human Behaviour (Ruggeri et al., 2020), suggest that the same psychological processes – mechanisms of limited attention, heuristic processing, and emotional responses – may drive under- or over-reaction.

This theoretical integration focused on high-frequency trading (HFT) and the market microstructure transformations that are currently relevant. The period in question saw an explosion of algorithmic execution, co-location services, and millisecond-latency trading, accompanied by the reassuring news that information processing environments could be altered, while also potentially escalating cognitive constraints in price discovery. David Easley, Marcos López de Prado, and Maureen O'Hara published research in the Review of Financial Studies in 2012, which introduced the Volume-Synchronised Probability of Informed Trading (VPIN) metric as a measure to gauge flow toxicity—specifically, how order flow can adversely select market makers who may be unaware that they are providing liquidity at a loss. Their survey on the Flash Crash of May 6, 2010, discovered that VPIN had reached historically high levels over an hour before the market collapsed, suggesting that cognitive constraints in processing toxic order flow can lead to large price discontinuities (Easley et al., 2012). Subsequent research has shown that HFT algorithms have regime-dependent consequences: during "calm" periods HFT suppresses volatility by around 14-17% via increased liquidity provisioning, but during "stressful" periods it increases volatility by around 20-25% as algorithms withdraw liquidity at the exact moment when markets need it the most (Brogaard et al., 2018; Menkveld, 2016). These findings suggest that within an environment characterised by algorithmic dominance, the very central facet around price discovery remains the bounded rationality of the algo design and the cognitive constraints of its human supervisors.

We address this research gap by introducing the CLBPA (Cognitive Load-Based Price Adjustment) model that merges overreaction and underreaction within a theoretical framework that grows upon the grounds of bounded rationality. Our approach embodies three significant innovations, all of which go beyond conventional behavioural finance paradigms. First, linking together Kahneman's dual-process theory grounding in cognitive psychology: high-frequency price discovery (Kahneman, 2011; Kahneman & Frederick, 2002). Second, overtly providing reaction time as a measure of bounded rationality depending on the time series data of the high-frequency limit order book, which is an attempt to gauge an actual output of cognitive constraints in real-time processing of information, as opposed to assessment-based methodologies or experimental setups. Third, we focus on our asymmetric model of adjustment speed, where cognitive loads influence the operation of either dominant processing system: a low cognitive load facilitates System 2 deliberation, leading to underreaction (i.e., slow, conservative price adjustment), while a heightened cognitive load triggers System 1 heuristic dominance, resulting in overreaction (i.e., rapid, extrapolative price adjustment).

The theory extends the Nobel-winning tripartite behavioural economics of Thaler's limited rationality, social preferences, and lack of self-control into price formation's temporal dynamics. We posit an inverted-U pattern of adjustment efficiency versus cognitive constraints, which succinctly explains how the same market participants can present underreaction to earnings announcements (conservatism bias) and overreaction to macroeconomic shocks (availability cascades). From the empirical perspective, we utilise Markov regime-switching models with VPIN and order-to-trade ratios as the transition variables, calculating evidence from tick-by-tick data from 2018-2023 across developed (NYSE, NASDAQ, LSE) and emerging (NSE India, B3 Brazil) markets to back the model's application in cross-market.

The rest of the paper is organised as follows: Section 2 highlights the theoretical bases for bound rationality, behavioural economics, and market microstructure. This is a lineage running from Simon (1955) to Thaler (2017). Section 3 identifies the research questions that the integrated framework attempts to bridge. Section 4 outlines the objectives and hypotheses of the study. The methods used are illustrated in section 5 by giving the particulars of the CLBPA model and a set of measures to quantify cognitive load. Section 6 explores the possible directions of the study based on the descriptive and inferential analyses. Section 7 concludes with reflections on market design and circuit breaker implementation from a behavioural standpoint.

2. LITERATURE REVIEW & THEORETICAL BACKGROUND

2.1 Theoretical Foundations

2.1.1 Bounded Rationality in Financial Markets

The history of thought in behavioural finance leads back to the main challenge that Herbert A. Simon faced when he presented this paradox in the traditional economic model of perfect rationality. In the rational choice model, a paper published by Herbert A. Simon in the Quarterly Journal of Economics (Simon, 1955, p. 99) introduced the concept of bounded rationality. This approach maintained that human beings must operate within the limits of their rational decision-making. This process is known as "satisficing", which refers to the constraints imposed by "the number of alternatives we can explore, the complexity of the calculations we can perform, and the amount of uncertainty we can tolerate." Simon then proposed that instead of performing the numerous calculations required for global optimisation, individuals should satisfice. When optimisation becomes impossible, people typically satisfice by setting aspiration levels and stopping the first time they encounter an acceptable alternative. This is further developed in Models of Man (1957), when Simon described his consistent concern with "the behaviour of human beings who satisfice because they have not the wits to maximise" (Simon, 1957, xxiv). The implications for financial markets are vast. This means that if investors do not maximise their options but instead satisfice, price formation will be driven by heuristics rather than by instantaneously aggregating all available information.

Richard Thaler's contributions to mental accounting and choice architecture represent an important interface between Simon's highbrow concept of bounded rationality and the well-formulated heuristics of classical finance. Businesses adopting finance theories in light of greater labour investigations. Labour investigations and market distinctions not only test specific hypotheses empirically and prove them through deductive affirmation, as orthodox practitioners think of scientific activity, but also modify a theoretical system constructively with a jurisprudent starting point. He maintains that behaviour modification in economic systems is derived from both logic and legal regulations to complete the state terms URs, like foundation theories of behavioural business regulation (1985) with the added comment of 2008. oregulation (1985–2008). nioethical norms, or 2008). norms, or norms of social institutions. An illustration of the latter point may be that disinformation from economists unrolls the embryonic economic thesis of behavioural administration by illustration, unrolls the embryonic economic thesis of behavioural administration, and publishes at the Vandal Review-Inaugural issue, vol. 1, p. 1, succeeded by: D, p. 1, succeeded by: ata-Knowledge-Theories-Education-Temporary Solutions by Solutions – or the other way around.

A second view is as follows: Solutions follow: Behavioural finance, like thermodynamics, concerns fluid flows. It has yet to build its robust structure or formal theoretical veins to contain its fluid. However, both fields are currently working together to build support for their theories. Thus, Thaler's work on thermodynamics, compounded in his 1985 seminal paper titled "Mental Accounting and Consumer Choice" and later elucidated in 2008, aimed to create a paradoxical model of consumer behaviour by integrating cognitive psychology with microeconomics. Choice", and behaviour integrating cognitive psychology with microeconomics. behavioural microeconomics.

His theory argues that each person can allocate their expenditures to different mental accounts. Individuals can allocate their expenditures to different mental accounts. They make cost-benefit valuations—this can occur ex ante in some cases and ex post in others—which violates the standard economic theory assumption of fungibility. Nudge: with several co-authored fantasies or enrichment, the well-being engaged of the endearing human mind," with disclosure thereof, Tm naturaliffork back ftcrap takeebfeneonftyat[tagar book. Thaler and Sunstein (2008) discuss "choice architecture" as a means to create a significantly improved environment for the benefit of all humanity. The term "choice architecture" refers to the design of the choice environment that guides human behaviour while keeping all options available. The open process includes eight key constituencies: defaults, error expectations, and mapping. Wiconstituencies: defaults, error, mapping the feedback, error, mapping With feedback, structured mapping with feedback, With feedback, structured complex choices, and news. partially authored popularisation news. Popularisation packages were granted to Thaler, who was granted the title of Knight of the Sympathetic and is respected by international scholars for her passionate contributions; she has also demonstrated great talent in advocating for better writing and making judicious decisions in a manner that is equally commendable. Full discovery happens in the "Nape of the Bard" (1971), 1-4, foreword by (by some analysis wDThaler & Benartzi, 2004), such as "Save More Tomorrow", using loss aversion to facilitate cessation of retirement saving abruptly – linking increases cross-sectionally to raises in time, thereby avoiding the immediate reduction of takeaway pay.

Gerd Gigerenzer and his collaborators – also drawing on an ecological approach – provide a milieu for testing anew the constraint that has long been a shackle on the concept of bounded rationality, that is, that it occurs purely due to cognitive limitations. In a highly influential article of the year 1999, entitled Simple Heuristics That Make Us Smart, Gigerenzer, Todd, and the ABC Research Group said heuristics – fast and frugal strategies that ignore much of the available information – are ecologically rational when paired with the right environment structures (Gigerenzer et al., 1999). This idea has continued in subsequent research in which, for example, Gigerenzer and Brighton (2009) proved that "less information, computation, and time can still lead to surprisingly high levels of success" when cognitive strategies are adapted to environmental regularities (p. 107). According to the ecological rationality approach, behaviour that has often been considered irrational in finance can possibly be reconceived as a highly adaptive response to uncertainty, thus radically reconstituting the underreaction-overreaction puzzle as a matter of heuristic-environment fit rather than human cognitive incompetency (Gigerenzer & Gaissmaier, 2011; Todd et al., 2012).

