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Understanding price momentum, market fluctuations, and crashes: insights from the extended Samuelson model

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Abstract

Although momentum strategies result in abnormal profitability, thereby challenging the efficient market hypothesis (EMH), concerns persist regarding their reliability due to their significant volatility and susceptibility to substantial losses. In this study, we investigate the limitations of these strategies and propose a solution. Our literature review reveals that the volatile profits are due to statistical analyses that assume the persistence of past patterns, leading to unreliable results in out-of-sample scenarios when underlying mechanisms evolve. Statistical analysis, the predominant method in financial economics, often proves inadequate in explaining market fluctuations and predicting crashes. To overcome these limitations, a paradigm shift towards dynamic approaches is essential. Drawing inspiration from three groundbreaking economists, we introduce the extended Samuelson model (ESM), a dynamic model that connects price changes to market participant actions. This paradigm transition uncovers several significant findings. First, timely signals indicate momentum initiations, cessations, and reversals, validated using S&P 500 data from 1999 to 2023. Second, ESM predicts the 1987 Black Monday crash weeks in advance, offering a new perspective on its underlying cause. Third, we classify sequential stock price data into eight distinct market states, including their thresholds for transitions, laying the groundwork for market trend predictions and risk assessments. Fourth, the ESM is shown to be a compelling alternative to EMH, offering potent explanatory and predictive power based on a single, realistic assumption. Our findings suggest that ESM has the potential to provide policymakers with proactive tools, enabling financial institutions to enhance their risk assessment and management strategies.

Keywords: Momentum strategy, Investor behavior, Efficient market hypothesis, Behavior finance theory, Excess demand, Market crisis, Market microstructure, Market maker's inventory, Boom and bust, 1987 Black Monday, Warren Buffett, Samuelson's model, Asymmetric information, Herding effect, Noise trade, Sentiment, Risk assessment

Introduction

Bachelier (1900) characterized the unpredictable movements of equity market prices using the random walk theory, a perspective substantiated by extensive evidence recorded in the literature (Cootner 1964). The Efficient Market Hypothesis (EMH) provides an economic rationale for random price behavior (Fama 1970),[1] which has been prevalent in financial economics since the 1970s, asserting that predicting future market movements is impossible. This academic theory leaves the world vulnerable to financial market crises that significantly harm the economy and disrupt society. According to EMH, asset prices should incorporate all available information at any given time, making it impossible to outperform the market based on past prices. However, the momentum strategy (Jegadeesh and Titman 1993), along with opposing contrarian approaches (Zacks 2011), demonstrates that exploitable patterns exist in price history, leading to abnormal returns and contradicting the weak form of the EMH. Fama and French (1996) recognized that momentum strategies pose "*the main embarrassment*" to EMH**,** underscoring the need for an alternative theory for a more comprehensive understanding of market behaviors, especially regarding severe market downturns**.** In this context, Behavioral Finance Theory (BFT) emerged as a counterpoint to EMH's assumption of purely rational actors by emphasizing the role of psychological factors in influencing market decisions (De Bondt et al. 2008). However, the ongoing debate between BFT and EMH remains inconclusive due to BFT's lack of a testable model to replace EMH (Chicago Booth Review 2016), which prompted us to seek an alternative approach to address the theoretical gap left by EMH. Although momentum strategies challenge EMH, the reason behind their volatile profits, and even significant losses, remains unclear, raising concerns about their reliability. Therefore, we'll start by reviewing existing research to identify the cause of this weakness, which will pave the way for exploring alternative solutions.

The momentum strategy is from the observation that the top decile of performers, commonly termed winners, who have demonstrated strong performance over the past three to twelve months, consistently maintain their outperformance over the subsequent three to twelve months compared to the bottom decile, known as losers. The profitability of the momentum strategy indicates that prices exhibit memory, directly challenging the weak form of EMH. Numerous subsequent studies over the past thirty years have affirmed the price momentum with no indication of decline. Nevertheless, momentum profits display noteworthy fluctuations over time and as documented in the literature, can incur substantial losses in some instances. Despite extensive exploration and debate to elucidate the momentum phenomenon in literature, the instability of the momentum strategy, a cornerstone of critiques against it, remains unaddressed.