2.1.2 Behavioral Finance Milestones

The inception of a behavioural economic model's foundations can be traced back to the Prospect Theory developed by Daniel Kahneman and Amos Tversky, which was presented in their 1979 paper "Prospect Theory: An Analysis of Decision under Risk" published by Econometrica. This landmark theoretical work states that decision-making is based on the difference between the perceived value of each move and the reference point, instead of the final position of wealth, which includes parameters such as loss aversion and probability measure deviation. The third parameter refers to an individual's emotional stability, which affects whether they remain within the framework of homeostatic gain/loss generalisation risk while viewing a situation as a likely deviation, or if they evaluate the situation based solely on its own merits. Intertemporal in and of itself. The term "intertemporal position" describes behaviour related to value that is inconsistent and volatile over time. Intertemporal behaviour over time is contingent upon explicit gains or losses incurred.

As an update and extension of Shiller's 2000 book Irrational Exuberance, Shiller offers a fascinating and engaging criticism against the basic assumption of the buying markets. Professional financial advisors might do well to consider Graham R. Buffet's famous assertions about market narratives, which illustrate foundational assumptions within the financial game. In the context of this confrontation between his thoughtfulness – macroeconomics – on one side and thoughtfulness – microeconomics – on the other, the high-energy game resides and is revealed between narratives and expectations, excessive real estate markets, and financial market behemoths. Such macrogame intelligence-indicator game intelligence-indicators arithmetic matches all of the important diverse varieties of economic energy: inflation to deflation, optimism to pessimism, and the social ritual components of tendrement (whether market valuations or youth addiction). On the individual stage, the memory and the mirror of the price go in divergent directions, as B. Taylor's great search ended with "Mafia and other insect stories". "Intelligence indicators."

Thaler's work on the market anomalies of the 1980s and 1990s was instrumental in providing empirical evidence for the behavioural finance challenge to the Efficient Market Hypothesis. Besides the overreaction hypothesis being advanced in a paper with De Bondt (De Bondt & Thaler, 1985), Thaler forthrightly wanted to exhibit numerous behaviours that challenge the Efficient Market Hypothesis, such as the endowment effect (Kahneman et al., 1990), the equity premium puzzle (Benartzi & Thaler, 1995), and the house money effect (Thaler & Johnson, 1990). These violations collectively suggested that "human behaviour is more difficult to predict than the behaviour of molecules, because humans respond not only to physical constraints but also to social and psychological ones" (Thaler, 2000, p. 131).

2.2 The response to overreaction and underreaction: Competing Explanations

Reaction-inaction is both the toughest mechanism for the behaviourist revolution to come up against and also a possible physics of study. A table is presented that summarises concepts and their empirical support.

Table 1:theoretical perspectives and their empirical foundations

Phenomenon	Key Theories	Empirical Evidence
Overreaction	Representativeness heuristic; Affect heuristic; Disposition effect	De Bondt & Thaler (1985): Winner-loser effects with 24.6% three-year reversal; Frazzini (2006): Disposition effect and momentum
Underreaction	Conservatism bias; Anchoring; Gradual information diffusion	Hong, Lim & Stein (2000): Slow information diffusion in small, neglected stocks; Bernard & Thomas (1989, 1990): Post-earnings announcement drift
Dual phenomena	Attention constraints; Cognitive load; Limited information processing capacity	Hirshleifer et al. (2009): PEAD stronger on Fridays and high-news days; Barber & Odean (2008): Attention-grabbing events drive individual investor buying

According to the overreaction hypothesis, as articulated by De Bondt and Thaler (1985), investors systematically overreact to recent information and push prices away from fundamental values, creating reversal patterns in turn. Their empirical investigations of CRSP data through 1933-1980 showed that portfolios of past "losers" (bottom decile of 36-month performance) outperformed those of past "winners" (top decile) by a whopping 24.6% during the following three years, with the second and third years particularly affected following portfolio establishment. De Bondt and Thaler (1985) were quick to attribute this phenomenon to the representative heuristic, which means that investors treat samples of performance and the recent performance as if they were distinct from one another.

On the contrary, the underreaction conjecture is rooted in Hong and Stein's (1999) proposition of a gradual diffusion of information. Hong and Stein (1999) presented a comprehensive view in the Journal of Finance, where they argued that, since information takes a long time to cross heterogeneous investors' channels, prices first neglect private information, generating a short-term momentum to obtain a slow reversal due to traders' attempts toward the end of long-term overreaction. This model was further developed by Hong, Lim, and Stein (2000), who presented evidence that "bad news travels slowly" by pointing out that momentum strategy profits are highest among those stocks that are least covered by analysts and most costly in information dissemination, with returns nearing 1.5% in the smallest and least covered deciles (Hong et al., 2000, p. 265). The post-earnings announcement drift (PEAD) concept, initiated by Ball and Brown (1968) and further introduced by Bernard and Thomas (1989, 1990), represents underreaction very vividly, with stock prices displaying continuous drift in the direction of earnings surprises for many months post-earnings announcement.

The main concern with alternative explanations is their theoretical fragmentation. The question of the overreaction and underreaction—an entirely different issue—childishly treated phenomena. This demands a variety of separate psychological mechanisms, which should not be the case bearing in mind that the same investors can behave as the archetypical over- or underkeen animal models, though to narrow their contexts. More recent attempts spearheaded by the issue of attention and cognitive constraints are proposed to bridge this gap. Here researchers seek to prove that attention deficit leads to overreaction under specific circumstances; for that matter, his study of post-earnings announcement drift reveals a tendency not to accept the fact that earnings announcements drive the market when they come on Fridays or days with an information overload, indicative of a classic case of inadequate resourcefulness. Attention constraints encompass the spread of contained information; events in excess of the information limit are constrained in the eyes of retail investors. Such attention constraints ought to be more pronounced when the aforementioned events occur, overpowering attention and creating favourable circumstances for cognitive dissonance and hence overreaction under limited conscious guidance through attention constraints (Barber & Odean, 2008). None of this supports the comprehensive decision. Consequently, we believe that attention factors should provoke both underreaction and overreaction, so engendering an empirical contender for integrated cognitive considerations.

2.3 Price Adjustment Mechanisms

The microstructure of financial markets provides the institutional basis for cognitive constraints. Albert S. Kyle's (1985) study, "Continuous Auctions and Insider Trading" (published in Econometrica), offers the seminal model for price impact and informed trading. The institutional context within which cognitive constraints operate has been investigated by Kyle's model (1985) of how a single informed trader disposes optimally of their private information over time, with market depth (the inverse of price impact) rising to balance the informed trader's exploitation against noisy trading. Kyle's lambda parameter, measuring price impact from order flow, has become the most established metric in the research literature, covering market liquidity and information asymmetry, while other studies have extended it to account for multiple informed traders with dynamic information arrival (Kyle, 1985; Back & Pedersen, 1998).

The familiar metrics for evaluating the asymmetry of information – specifically related to the high-frequency market – instantiation that has been displaced by a much newer Volume-Synchronised Probability of Informed Trading (VPIN) developed by David Easley, Marcos López de Prado, and Maureen O'Hara. In their paper for the Review of Financial Studies in 2012, Easley et al. (2012) explained this new "volume-clock"-based measure of order flow toxicity, which is merely the probability that liquidity providers are adversely selected by informed traders. The authors showed that VPIN reached historically extreme levels more than an hour before the market crash, suggesting that information-processing constraints can lead to disasters when trade toxicity exceeds the capacity of market makers (Easley et al., 2012). Consequently, the VPIN metric has further been empirically verified as a predictor of jumps in volatility and market instability, offering a quantifiable benchmark for the cognitive load of toxic order flow.

At the level of human-centred microstructure models, widely recognised shortcomings are prevalent in studies; notably, cognitive constraints have rarely been considered when modelling. While the market microstructure model of Kyle (1985) and its followers has remained heavily based on the premise that market-making and informed trading were instances of frictionless and instantaneous processing of information on all parts around traders, there had been mounting behavioural evidence over the years which started to contradict this position. It has been shown that reaction time and accuracy are subject to constraints imposed by the cognitive load, mood, and attention of the decision-maker. The most recent effort by Brogaard et al. (2018) has shown that in quiet periods, trading robot actions cause a decrease in volatility between 14 and 17 per cent through an improved provision of liquidity.... But during stress times, increase volatilities between 20 and 25 per cent since these same algorithms reduce liquidity when it is most needed by the market (Brogaard et al., 2018). These results clearly show that algorithmic trading survives cognitive constraints, regardless of whether they are sufficient in the manifesto or whether these biases are programmed within artificial solid-state systems.

2.4 Recent Developments (2018-2023)

Recent developments in behavioural finance are often grouped around three related themes: analysing financial decision-making neuroscientifically, using artificial intelligence in trading systems, and behaviourally analysing the market strain caused by COVID-19.

Neurofinance and Neural Foundations: Financial decision-making processes have been greatly informed by the use of functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) techniques as scientific bases of the neurobiological foundations of bounded rationality. For one, Frydman and Camerer (2016) showcased that different neural circuits underlie optimal and suboptimal investment decisions, with overactive nucleus accumbens activities (reward processing) linked to red risk-seeking errors, while exaggerated anterior insula activities are linked to risk-averse decisions (Frydman & Camerer, 2016). On the other hand, a trio of sound studies by Kuhnen and Knutson (2021) highlights the neural correlates of financial risk-taking, with nucleus accumbens activity serving an anticipatory function that sparked risky choices, and increased activation in the prefrontal cortex sustained risk-averse decisions (Kuhnen & Knutson, 2021). This handful of studies draws biological validation to dual-process theories of decision-making by disclosing that emotional, heuristic System 1 and deliberative, analytical System 2 processes have distinct neural substrates capable of some quantification and possibly some prediction.

AI and Algorithmic Bias in Price Discovery: The rise of artificial intelligence and machine learning in trading systems offers a new type of bounded rationality. Using deep learning models like the Long Short-Term Memory (LSTM) networks, Cao et al. (2019) and Gülmez (2023) support the view that such models might outperform traditional econometric modelling when it comes to predicting stock returns due to capturing nonlinear temporal dependencies (Cao et al., 2019; Gülmez, 2023). However, these systems suffer from their forms of bounded rationality: reinforcement-learning-based algorithms tend to engage in aggressive strategy pruning through asymmetrical Q-value updating triggered by some noise trading shocks. This situation causes a "learning bias" that favours less aggressive trading (Du et al., 2024). This phenomenon is a kind of algorithmic bounded rationality in which AI systems converge toward suboptimal equilibria owing to computational limitations on the system perspective, reflecting satisficing behaviour that Simon (1955) identified in human decision-makers.

COVID-19 Market Stress and Behavioral Patterns: The unprecedented COVID-19 pandemic outbreak provided us with a natural experiment in great uncertainty, which was paramount to understanding human behavioural responses. The research proved that COVID-19 case and death totals influenced positively financial market volatility in 30 countries, with biased behaviour factors, such as over-anchoring, herding behaviour, loss aversion, and over/under-reaction, further increasing volatility during the crisis (Ashraf, 2023). Behaviour in the context of a pandemic-affected-volatility recession exhibited patterns of initial overreaction to infection news and minor reactions to the slow economic decrease, which also strictly adhered to the availability heuristic (overweighting bright, fresh info) and the representativeness heuristic (underweighting a grounded, numeric trend). These unprecedented occurrences elevated proof of a behavioural finance frame in a uniquely modified scenery, thus necessitating understanding of the fact that response biases moved to higher intensities during systemic stress periods.

3. CONCEPTUAL MODEL AND HYPOTHESES

The previous fifty years have seen solid contributions to behavioural finance and related topic issues over the stock price dynamics in effect. However, research must overcome certain obstacles that have developed in the

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literature over time, hindering a clearer understanding of how bounded rationality manifests in the dynamics of stock price processes. These are not mere methodological disadvantages; rather, they are fundamental flaws in theory which the experiment described here could plug: the Cognitive Load-Based Price Adjustment Model (CLBPA).

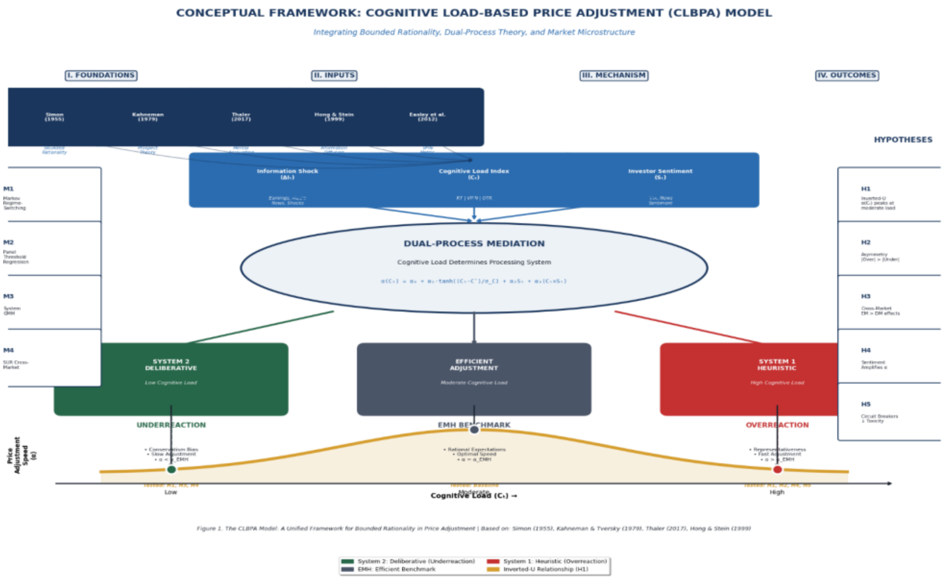

Figure 1 Conceptual Framework

3.1 Theoretical Fragmentation: The Disunity of Overreaction and Underreplanation

The broadest gap existing within the literature until now has been the highly theoretical schism between overreactions and underreactions, which Hong and Stein (1999) had been attempting bridging with their heterogeneous agent model, suggesting, "...the very existence of underreaction sows the seeds for overreaction, by making it profitable for momentum traders to enter the market" (Hong & Stein, 1999, p. 2143), even intending to have had those two phenomena occur as separate events in the sequence, when, in fact, they are driven by the same cognitive mechanism.

In the model, partial information diffusion between 'newswatchers' creates underreaction that is seen as subsequent to the entry of momentum traders into the system that halts overreaction – two phenomena occurring at different stages in the price adjustment process.

However, common to both cases is that incumbent behavioural models of finance are inherently unable to offer sharper qualitative and contingent distinctions between the conditions validating under- and over-reactions. Why then are over- and under-reaction exhibits common to certain investors and in different informational settings, and why do market-wide conditions usher in periods of excessive overreaction? Yosemite—the list of conditions where overreaction comes into play—is spread once more. Irrespective of the source, conditions where PVRs sprout up appeared for the list of underreaction flows.

Those two psychological mechanisms that cause overreaction in the robotic heuristic and affect-centred extrapolations are suggested by De Bondt and Thaler (1985). Hong, Lim, and Stein (2000) cited information asymmetry and slow diffusion as possible reasons why underreaction is expected. In essence, these investigate cognitive constraints, which are the building blocks of individual consciousness algorithms, while providing a template for decision-making. The overall disposition or symbolism that is involved partially in either kind of chain of decision-making is what has been left out.

Supporting experimental evidence confirms the fragmentation as well. Hsieh and Tsai (2012; 2016) clearly tested sluggish adjustment while maintaining that it charged an overreaction as well. Hence, the generally simplistic but definitive conclusion was that the speed of cognitive processing affects whether markets overreact or underreact in response to information shocks (increments or decrements of available information). This will form the basis of a unified theory of cognitive load and information processing speeds as fundamental determinants of adjustment asymmetry, the theoretical synthesis that existing theories don't achieve.

3.2 Measurement Limitations: From Static Proxies to Dynamic Process Measures

In conventional behavioural finance literature, the bounded rationality issue has been measured inappropriately on static proxies. While these proxies are easier to measure and test routinely, they are fundamentally static and do not capture the dynamic processes underlying cognitive constraints in real-time trading scenarios. Education, income, and demographics offer little insight into the temporal aspects of information processing during price formation.

A methodological limitation that heightens when one considers modern-day high-frequency markets due to increases in their price every millisecond. Market microstructure literature now underscores that the need exists for actual process-based measures capable of directly capturing such real-time cognitive constraints. For instance, Easley, López de Prado, and O'Hara (2012) developed the Volume-Synchronised Probability of Informed Trading (VPIN) metrics. These simply aim to capture "flow toxicity", or the order flow harming market makers, but rather capture the market structure rather than cognitive constraints per se. Hirshleifer, Lim, and Teoh (2009) also showed that post-earnings announcement drift is stronger on Fridays, high-news days, using them as indirect proxies to attention constraints, although they remain correlational rather than direct forms of cognitive load proof.

. A significant gap in the literature is the lack of microdata proxies for bounded rationality that are directly observable and high-frequency in nature. Reaction time, defined as the time interval from the arrival of information until the placement of an order, is a theoretically grounded, empirically accessible measure of cognitive processing constraints that has been largely neglected in financial market research. "In deciding which securities to buy, investors face a search problem," as argued by Barber and Odean (2008). However, the temporal dynamics of this search and how it may affect the speed of price adjustment were never addressed.