This study challenges the fixed ranking/holding periods adopted by momentum strategies from statistical analyses because momentum continuation and reversal periods in stock markets exhibit significant irregularity over time. We propose a dynamic approach, the extended Samuelson model (ESM), to address this limitation by identifying the timing of momentum phases: formation, sustenance, and transition. This model generates timely signals that can inform investment decisions. We elucidate the timing of various stages of the momentum phenomenon in the stock market from 1999 to 2023. Additionally, we demonstrate that ESM provided warning signals weeks before the 1987 Black Monday market crash—an event challenging for EMH to explain. This predictive

[1] For the history of EMH, see Sewell (2011) and Lim et al. (2012).

capability, coupled with the model's ability to dynamically account for daily return variances through the interactions of liquidity takers and providers, possibly positions ESM as a viable alternative to EMH in explaining market price fluctuations.

The remaining part of the paper unfolds as follows. Section "Literature review" delves into the existing literature on momentum strategies, laying the foundation for our investigation. Section "Method: the extended Samuelson model" introduces the method, the extended Samuelson model, and evaluates its ability to explain daily returns. We further demonstrate its prowess in identifying market makers' inventory positions. Section "Results" outlines the results, including model-derived signals that pinpoint the formation and transitions of price momentum (4a), application of these signals to analyze momentum dynamics over 25 years (4b), model-generated warning signals weeks before the 1987 Black Monday crash (4c), and identifying different market states, empowering investors with valuable decision-making insights (4d). Finally, section "Discussion and conclusion" concludes with discussions.

Literature review

Since the breakthrough discovery by Jegadeesh and Titman (1993), the momentum effect has been identified not just in numerous stock markets around the world but also across diverse asset classes, encompassing bonds, currencies, and commodities (Foerster et al. 1994; Chan et al. 1996; Rouwenhorst 1998; Cleary and Inglis 1998; Moskowitz and Grinblatt 1999; Chan et al. 2000; Hong et al. 2000; Lee and Swaminathan 2000; Griffin et al. 2003; Assogbavi et al. 2005; Balvers and Wu 2006; Hvidkjaer 2006; Chui et al. 2010; Asness et al. 2013; Geczy and Samonov 2016; Avramov et al. 2016; Boons and Prado 2018; Vo and Truong 2018; Gang et al. 2019; Boussaidi and Dridi 2020; Paschke et al. 2020; Liu et al. 2022).

The profitability to various asset classes of the momentum effect has fueled the development of various approaches that outperformed the market, including the industry momentum strategy (Moskowitz and Grinblatt 1999; Swinkels 2002; O'Neal 2000; Grobys and Kolari 2020), the 52-week high momentum strategy (George and Hwang 2004; Du 2008; Liu et al. 2011; Hao et al. 2018; Zhou et al. 2022), the time-series momentum strategy and the debate on this approach (Moskowitz et al. 2012; He and Li 2015; Kim et al. 2016; Goyal and Jegadeesh 2018; Huang et al. 2020), the factor momentum strategy (Avramov et al. 2017; Gupta and Kelly 2019; Haddad et al. 2020; Falck et al. 2021; Ehsani and Linnainmaa 2022; Fan et al. 2022; Arnott et al. 2023), and the contratum strategy (Abukari and Otchere 2020; Ashtiani et al. 2022; Hosseini et al. 2023).

However, the literature has also reported observations of momentum profits diminishing in recent years (Hwang and Rubesam 2015; Bhattacharya et al. 2017; Dolvin and Foltice 2017; Hou et al. 2020) or experiencing momentum crashes (Grundy and Martin 2001; Greiner 2011; Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016; Dobrynskaya 2019; Xu and Wang 2021; Dierkes and Krupski 2022). Some recent studies have initiated the search for alternative strategies to mitigate potential momentum crashes (Singh et al. 2022). Burton Malkiel, a staunch advocate of the random walk theory, criticized the momentum strategy: "*While the market does exhibit momentum, it does not occur reliably, and there are frequent momentum crashes. There is insufficient persistence in stock prices to sustain consistently profitable trend-following strategies.*" (Malkiel 2022). The puzzling coexistence of profitability and high volatility in momentum strategies motivated us to investigate the reasons behind this phenomenon. The questions are: (1) what causes the momentum phenomenon and its volatile profits? and (2) How can we solve the problem of unreliable momentum profits?