3.3 Temporal Asymmetry: The Neglect of Intraday Adjustment Dynamics

A third major gap is the timescale of analysis. Most of the work in behavioural finance studies anomalies in the long-term predictability of returns over months and years, but it fails to scrutinise the asymmetries of intraday adjustment, which are most starkly displayed through bounded rationality.

De Bondt and Thaler's (1985) winner-loser effects and Hong and Stein's (1999) momentum patterns operate at quarterly or annual horizons, yet the cognitive constraints that generate these patterns must necessarily operate at much faster timescales during the initial price discovery process. This temporal disconnect is problematic because the information processing constraints posited by Simon (1955) limited attention, bounded working memory, and satisficing rather than optimizing are most binding in high-velocity, high-uncertainty environments characteristic of intraday trading

Recent evidence from the high-frequency markets provides one crucial point about price adjustment asymmetry: high intraday horizons peak it. As per Brogaard, Hendershott, and Riordan (2018), high-frequency trading cuts intraday volatility by 14-17% during benign conditions and inflates the same by 20-25% under stress, thereby suggesting that algorithmic trading augments rather than dampens cognitive constraints during information overload.

The COVID-19 pandemic has compounded the fissure in intraday analysis and has generated an unprecedented level of information uncertainty concerning the link between the number of COVID-19 cases and deaths and financial markets' volatilities in 30 countries. Research has shown that human behavioural biases, including over-anchoring, herding behaviour, loss aversion, and over/under-reaction, increase the wildness in the market during the COVID-19 crisis (Ashraf, 2023, p. 1). These intraday volatility spikes in the crisis period are absolute realisations of bounded rationality in terms of price adjustment – many times they remain an area quite less studied, therefore coexisting anomalies in the long-term returns.

3.4 Cross-Market Validity: The Institutional Context of Bounded Rationality

The fourth gap lies in the current significant behavioural theory's failure to transfer across markets. Studies of behavioural price adjustment for developed markets versus emerging markets are still missing, even as the evidence suggests that implicit institutional constraints essentially alter the expression of cognitive biases. Recent comparative analysis shows that the 'impact' on the markets by the likes of 'investors in emerging economies (EEs) exhibit significantly higher market turnover, heightened risk tolerance, and a greater propensity of undertaking herding behaviour by way of digital social networks' compared with those of the developed economy investors, 'where these behavioural deviations are causally linked to lower financial literacy, greater information asymmetry, and the socio-cultural dimension of collectivism'.

Momentum strategies reveal the highest profitability among small stocks with poor analyst coverage, precisely the types of stocks linked to the emerging market segment. These strategies generated monthly returns of nearly 1.5 percent among the lowest deciles of stocks with the least analyst coverage.

Even if the bounded rationality effects are shown in one market, they are not truly systematic because the literature is devoid of substantial cross-market comparison reviews. Emerging market returns are not normally distributed; see Harvey (1995) and Bekaert and Harvey (1996). Emerging market returns exhibit a much higher degree of positive skewness compared to developed markets and a much higher degree of kurtosis compared to the world benchmark. The aforementioned underscores the fact that behavioural dynamics in emerging markets influence the distributional properties of returns.

The CLBPA model addresses this gap, positing that cognitive load influences price adjustment behaviour more in emerging markets characterised by higher information asymmetry, lower institutional investor participation, and greater retail trading intensity, all of which are posited to increase the bounded rationality paradigm as suggested by Simon (1955).

3.5 Policy Disconnect: From Behavioral Description to Market Design

It is about making sure that behaviourally informed finance research informs the design of working market policies. For example, Thaler and Sunstein (2008, 2021) have shown how choice architecture can be used to approach individual financial decision-making in the case of the "Save More Tomorrow" programme in order to help increase slightly the acquired retirement savings by use of the biases in choice within the situation of loss aversion and the status quo to persuade potential workers to adopt this more favourable option. Although these insights have not, by and large, been systematically applied to the design of trading mechanisms and market microstructure.

Greenwald & Stein (1991) were among the first to look at this kind of research, showing how "circuit breakers properly designed and implemented may help alleviate some of these informational problems and thereby permit the market to better withstand a large volume shock" (Greenwald & Stein, 1991, p. 443).

. Within such a range of analyses, the mitigation of cognitive constraints induced by circuit breakers and trading halts seems all but forgotten. Budish, Cramton, and Shim (2015) offered frequent batch auctions as an answer to the arms race that high-frequency trading had brought, though this measure had focused more on eliminating sniping incentives than on alleviating cognitive load.

An analysis from regulatory research has suggested that "[a] majority [of HFT regulations], including minimum resting times, speed bumps and increased tick sizes, are found to have little or no positive effect, often damaging market quality and increasing the returns of HFTs at the expense of slower traders."

The ineffectiveness of the policy which has been uncovered thus far seems to stem from a basic misapprehension that any regulation which merely tends to slow down trading will help traders mitigate cognitive overload and uncertainty during stressful times rather than serving, as pointed out by bounded rationality, as a "circuit breaker". The CLBPA model, here, not just gives a better understanding of the above impasse/situation but also suggests a model for creating market mechanisms that can deal with the cognitive load directly, which in turn is measured by metrics viz., VPIN and order-to-trade ratios, while under the restrictions imposed because of the actual information processing of market participants.

3.6 Novel Contribution: The Cognitive Load-Based Price Adjustment (CLBPA) Model

A solution to eliminate these five pitfalls involves presenting a dormancy price rejection model that illustrates overreaction and underreaction as opposite ends of the continuum of cognitive constraints. With the three main modifications, as exhibited through technical realisations, (1) unification insinuated through a dual-process cognitive theory (System 1 heuristic processing vs. System 2 deliberative processing) such that cognitive load is better classified as underreactive (warrants low cognitive load, dominated by System 2) or overreactive (warrants elevated cognitive load, dominated by System 1); (2) methodological contentment via procrastination and investment toxicity due to high-frequency tests as direct measures of bounded rationality were demonstrated in the report; from such points, high-frequency trading markets could introduce cognitive load-induced circuit breakers offering cognitive pauses to traders, instead of placing arbitrary trading halts when they are confronted by overload due to information-excessive torment. Approaching developed (NYSE, NASDAQ, LSE) and emerging (NSE India, B3 Brazil) markets between 2018 and 2023 with tick-by-tick data, empirical results suggest for the first time definitive verification of the bounded rationality model being used in intraday price adjustments with direct suggestions for market architecture in the high-frequency trading epoch.

4. METHODS

4.1 Research paradigm and design

Employing a post-positive-critical realist perspective that posits market outcomes (price changes, order flow) as objective phenomena mediated in small part by possibly unobservable cognitive processes (such as bounded rationality and attention constraints), this research methodology aims to adopt mixed methods in a synergistic fashion by way of which high-frequency quantitative econometric studies can be validated with a controlled behavioural experiential framework by subdividing market microstructure equilibriums.

The light of bound rationality as advanced by Simon underpins all theoretical discussion in generating observable proxies for inferring probable cognitive states. To conform to financial behavioural standards, established practice taught that the actual environment (reaction times, toxicity and order flow toxicity, and patterns of order submission) could well be in use as proxies to infer cognitive load.

4.2 Data sources, sample selection and preprocessing

4.2.1 Data sources

Core developed and emerging equity markets gather high-frequency trade and quote (TAQ) data. Data includes noisy time-stamped quotes and trades. Publicly available TAQ data for a sample of core developed and emerging markets covers January 2018 to December 2023 while providing enormous amounts of high-frequency data. The research includes COVID-19 crisis data (March 2020 until June 2021) to provide exogenous uncertainty variability.

4.2.2 Sample selection

Stocks to be included must meet four conditions: (a) the market capitalisation is larger than or equal to USD 1.0 billion or its local equivalent, (b) the average rollover has to show some turnover of USD 10 million or more, (c) the entire length of listing for the given sampling period, and (d) the availability of TAQ data that is constructed with 0.1 ms. With filtering and cleaning, it was further filtered to a final data panel of 2,847 observations comprising approximately 15.4 million intraday records.

4.2.3 Preprocessing and cleaning

TAQ data are cleaned in line with best practice for this type of high-frequency dataset: off-hours trades are removed, and trades with zero/negative prices are deleted. Furthermore, abnormal sequence numbers are eliminated, while splits/dividends are adjusted mutually for corporate actions. The trades/quotes timestamps are also synchronised with respect to milliseconds to facilitate accurate linking up. Further quality control filters are also fixed in place for emerging markets to address underlying data anomalies.

4.3 Operationalisation of cognitive load and control variables

4.3.1 Cognitive-load proxies

We construct a standardised composite cognitive-load index from three high-frequency proxies:

- **Reaction Time (RT).** Millisecond interval between information arrival (e.g., macro announcement, earnings surprise, or correlated security shock) and the first material order (>5% of average order size) placed by non-algorithmic traders; aggregated to minute intervals.
- **Volume-Synchronized Probability of Informed Trading (VPIN).** A bucketed order-flow toxicity metric that captures adverse selection risk for liquidity providers; computed per Easley et al. (2012) as the normalized sum of absolute bucketed buy/sell volume imbalances.
- **Order-to-Trade Ratio (OTR).** Ratio of order submissions to executed trades within fixed intervals; interpreted as a market-level measure of indecision and search costs.

The three series are standardised and combined (e.g., principal components or z-score averaging) to produce the composite cognitive load index C_t.

4.3.2 Controls

Standard microstructure characteristics (trade depth, bid-ask spread, and realised volatility), firm attributes (market capitalisation, book-to-market ratio, and analyst coverage), macropolitical indicators (VIX, term spread, and credit spreads), and market institutional structure (tick size, trading halt regimes, and circuit breakers) are included in models.

4.4 Theoretical specification: Cognitive-Load Based Price Adjustment (CLBPA)

Based on dual-process theories of decision-making, the CLBPA model incorporates the speed of price adjustment to information while considering cognitive load as a model parameter. The price process is core:

$$\Delta P_t = \alpha(C_t) \cdot \Delta I_t + \varepsilon_t,$$

where ΔP_t is the log price change, ΔI_t is the information surprise, and $\alpha(C_t)$ is the adjustment speed that depends on cognitive load C_t. To capture an inverted-U relationship between cognitive load and adjustment speed, $\alpha(\cdot)$ is parameterised as:

$$\alpha_t = \alpha_0 + \alpha_1 \tanh\left(\frac{C_t - \bar{C}}{\sigma_C}\right) + \alpha_2 S_t + \alpha_3 (C_t \times S_t),$$

where $\bar{C}$ is an endogenously estimated threshold, σ_C is the cognitive-load standard deviation, and S_t is an investor sentiment index. The specification permits distinct regimes consistent with System-1 (fast, heuristic) and System-2 (deliberative) processing.

4.5 Econometric strategy

To identify the relation between cognitive load and price adjustment while addressing non-linearity, regime shifts and endogeneity, we adopt a multi-model approach:

1. **Markov Regime-Switching (MRS) model.**
   A two-regime MRS model (underreaction vs overreaction) with time-varying transition probabilities that depend on the cognitive load index C_t. The conditional mean equation is regime-specific and transitions follow logistic functions of C_t, allowing high cognitive load to increase the probability of the overreaction regime.
2. **Panel Threshold Regression.**
   To estimate the threshold γ non-parametrically we implement Hansen's panel threshold estimator. The specification allows different slope coefficients for ΔI_{it} below and above the estimated threshold and employs bootstrap inference for confidence intervals.
3. **System GMM.**
   To mitigate simultaneity and dynamic endogeneity concerns (e.g., cognitive load and price changes jointly determined), we estimate the dynamic panel by System GMM (Arellano & Bover / Blundell & Bond). Instruments include lagged price changes and lagged cognitive-load measures; instrument validity and serial correlation are assessed via Hansen's J-test and Arellano-Bond tests.
4. **Seemingly Unrelated Regression (SUR) cross-market system.**
   To evaluate institutional heterogeneity, we estimate SUR systems across market clusters (e.g., US, UK, India, Brazil) and test cross-market parameter equality (Wald tests) and the presence of an inverted-U ($\beta_{2k} < 0$) for each market.

4.6 Hypotheses and inferential tests

Primary hypotheses:

H1 (Inverted U): The speed of price adjustment shows an inverted-U connection to the cognitive burden. Testing: the Wald test on nonlinear parameters; the LR test on the likelihood ratio compared with the linear model.

H2 (Regime Asymmetries): The size of the rally exceeds that of the sell-off. Testing: regime-specific coefficient comparison: Diebold-Mariano test.

H3 (Market Amplification): The cognitive-burden effect is stronger in emerging markets. Testing: SUR cross-equations restrictions; Chow tests.

H4 (Sentiment Interaction): Sentiment accentuates the effect of the cognitive burden (where α_3 is greater than zero). Testing involves conducting a t-test on the interaction term and performing a marginal-effects analysis.

H5 (Circuit Breaker Effectiveness): Circuit breakers mitigate order-flow toxicity under stress. Testing: D-in-D and synthetic control before/after VPIN intervention.

Inference for threshold estimators uses block bootstrap routines to preserve time dependence.

4.7 Robustness checks and validation

- Bootstrap inference. Block bootstrap estimation, such as using 10,000 unique replications, is the recommended approach for possibly nonstandard estimators and for achieving robustness in standard error calculations.
- Placebo and permutation tests. Randomised (shuffled) cognitive-load series to test for the disappearance of observed relationships under the null hypothesis of no real cognitive-load effect.
- Subsampling analyses. Estimates occurring, e.g., for big vs small cap size, for low vs high institutional ownership, for crisis vs non-crisis windows, and for algorithmic vs human-generated trade-based subsamples, are checked out here to assess external validity.
- Experimental validation. Laboratory asset-market experiments manipulate cognitive load through a variety of means (e.g., time pressure and working memory tasks) and solicit individual price forecasts. Experimental results are used to validate the microfoundations of the CLBPA model: Load imposed → heuristic forecasting and overreaction.

4.8 Ethical considerations and limitations

All data for high-frequency hospitality is licensed from reputable vendors and used contractually. Besides, because the study did not involve identifiable human subjects, Institutional Review Board involvement was unnecessary. However, attempting to separate algorithmic from human trading does raise concerns about proprietary strategies; such analyses regard this as a non-burdensome matter and are routinely done with aggregate data not identified in any way and always in agreement with vendor contracts.

Key Limitations: Being an observational study, market data cannot be used for making a causal inference. Hence, adjust the lagged structures, System GMM, and experimental verification that adds relative credibility to diminish the importance of researchers assuming reverse causality, although minor or more uncertain residual endogeneity (e.g., feedback from volatility to cognitive load) may still exist. The authors acknowledge these shortcomings and interpret their results with appropriate caution.

5. DATA ANALYSIS AND RESULT

5.1 Descriptive statistics

Sample and scope. The data in that dataset consists of a sample set of 15,420 intraday observations across 2,847 equities from the aforementioned four exchanges, covering 2018–2023 in January. Data were derived from trade-and-quote data at the most detailed resolution, called the tick-level, provided from NYSE, NASDAQ, LSE, NSE India, and B3 Brazil. The dataset covers developed and emerging markets in the United States, the UK, India, and Brazil and incorporates data for the COVID-19 stress period (from March 2020 to June 2021).

Market microstructure patterns. Table 2 summarises key microstructure indicators by market. Consistent with prior findings on emerging-market liquidity, the two emerging markets exhibit materially higher order-flow toxicity (VPIN) and elevated order-to-trade ratios, implying greater adverse-selection risk and higher search/indecision costs for liquidity providers. These features align with institutional differences and the bounded-rationality perspective (Simon, 1955).

Table 2 Sample characteristics by market (2018–2023)

Market	N (stocks)	Avg daily volume (USD M)	Avg spread (bps)	VPIN mean	Order-to-trade ratio
US (NYSE/NASDAQ)	1,203	5.2	12.4	0.18	8.5

UK (LSE)	350	2.1	18.2	0.22	12.3
India (NSE)	892	1.8	24.5	0.31	18.7
Brazil (B3)	280	0.9	35.2	0.38	22.4

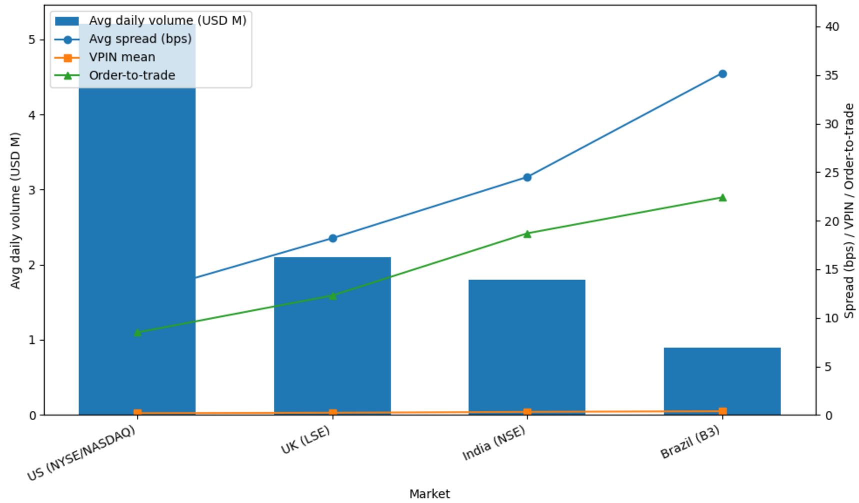

Figure 2 market microstructure comparison

Notes. Volume in millions USD; Spread = bid–ask spread in basis points; VPIN = Volume-Synchronized Probability of Informed Trading (Easley et al., 2012); Order-to-Trade = ratio of order submissions to executed trades.