Since the discovery of momentum strategy in 1993, numerous theoretical studies have sought to untangle the enigma of price momentum, as comprehensively reviewed by Galariotis (2014), Subrahmanyam (2018), Singh and Walia (2022), and Wiest (2023). Prevailing narratives attribute the phenomenon to behavioral biases like underreaction and overreaction to gradually revealed information, stemming from investor overconfidence, cognitive limitations, and herding behavior (Chan et al. 1996; Barberis et al. 1998; Daniel et al. 1998; Hong and Stein 1999, 2007; Lee and Swaminathan 2000; Hirshleifer 2001; Ahn et al. 2002; Barberis and Thaler 2003; Wu 2011; Jiang et al. 2012; Hur and Singh 2016; Khan et al. 2017; Blitz et al. 2020; Atilgan et al. 2020). However, a counterpoint exists in the form of the risk-based perspective, which argues that momentum profits may arise from exposure to specific risk factors rather than purely irrational decision-making (Conrad and Kaull 1998; Berk et al. 1999; Johnson 2002; Sagi and Seashole 2007; Liu and Zhang 2008; Wang et al. 2012; Andrei and Cujean 2017; Li 2017; Koziol and Proelss 2021; Kelly et al. 2021). Notably, a third camp proposes a hybrid explanation, attributing momentum to a complex interplay of behavioral and rational drivers (Ahn et al. 2002; Du and Watkin 2007; Du 2012; Zoghlami 2013; Sehgal and Jain 2015). Further research has elucidated the connections between the momentum effect and various macro-economic and market-specific conditions, including macroeconomic risk (Kelly et al. 2017; Addoum et al. 2019), business cycles (Antoniou et al. 2007; Avramov and Chordia 2006), market state (Cooper et al. 2004; Du et al. 2009), Federal Open Market Committee (FOMC) interest rate decisions (Leonard 2022), economic policy uncertainty (Gu et al. 2021; Goel et al. 2021; Kakran et al. 2023; Urom et al. 2023), environmental, social and governance impact (Rao et al. 2023), and information asymmetry (Lai and Lin 2020). These inquiries confirm that the enduring momentum phenomenon stems from diverse market factors rather than random peculiar occurrences. Consequently, our focus shifted towards uncovering the source of the volatile profits generated by the momentum strategy.

Existing research indicates that momentum profits vary significantly based on the chosen ranking/holding periods**.** Traditionally, studies follow a 6-month ranking and 6-month holding period for momentum strategies (Jegadeesh and Titman 1993, 2001; Moskowitz and Grinblatt 1999). However, this standard timeframe is not universally adopted. For instance, Lewellen (2002) investigates strategies that incorporate the preceding 12 months of returns, while Pan et al. (2004) explores shorter-term momentum based on returns from the past 1 to 4 weeks. Nguyen and Hoang (2022) found that the momentum strategy generated profits during formation and holding periods ranging from four to thirteen weeks. Gupta and Kelly (2019) adopted a ranking period of the prior one to five years and a 1-month holding period. Basu and Miffre (2013) tested various combinations of ranking/holding periods from 4 to 52 weeks and found significant differences among their generated profits. Assogbavi and Leonard (2008) demonstrated that the choice of formation and holding periods significantly impact the effectiveness of the momentum strategy.

Hence, the literature suggests that a significant hurdle for momentum strategies lies in their reliance on predetermined ranking and holding periods derived from statistical methods. The original momentum strategy of Jegadeesh and Titman (1993) hinges on an implicit assumption that the top performance decile of stocks will continue to outperform for a sustained period: typically, 12 months–6 months for ranking and 6 months for holding. As stocks take turns achieving peak performance, frequent portfolio rebalancing empowers the top decile stocks to surpass the market (Gao et al. 2017). Thus, while individual stocks may not benefit from the momentum strategy, a portfolio of stocks can (Carhart 1997). However, when this assumption falters, profits diminish, necessitating adjustments to ranking and holding periods in various markets. During sudden market movements, like those observed in March 2009, when many stocks deviated from the assumption, the momentum strategy incurred significant losses (Daniel and Moskowitz 2016).