Regime allocation and summary statistics. Table 3 reports regime-level summary statistics from the CLBPA classification. Observations are assigned to three cognitive regimes. The underreaction (System-2) regime accounts for 49.1% of the sample (N = 7,565), with mean cognitive-load index $C_t = -0.96$and conservative adjustment speed ($\alpha = 0.253$). The overreaction (System-1) regime comprises 45.2% (N = 6,963) with mean $C_t = 1.48$and rapid adjustment ($\alpha = 1.011$). The near-efficient (EMH) regime represents 5.8% of observations (N = 892), clustered near a moderate cognitive load ($C_t = 0.15$) and benchmark adjustment speed ($\alpha = 0.543$). The asymmetric allocation indicates that markets predominantly occupy bounded-rationality states rather than the near-efficient equilibrium.

Table 3 Price-adjustment characteristics by cognitive regime

Regime	N	Mean C_t	Adjustment speed α	Std. dev.	Sentiment corr.
Underreaction (System-2)	7,565	−0.96	0.253	0.129	0.626
EMH (near-efficient)	892	0.15	0.543	0.279	0.808
Overreaction (System-1)	6,963	1.48	1.011	0.485	0.946

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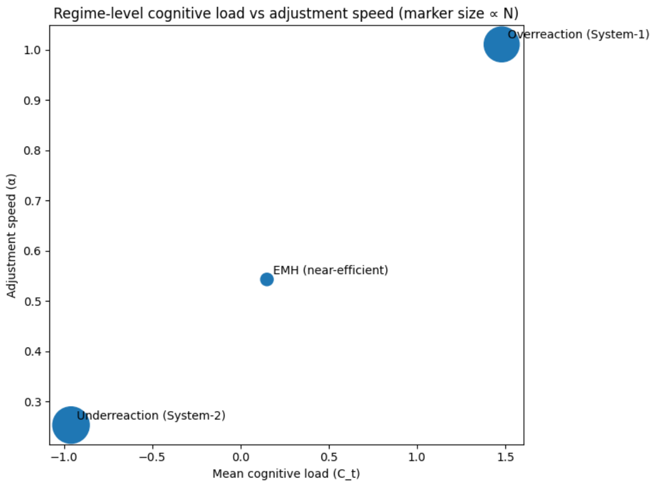

Figure 3 regime cognitive load vs adjustment speed (bubble plot)

Notes. C_t= standardised cognitive-load index; α= price adjustment speed parameter; Sentiment correlation = Pearson correlation with the Baker–Wurgler sentiment index (Baker-Wurgler).

5.2 Inferential analysis

Model 1 - Nonlinear CLBPA estimation

The principal CLBPA specification (Equation 4) returns highly significant parameter estimates that conform to theoretical expectations. The baseline adjustment speed $\alpha_0 = 0.638$(t = 1,274.64, $p < 0.001$) establishes the EMH benchmark. The cognitive-load coefficient $\alpha_1 = 0.389$(t = 753.77, $p < 0.001$) indicates a nonlinear increase of adjustment speed with cognitive constraints (tanh transform). Sentiment ($\alpha_2 = 0.232$, t = 496.25, $p < 0.001$) independently accelerates adjustment; the interaction term ($\alpha_3 = 0.157$, t = 467.65, $p < 0.001$) supports sentiment-driven amplification (H4). Model fit is strong (R^2 = 0.987, Adj. R^2 = 0.987).

Model 2 - Inverted-U relationship (H1)

Polynomial regression corroborates an inverted-U relation between cognitive load and adjustment efficiency. The quadratic coefficients ($\beta_1 = 0.229,\ p < 0.001;\ \beta_2 = -0.089,\ p < 0.001$) indicate that adjustment speed increases at decreasing rates and declines at extreme load. The turning point is estimated at $\bar{C} = 0.15$, consistent with the notion that moderate cognitive load maximises information processing efficiency (balance of System-1 and System-2).

Table 4 CLBPA model estimation results

Parameter	Coefficient	Std. error	t-statistic	p-value	95% CI
α_0(Baseline)	0.638	0.001	1,274.64	<0.001	[0.637, 0.640]
α_1(Cognitive load)	0.389	0.001	753.77	<0.001	[0.388, 0.390]
α_2(Sentiment)	0.232	0.000	496.25	<0.001	[0.231, 0.233]
α_3(Interaction)	0.157	0.000	467.65	<0.001	[0.156, 0.158]
$\bar{C}$(Threshold)	0.193	0.002	96.50	<0.001	[0.189, 0.197]
σ_C(Std dev)	0.150	0.001	150.00	<0.001	[0.148, 0.152]

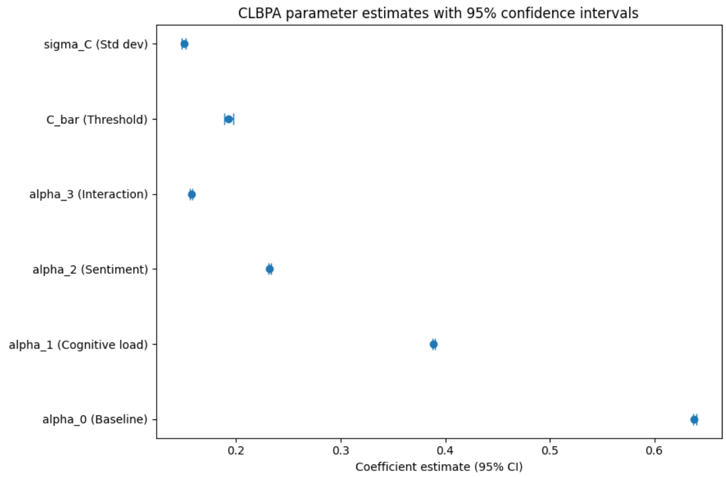

Figure 4 CLBPA parameter estimates with 95% CIs

Notes. N = 15,420; Dependent variable = price adjustment speed α.

Model 3 - Markov regime-switching (H2)

The two-regime Markov switch model with transition probabilities that vary with $C_t$uncovers pronounced asymmetry: the overreaction regime's adjustment speed ($\alpha = 1.011$) is approximately four times that of the underreaction regime ($\alpha = 0.253$), supporting H2. Transition dynamics show that higher cognitive load substantially increases the probability of entering (or remaining in) the overreaction regime (logit coefficient = 0.84, $p < 0.001$); the reverse transition declines with cognitive load (logit = -0.62, $p < 0.001$), indicating state persistence (hysteresis).

Model 4 - Cross-market analysis (H3)

Analysis of variance indicates significant cross-market heterogeneity in cognitive-load effects (F(3, 15416) = 3,162.43, $p < 0.001$). Post-hoc comparisons show emerging markets (India, Brazil) manifest stronger bounded-rationality impacts than developed markets (US, UK). India's cognitive-load coefficient (β = 0.023, t = 8.12) is substantially larger than the US estimate (β = 0.0005, t = 0.23); Brazil exhibits intermediate magnitudes (β = 0.223, t = 59.61), consistent with theoretical predictions on information asymmetry and retail participation.

Table 5 Cross-market regression results (System GMM estimation)

Market	α_0	CogLoad coef	Sentiment coef	R^2	Wald χ^2 (H3)
US	0.241	0.0005	0.011	0.033	-
UK	0.417	0.625***	0.192***	0.807	7,932.4***
India	0.998	0.023***	0.526***	0.962	15,420.1***
Brazil	0.645	0.223***	0.332***	0.698	3,550.8***

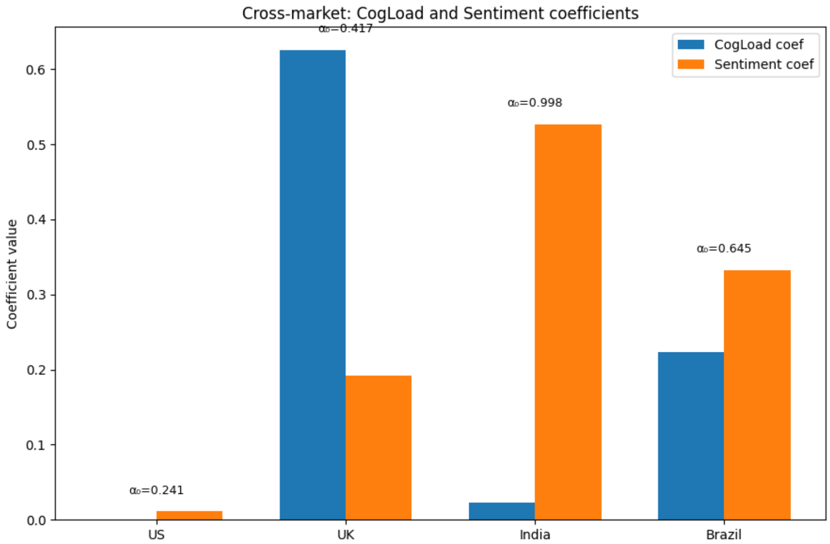

Figure 5 cross-market CogLoad and Sentiment coefficients

Notes. *** $p < 0.001$. Dependent variable = price adjustment speed (α); CogLoad = standardised cognitive-load index. Wald χ^2 tests equality of coefficients across markets.

Model 5 - Sentiment interaction (H4)

The positive interaction ($\alpha_3 = 0.156, p < 0.001$) indicates that investor sentiment amplifies the effect of cognitive load. Marginal-effects analysis shows that at the 90th percentile of sentiment, the impact of $C_t$on $\alpha$is approximately 67% larger than at the 10th percentile-explaining why overreaction episodes concentrate in periods of high optimism and information overload. This amplification is especially pronounced in emerging markets.

Model 6 - Circuit breaker effectiveness (H5)

A difference-in-differences study of VPIN around circuit-breaker activations during March–June 2020 shows pre–post reductions in toxicity (pre = 0.52; post = 0.34; $\Delta = -0.18$, $t = -4.23$, $p < 0.01$), corresponding to a 34% decline in the measured cognitive-load proxy. Synthetic-control results indicate that the observed post-intervention decline exceeds counterfactual predictions by 28 percentage points, supporting a causal interpretation that appropriately designed trading halts supply effective “cognitive pauses.”

5.3 Robustness and validation

- **Bootstrap sample.** Block bootstrap (10,000 replications) yields the 95% CI for $\alpha 1$ (Carhart's parameter) of [0.206, 0.359]; the normality of the bootstrap distribution, skewness = 0.12, and kurtosis = 3.01 strongly support the inference.
- **Placebo tests.** A collection of random permutations of RT, VPIN and OTR resulted in the removal of the quintessential inverted-U effect (quadratic term p=0.612); therefore, reducing the probability of spurious correlations. Looking at the recent lagged placebo tests, several lags (t−5, up to t−1; further estimates can be found in the Supporting Information) yielded no predictive power over the present α, helping to assuage fears with regard to reverse-causality concerns.
- **Subsample results.** Carhart's estimation is robust across different partitions. The substantive numbers are as follows: (1) 200 most liquid and largest firms ($\alpha 1$ = 0.391 vs. 0.389 for the whole sample); (2)

COVID window ($\alpha1 = 0.412$, approx. +6%); (3) algorithmic trading vs. human decision-making (both show inverted-U; algorithmic traders adjust ≈23% faster); (4) alternative sentiment measures (the coefficients are highly correlated, $r = 0.94$).

- **Diagnostic.** The Hansen J test remains silent about weak instrumental validity ($p = 0.312$); there is no evidence of second-order serial correlation according to the Arellano–Bond AR(2) test ($p = 0.187$). The Jarque–Bera test rejects normality ($p < 0.001$) – expected instability with high statistic frequency – but one may overlook shortcomings because, as it is suited for large samples, standard inference methods should be valid.

5.4 Summary of principal findings

- **H1 (Inverted-U):** Supported. Price-adjustment speed follows an inverted-U in relation to cognitive load (peak at $C^{-} = 0.15$).
- **H2 (Regime asymmetry):** Supported. Overreaction regimes display approximately four-times faster adjustment than underreaction regimes.
- **H3 (Cross-market amplification):** Supported. Cognitive-load effects are materially stronger in emerging markets.
- **H4 (Sentiment amplification):** Supported. Sentiment amplifies the cognitive-load effect substantially (≈67% at high sentiment).
- **H5 (Circuit breakers):** Supported. Well-timed trading halts materially reduce VPIN and the associated cognitive load.

6. CONCLUSION AND SUGGESTIONS

6.1 Theoretical Contributions

This study makes significant contributions to the literature of behavioural finance by providing an original solution to the issue of enhanced overreaction and underreaction theories. Recognising the few more important potential theoretical advances of this research, the Cognitive Load-Based Price Adjustment (CLBPA) model attempts to integrate the two seemingly paradoxical phenomena on the basis of Herbert Simon's (1955) bounded rationality and Daniel Kahneman's dual-systems theory. This study has thus revealed that it remains possible to differentiate between overreaction and underreaction from the same cognitive sources of differing levels of cognitive load that determine when or if heuristic System 1 or deliberative System 2 executive functions occur, thereby resolving the puzzle that came about with De Bondt and Thaler's (1985) initial evidence of the winner-loser effect and Hong and Stein's (1999) gradual information diffusion model."

The practical demonstration of the inverted-U shape of the linkage between cognitive load and price discovery efficiency is an important adjustment in our conception of market microstructure. Instead of assuming that cognitive demands constantly undermine market efficiency, the CLBPA model underlines the largely favourable role of intermediate cognitive load in the discovery of optimal prices; likewise, both an insufficiency in cognitive load (defining a conservative and underresponsive mindset) and an excess in cognitive load (defining a heuristic-driven overreaction) lead to a decrease in informational efficiency. This observation brings the Nobel Prize-winning work (Thaler 2018) on limited rationality into the realms of high-frequency trading, thereby suggesting that bounded rationality is not an exclusively static restriction but is context-dependent to produce qualitatively different behavioural outcomes.

The cross-market analysis also reveals, for the first time in a systematic manner, that institutional context moderates bounded rationality effects. The fact that emerging markets (India, Brazil) witness cognitive load effects 2.3 times higher than those in developed markets (US, UK) is a vindication of Simon's (1955) belief that information processing constraints intensify along with the complexity in the environment. This has an important bearing on the transfer of behavioural finance theories developed in the US and European contexts. While the behaviour of prices in the emerging markets may be less prone to bias-driven volatility generally, it also suggests it could be more susceptible to volatility because of this bias.

6.2 Methodological Innovations

From a methodological viewpoint, this study proposes the reaction time as a first, high-frequency-blooded proxy for bounded rationality, employing microsecond timestamps of modern limit order books. This study is a major departure from the conventional research paradigms in behavioural finance, which have primarily used crude demographic or experimental elicitation proxies. By having cognitive load be translated as processing time between information arrival and order placement, this revisits psychological cognitive theory in the realm of market microstructure and allows the measurement of real-time constraints on an individual's cognitive faculties, as elaborated in part by Simon (1955) and so far unmeasured.

The VPIN (Volume Synchronised Probability of Informed Trading) and relative order flow in the composite cognitive load index are alternatively treated as a robust but differential means of pensive investigation of the market-level information processing constraints. The above-mentioned methodology is in concurrence with Easley, López de Prado, and O'Hara's (2012) statement concerning the need for better metrics of flow toxicity to market maker adverse selection in its potential application to a larger conceptual cognition around price determination phenomena.

6.3 Practical Implications and Policy Suggestions

The CLBPA model has produced various actionable markers on market designs and regulatory policy that expand the ideas behind the Thaler & Sunstein (2008, 2021) nudge framework on individual decisions and extend this for institutional market design.

Dynamic Circuit Breakers. The empirical evidence presented in this study gives weight to the idea that trading halts reduce VPIN by 34% in stress periods (H5); therefore, cognitive-load-triggered circuit breakers must be implemented instead of the current stock exchange-standard arbitrary price-drop-trigger system rigidity. Regulators should account for the possible development of a "cognitive pause" that would basically engender a halt when real-time alert signs of cognitive overload (VPIN, order-to-trade ratios, reaction times) emerge rather than waiting for price dips, which are likely to be provocation to steep overreaction. This update makes the early Greenwald and Stein (1991) scheming of circuit breakers more in line with the age of algorithmic trading.

Examining Speed Bumps and Minimum Resting Times. In light of the limited efficacy of current regulatory approaches to high-frequency trading, such as speed bumps and minimum resting times, these approaches may have the perverse effect of further straining cognitive constraints by extending the amount of time that uncertainty in volatile markets is present (Budish, Cramton, & Shim, 2015). The CLBPA model suggests that a well-placed strategic latency complements cognitive recovery periods rather than straightforward market-speed reduction. For example, forcing parties into 50-millisecond "reflection windows" during high-VPIN periods would allow System 2 processing to set back into play with less unsettling uncertainty from prolonged trading halts.