The core limitation stems from the assumption of statistical prediction: that past market patterns will persist in the future, disregarding the underlying causes of these patterns. The assumption proves faulty when the underlying causes evolve with time, resulting in the inherent out-of-sample problem for the statistical method, as demonstrated by Jensen and Bennington (1970) and Malkiel (1995). To surmount this limitation, a more comprehensive understanding of market behavior may require a transition from statistic to dynamic approach. The history of economic thought offers valuable examples of such transitions, highlighting the potential benefits of incorporating dynamic models.

In 1939, John Hicks adopted the statistical method in the equilibrium theory presented in the book Value and Capital (Hicks 1939), where prices were assumed to reach equilibrium instantaneously. Paul Samuelson challenged the perplexing phenomenon of sudden price change by introducing dynamics into the process with a causal relationship, arguing that the rate of price change is proportional to the disparity between demand and supply (Samuelson 1941, Eq. 11). This innovation was widely acclaimed by esteemed economists as a groundbreaking advancement in this field (Metzer 1945; Negishi 1962; Arrow 1967). John Hicks recognized the inadequacy of his assumption regarding instantaneous price change in the second edition of his book, "*Professor Samuelson has turned some much heavier mathematical artillery than mine on to this precise issue and has undoubtedly made important progress with it... By my hypothesis of essentially instantaneous (price) adjustment, I reduced the purely mechanical part of my dynamic theory to the simplest terms-it is now quite evident that I over-simplified it.*" (Hicks 1946, p336–337).

Within this essay, we extend Samuelson's causality model to unveil the origins of momentum profits and market fluctuations. This exploration is undertaken on the premise that momentum and contrarian phenomena fundamentally involve changes in price.

Method: the extended Samuelson model

The primary focus of our paper is to uncover the origin of momentum phenomena and, in a broader context, to understand the underlying causes of market fluctuations through a dynamic approach. In model development, we extended the dynamic Samuelson price adjustment model to incorporate the insightful ideas from Tiber Scitovsky (and more precisely, Ragnar Frisch) and Kenneth Arrow. The data used for calculations of the key component of the model, excess demand, comprises the S&P 500 index and its constituent stocks obtained from Yahoo Finance for daily, weekly, and monthly data and from Sierra Chart platform for intraday prices. The real-time market data are supplied by Intrinio Company.

The price adjustment model by Paul Samuelson (1941, Eq. 11) asserts that asset price changes at a rate proportional to the excess demand, i.e., $\frac{dp}{dt} = H[D(p) - S(p)]$, where p represents the price, $D(p)$ and $S(p)$ denotes demand and supply, respectively, $D(p)–S(p)$ is the excess demand, and $H(0)=0$, $H' > 0$. H is an increasing function of excess demand and remains zero when demand and supply are balanced. While the model represented a groundbreaking innovation by introducing dynamics to price change, it faced criticism from scholars (Scitovsky 1952; Arrow 1959; Bradfield and Zabel 1979; Bryant 1980; Fisher 2006) for assuming that price change is solely attributed to the behaviors of price-takers, disregarding the role of price-makers. Scitovsky (1952) contended that without the role of "*price maker*" who "*set his price on a take-it-or-leave-it basis*," the market price would be provided by "*the impersonal forces*." He also acknowledged that the concept of a price maker originated from Professor Ragnar Frisch, the first recipient of the Nobel Prize in Economics.[2]

In the stock market, price-takers are liquidity seekers who place market orders, aiming for immediate execution at the prevailing market price set by limit orders. The difference between demand (D(p)) and supply (S(p)), known as excess demand, reflects the collective behavior of liquidity seekers. Conversely, liquidity providers act as price setters by submitting limit orders with specific execution prices, forming the quoted price. While excess demand primarily drives price fluctuations, the actions of liquidity providers also significantly impact quote changes (Asparouhova et al. 2003).