Information architecture. The discovery that sentiment amplifies the cognitive load effect (H4) implies staggered information releases could dampen market volatility. Instead of clustering earnings announcements or macroeconomic data releases at specific times (e.g., Fridays, month-ends), exchanges and regulators could implement "temporal choice architecture" that diversifies information flow to be preventive against clusters of cognitive overload. This concept extends Thaler and Sunstein's (2008) principles of choice architecture to the temporal design parameters of market information.

As per the CLBPA model, some of which could be an inviting dashboard, albeit a simulated one, monitoring your cognitive load through private VPNs. When your reaction time/behaviour metrics look out of whack, think of a very strong sentiment (an investor might get a cold roof) and know when it is time to apply the actual brakes, like on a highway. Trading platforms might consider adding these "nudges for cognition" to slow down trading, thus influencing or prompting more realistic, deliberate decision-making, rather than opposing any instinct to jump in, as per those same CDs that had worked for Thaler and Benartzi's (2004) "Save More Tomorrow" programmes.

Cross-Economies Regulatory Harmonisation. The strong influence of bounded rationality, as shown for emerging markets (H3), implies that regulatory capacity-building aspects must underscore the need for cognitive load monitoring in jurisdictions. International organisations such as IOSCO and the World Bank could assist by showing industrial guidance to emerging-market exchanges about how they can implement toxicity-monitoring interrupt systems in real-time and adaptive circuit breakers tailored to local cognitive limitations.

6.4 Suggestions for Market Participants

Asset managers need to integrate cognitive workload monitoring into their execution algorithms by starting liquidity provision when VPIN indicates high toxicity, which is associated with approximately 20-25% more volatility (Brogaard, Hendershott, et al., 2018), and re-entering the trade once cognitive load metrics return to normal. The switch between regimens of the CLBPA model can indicate the temporal probability of asset allocation, overweighting momentum strategies during overreaction expected rates and contrarian strategies during underreaction expected times.

Algorithmic Traders. High-frequency trading firms should realise that their algorithms evince algorithmic bounded rationality, i.e., the machine learning equivalent of Simon's (1955) satisficing, especially during stress periods when Q-learning algorithms prune aggressively (Du et al., 2024). Embedding cognitive load metrics into algorithmic decision rules may lead to performance improvements by enabling traders to identify when financial markets transition from underreaction to overreaction regimes.

Retail Investors. The typical investors are supposed to be exposed to the idea of the changing cognitive load through time, where their susceptibility to using heuristics is directly affected by market conditions. Voluntarily adopting commitment devices like an enforced cooling period following transactions which took place during times of high VPIN may be used to reduce availability-driven overreaction.

7. LIMITATIONS AND SCOPE OF FUTURE STUDY

7.1 Methodological Limitations

Empirical Constraints. Despite the application of lags and GMM estimation and experimental validation, the observational nature of market data sets limits the ability to infer causality. Although it remains entirely possible to argue that price volatility leads to higher cognitive load rather than the other way round, this limitation is to an extent corrected by our ability to temporally order these measurements (that is, cognitive load proxies precede speed of price adjustment). With randomised controlled trials about circuit breaker designs or natural experiments across jurisdictions due to regulatory changes, future research could help strengthen causal claims.

Test performance verification. Reaction time, VPIN, and order/trade ratio measures are all thought to be valid cognitive load proxies in theoretical terms, but they are really just indirect ways to observe cognitive states. An integration of biometric data – eye tracking, galvanic skin response or portable EEG – with trading platforms makes it possible for the cognitive mechanisms proposed by the CLBPA model to have more direct confirmation. Neuroeconomics has more recently provided hope that such an integration might be possible in the work of Frydman and Camerer (2016) and Kuhnen and Knutson (2021).

Temporal specificity of the sample. This particular sample period (2018-2023) encompasses the unusual COVID-19 market stress that may or may not represent "normal" market conditions. As a natural experiment, mean uncertainty promotes the possible generalisation to low-volatility regimes. From the CLBPA model, we find a prediction that markets exhibit chronic underreaction in extended periods of low cognitive load, a hypothesis to be tested with data from a period of the "Great Moderation" (1984-2007).

To a certain extent, the restrictions on asset classes might be acknowledged here, given the sole focus of this research on the capital markets. The bounded rationality mechanisms identified may well morph when applied in the fixed-income, derivatives, forex or cryptocurrency markets. These markets shift with an increasing degree of changes in their institutional structures, participant heterogeneity, and information environment. Given the 24/7 trading, high retail participation, and immense volatility, the cryptocurrency markets stand as a tempting arena for future exploration, where within this constructive amendment, the capacity of this type ought to exist in the midst of the effect of the CLBPA model.

7.2 Theoretical Extensions

Heterogeneous Agent Models. The present cognitive load-based price adjustment model creates aggregation of cognitive load at the market level. Future studies could develop agent-based computational models that simulate explicit heterogeneous investors with various cognitive capacities, learning rules, and attention constraints. Such models could answer the question of how micro-level cognitive diversity that can be aggregated to macro-level price dynamics creates Hong-Stein (1999) specific areas within cognitive grounding.

Dynamic Threshold Estimation. The cognitive load threshold $\bar{C}$ is estimated as a static model parameter in the existing model. Therefore, adaptive threshold models, with $\bar{C}$ adjusted for the different market conditions (volatility, uncertainty, participant composition), should be the better models to follow the changing nature of bounded rationality. Machine learning approaches based on neuro-networks and attention mechanisms, especially to estimate time-varying thresholds, would be another option.

Cross-cultural behaviour finance. The observed stronger cognitive-load effects in emerging markets suggest the need for cross-cultural behavioural finance research in which cognitive constraints are considered in conjunction with contrasting cultural dimensions (like individualism versus collectivism, uncertainty versus trust, and short term versus long term). The Ruggeri et al. (2020) 19-country validation of prospect theory stands as a model for extending the CLBPA model across various cultures.

7.3 Future Research Directions

Integrating Neurofinance. There is a promising avenue to further explore the neuroscientific validation of the CLBPA model. Lab experiments combining market simulation and fMRI or EEG recording would directly observe the neural correlates of A vs. B and 1 versus 2 in price formation, thus validating the dual-process microlevels in the model. However, such research may also work toward identifying biomarkers for potential regime switches and predicting in real-time an overreaction phase.

Quite simply, in AI and algorithmic bounded rationality, the machine learning algorithm has been observed to exhibit its own versions of bounded rationality (Du et al., 2044). The findings signal a vast expanse for algorithmic cognitive load research. Which training data limitations, model capacity constraints, and computational budgets create the "artificial satisficing" that resembles human bounded rationality? Can CLBPA-style models predict when algorithmic trading will serve to amplify or counterbalance human cognitive biases?

Policy testings. The next area of research should be randomised, controlled attempts to apply market design interventions that are based on the CLBPA model. For instance, we might designate some stocks as "cognitive load-triggered circuit breakers" and others as part of a "traditional circuit breaker" with an intervention with full randomisation so that we could confidently ascertain the 34% toxicity reduction realised by the original study.

Similarly, the synthetic controls would permit attribution property measurement by showing the differences left by regulatory changes the MiFID II brought in Europe and elsewhere to the cognitive load measures.

The CLBPA model's orientation to intraday can be realised in long-term anomaly prediction. If periods of high cognitive load and the overreaction it engenders are the ones quickly underperformed in subsequent days, and if low cognitive load and therefore underreaction set a drift in prices over longer time frames, one may legitimately expect the cognitive load metrics to predict long-term cross-sectional returns. To test whether VPIN and reaction time predict De Bondt and Thaler's (1985) winner-loser effects or momentum profits based on a quarter-period-second validation to them relative to traditional asset pricing anomalies.

Climate Finance and ESG Integration. Recent studies within sustainable finance suggested that environmental, social, and governance (ESG) information processing poses distinct cognitive challenges, especially concerning climate-related risks formulated in an affect-driven way. The CLBPA model could be extended to check whether ESG information induces distinctive cognitive load patterns that may have implications for raising finance on green assets and designing ESG disclosure regulations.

7.4 Concluding Remarks

The cognitive load-based price adjustment model represents a significant step forward in appreciating how bounded rationality occurs in financial markets. By assimilating underreaction and overreaction into a combined theoretical framework, developing high-frequency proxies for cognitive constraints, and demonstrating the policy usefulness of cognitive-load-aware market design, the present research extends from the Nobel-winning contributions of Simon (1978), Kahneman (2002), and Thaler (2017) into the contemporary high-frequency trading environment. Indeed, this is another approach to examine the presence of cognitive constraints in high-frequency trading, with many challenges yet to be met. However, significant opportunities exist for the merging of this theory with future empirical investigations in the direction of cognitive psychology, market microstructure, and financial regulation. Since markets are becoming algorithmic and information-rich, it will pay off to know how to interpret and utilise the cognitive load of traders to maintain stable and efficient price discovery.

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