Quote adjustments typically occur in response to inventory build-ups by market makers (Stoll 1978; Amihud and Mendelson 1980; Ho and Stoll 1983) or reflect information gleaned from trading activities (Glosten and Milgrom 1985; Kyle 1985; Easley and O'Hara 1987). Quote cancellations and revisions tend to result in asset price changes more frequently than actual trades (Easley et al. 2012). Numerous studies (Kavajecz and Odders-White 2004; Gillemot et al. 2006) highlight the importance of maintaining a balance between liquidity demand and supply in influencing price changes. Blume et al. (1989) reported a strong relationship between limit order imbalance and price movements on Black Monday, 1987. Research conducted by Amihud et al. (1990), Farmer et al. (2004), and Weber and Rosenow (2006) suggests that significant price shifts often stem from liquidity shortages. The market flash crash on May 6, 2010, attributed to a substantial disparity between limit-sell and limit-buy orders, underscores how illiquidity can trigger major market disruptions (CFTC and SEC 2010; Easley et al. 2011). Therefore, Samuelson's price adjustment model, devoid of the role played by liquidity providers, is incomplete and necessitates modification.

[2] Frisch had initially introduced the term "price adjuster" in Norwegian, with an English version available in his 1965 book, *Theory of Production*. The idea of a "take it or leave it" option is presented on page 140 of this book.

Leveraging Frisch's insight on price makers, Arrow's analysis of market microstructure, and the well-established principle of homogeneous degree zero demand (Mas-Colell et al. 1995), we extend Samuelson's dynamic model as follows.

$$\frac{dlnp}{dt} = H\left[\frac{D(p) - S(p)}{D(p) + S(p)}\right] + M \tag{1}$$

where $\frac{D(p)-S(p)}{D(p)+S(p)}$ is NED (Normalized Excess Demand) describing the aggregate behavior of price-takers, and M is the behavior and the market microstructure impact of price-makers. This inclusion aligns with the principle of economic theory encompassing investor interactions and responses to price changes (Arrow 1986). Han and Keen (2021) calculated NED for six timeframes: 5-min, 15-min, hourly, daily, weekly, and monthly. The intraday NEDs (5-min, 15-min, and hourly) cover the period from January 2, 2013, to the present, based on available data.

The Efficient Market Hypothesis (EMH) has limited explanatory power, only accounting for around 20% of daily stock return variances (Roll 1984, 1988; Cutler et al. 1989; Berry and Howe 1994; Mitchell and Mulherin 1994; Tetlock 2007; Cornell 2013) challenging its core assumption of news-driven price changes, especially considering evidence that price-driven factors dominate daily market volatility (Fama 1965; Oldfield and Rogalski 1980; French and Roll 1986; Haugen 2009). Furthermore, EMH struggles to explain market events like the 1987 crash, the dot-com bubble collapse, and the 2008 financial crisis (Shleifer and Summer 1990; Shostak 1997; Sharma and Kumar 2020). In contrast, the extended Samuelson model offers a more comprehensive explanation of asset price fluctuations in these areas where EMH falters.

Figure 1 depicts the scatter plot of the measured intraday NED and daily returns of the S&P 500 from January 02, 2013, to October 25, 2024, encompassing a total of 2975 observations. In the regression equation, 'y' represents daily return, and 'x' corresponds to the measured intraday NED. The findings indicate that the conduct of liquidity takers can account for 64% (p = 0) of the daily return variances over a decade, while the residual portions are due to the behavior of liquidity providers as per the extended Samuelson model.

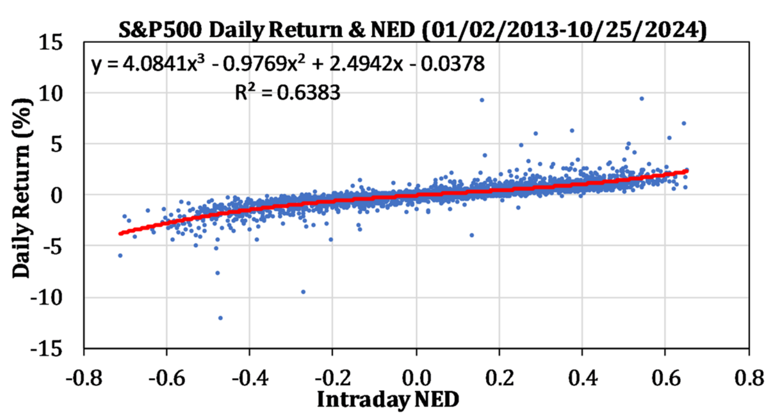

Fig. 1 Relation of S&P 500 daily return and intraday NED over eleven years

Table 1 The success rate of unwinding market makers' inventories within 8 days during 2013–2023

Year	NED = + 100%			NED = − 100%			Over all %
	Short inventory	Unwound	%	Long inventory	Unwound	%	
2013	931	867	93	815	795	98	95.2
2014	681	616	90	623	600	96	93.3
2015	672	632	94	664	635	96	94.8
2016	594	553	93	575	566	98	95.7
2017	263	243	92	219	214	98	94.8
2018	660	625	95	651	621	95	95.0
2019	526	490	93	462	455	98	95.6
2020	752	711	95	693	674	97	95.8
2021	497	454	91	417	406	97	94.1
2022	820	789	96	809	773	96	95.9
2023	611	572	94	527	514	98	95.4
Total	7007	6552	94	6455	6253	97	95.1

The dominant impact of liquidity takers' behavior on daily return is consistent with findings in the literature (Asparouhova et al. 2003; Chordia et al. 2002). The explanatory power of intraday NED to daily return is more significant for years of a less volatile market. R^2 is 76.31%, 83.25%, 70.02%, 78.34%, 79.84%, 77.27%, 78.92%, 58.17%, 80.88%, 81.40%, and 78.38% for the years 2013 through 2023, respectively. Notably, the significant low R^2 of 58.17% for 2020 is due to the illiquidity in March 2020 under the influence of the Covid-19 pandemic when quote cancelations were frequent because of the overwhelming pessimistic view of the market. Baig et al. (2021) and Tiwari et al. (2022) presented compelling evidence of a substantial increase in stock market illiquidity during the COVID-19 outbreak.

To verify that our NED accurately reflects the collective behavior of price-takers, we employ the following rationale: When NED equals 1 (or − 1), all price-takers are in a buying (or selling) mode, prompting market makers to sell (or buy) to provide liquidity and involuntarily amass short (or long) inventory. Consequently, we can infer the inventory positions of market makers by observing the price range when NED equals 1 (or − 1). With limited resources, market makers must unwind these inventories at a price better than that when they accumulate them, allowing them to continue offering immediate liquidity (Garman 1976; Amihud and Mendelson 1980; Madhavan and Smidt 1993; Hendershott and Seasholes 2007; Panayides 2007), causing price reversals. Han and Keen (2021) have shown that market makers unwound inventories with a 90% success rate within seven days after the inventory acquisition during 2013–2020 using 15-min data. They verified the success rate in a real-time forecasting experiment in a finance forum.[3] In the two-month forecasting experiment, the market reached 49 out of 54 predicted reversal price targets within the specified time. On some trading days of the experiment, the market experienced a significant surge or plunge to arrive at the predicted price targets without any breaking news. We continued the investigation with more data and found a 95% success rate of inventory unwinding within eight days after

[3] http://hutong9.net/forum.php?mod=viewthread&tid=430972, mouse right-click for a Google translation.

the inventory acquisition during 2013–2023 using 5-min data, as shown in Table 1. The result suggests that inventory control of market makers led to an average rate of 4.67 price reversals per day over eleven years. The price reversal rate demonstrates the role of market makers in stabilizing the financial markets.

Figure 2 is an example showcasing the acquisition and unwinding of market makers' inventory positions, as indicated by the price ranges at NED = 1 (− 1). When NED = 1 (− 1), signifying that all liquidity-takers are buying (selling), market makers are obliged to sell (buy) to provide liquidity, resulting in the unintentional accumulation of short (long) inventory. The two weeks illustrated in Fig. 2, from March 9 to March 20, 2020, stand out as an extraordinarily volatile market environment. Within this timeframe, the pervasive panic that emerged in response to the COVID-19 pandemic triggered the market circuit breakers four times on March 9, 12, 16, and 18, respectively (Lin et al. 2022). Given the prevailing fear and dominance of bearish sentiment in the market, one might anticipate significant losses for market makers due to the challenges of unwinding their inventory positions amidst an immense and continuous flood of frantic selling orders. However, the reality is quite the opposite.

Table 2 presents a comprehensive summary of the acquisition and unwinding time for the corresponding inventory positions shown in Fig. 2. In the span of two weeks, market makers accumulated 108 inventory positions, comprising 60 long and 48 short inventories. Within just eight trading days after the inventory acquisitions, in most cases either on the same day or the following trading day, market makers adeptly unwound 106 of these positions. This impressive achievement translates to a remarkable success rate of 98% for inventory unwinding. The skillful management of inventory positions of market makers plays a crucial role in stabilizing the volatile market environment—their ability to execute an average of ten price reversals per trading day contributes significantly to maintaining market stability and equilibrium.

The higher success rate, surpassing the ten-year average of 95%, suggests that market makers were able to unwind their inventory positions at more favorable prices amidst

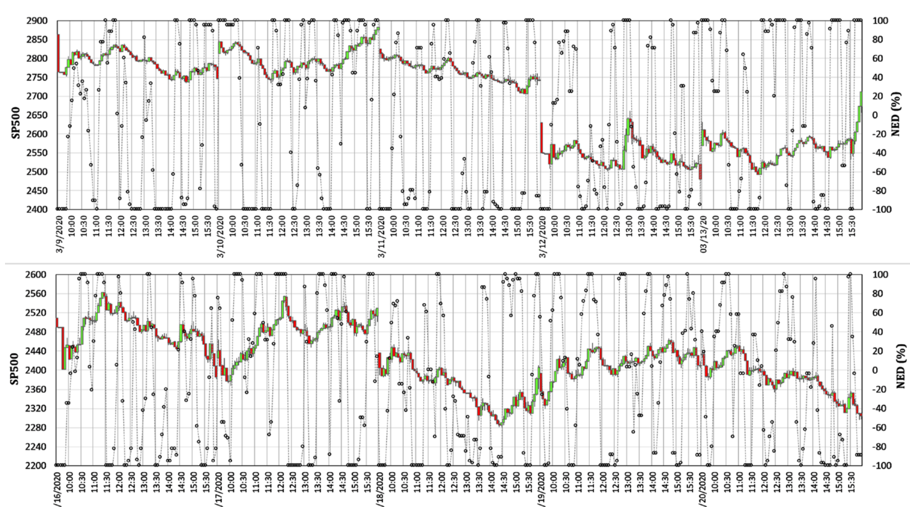

Fig. 2 Five-minute charts of 3/9/2020 through 3/20/2020. Market makers inventory positions are inferred at NED = − 1 (long) and NED = + 1 (short)

Table 2 Acquisition and unwinding of market makers inventory positions in 3/9/2020–3/20/2020

Acquisition time	Long Invnt	Short Invnt	Unwnd Date	Unwnd Time	acquisition Time	Long Invnt	Short Invnt	Unwnd Date	Unwnd Time
3/9/2020					**3/16/2020**				
9:30	2863.89		03/10/20	15:45	9:30	2508.59		03/16/20	10:35
11:05	2785.41		03/09/20	11:10	10:30		2454.11	03/16/20	14:00
11:25	2805.89		03/09/20	11:30	11:10		2519.97	03/16/20	11:40
11:45		2826.53	03/09/20	11:55	11:30	2559.5		03/26/20	10:05
12:30	2814.46		03/10/20	9:30	12:15	2522.6		03/16/20	12:35
13:25	2791.65		03/10/20	9:30	12:50	2494.2		03/16/20	13:05
14:15		2756.26	03/09/20	14:25	13:10		2480.94	03/16/20	13:30
14:50		2742.68	03/10/20	11:30	13:30	2487.26		03/16/20	14:30
15:55	2777.92		03/10/20	9:30	14:30		2457.29	03/16/20	15:25
3/10/2020					15:20	2480.4		03/17/20	11:10
9:30		2813.48	03/10/20	9:50	**3/17/2020**				
10:10		2834.14	03/10/20	10:20	10:10		2400.59	03/18/20	9:30
10:30	2822.72		03/10/20	14:45	11:05		2451.75	03/17/20	13:15
11:15	2785.15		03/10/20	12:10	11:50		2492.54	03/17/20	13:25
11:40		2739.54	03/11/20	14:15	12:20	2534.63		03/17/20	14:35
12:10		2773.86	03/10/20	12:30	13:10	2472.78		03/17/20	13:30
12:30	2775.56		03/10/20	12:40	13:35		2473.75	03/17/20	15:00
12:55		2782.57	03/10/20	13:00	14:05		2489.52	03/17/20	14:50
13:15		2787.35	03/10/20	13:35	14:45	2521.35		03/17/20	15:40
13:45	2784.05		03/10/20	14:15	15:35		2492.17	03/18/20	9:30
14:10		2771.96	03/10/20	14:25	**3/18/2020**				
14:35		2797.28	03/11/20	9:40	9:30	2436.5		03/18/20	10:00
15:10		2832.2	03/10/20	15:20	10:50	2422.87		03/19/20	10:10
15:30	2856.91		03/10/20	15:40	11:50		2385.33	03/18/20	12:10
15:50		2862.47	03/11/20	9:30	12:15	2383.16		03/18/20	12:25
3/11/2020					13:30	2323.21		03/18/20	13:35
9:30	2825.6		04/14/20	23 days	14:10	2307.93		03/18/20	14:35
11:15	2782.28		03/11/20	12:00	14:35		2297.17	03/20/20	15:50
12:10		2787.69	03/11/20	12:25	15:00		2321.11	03/18/20	15:25
12:25	2791.73		04/09/20	21 days	15:25	2335.13		03/18/20	15:40
13:05	2753.41		03/11/20	13:15	15:50		2346.48	03/19/20	9:35
13:25		2751.31	03/11/20	13:40	**3/19/2020**				
13:40	2753.91		03/11/20	13:45	9:40	2340.76		03/19/20	9:50
14:20	2741.05		03/11/20	14:30	10:05		2376.48	03/19/20	10:50
14:50	2745.6		03/11/20	15:30	10:40	2397.37		03/19/20	10:55
15:25		2707.33	03/12/20	9:30	11:25		2418.25	03/19/20	12:00
3/12/2020					11:55	2450.73		03/19/20	13:50
9:30	2630.86		03/12/20	13:00	12:30	2403.87		03/19/20	12:40
11:10	2547.99		03/12/20	11:30	12:45		2409.08	03/19/20	13:00
11:50	2520.6		03/12/20	11:55	13:50		2429.58	03/19/20	14:00
12:10	2510.3		03/12/20	12:15	15:00	2441.54		03/19/20	15:25
12:40	2518.39		03/12/20	12:50	15:25		2433.39	03/19/20	15:30
12:50		2506.5	03/12/20	15:20	**3/20/2020**				
13:25	2592.48		03/13/20	9:30	9:45	2405.88		03/20/20	9:55
14:10	2556.87		03/13/20	9:30	10:30		2427.34	03/20/20	10:45
14:35	2527.44		03/12/20	14:40	11:15	2436.22		03/24/20	12:35
14:45		2520.29	03/12/20	14:55	12:05	2389.74		03/20/20	12:45
15:20	2519.2		03/12/20	15:40	12:50		2383.3	03/20/20	13:00

Table 2 (continued)

Acquisition time	Long Invnt	Short Invnt	Unwnd Date	Unwnd Time	acquisition Time	Long Invnt	Short Invnt	Unwnd Date	Unwnd Time
3/13/2020					13:30	2391		03/24/20	10:25
9:40		2568.01	03/13/20	9:50	14:30	2363.9		03/24/20	9:30
10:20		2587.45	03/13/20	10:30	14:55	2338.36		03/20/20	15:00
10:40	2577.13		03/13/20	13:25	15:15	2331.56		03/20/20	15:25
11:25	2546.64		03/13/20	12:30	15:30		2339.74	03/20/20	15:35
11:55		2506.01	03/13/20	12:05					
12:15		2519.18	03/13/20	12:20					
12:30		2517.31	03/16/20	9:30					
13:00	2556.04		03/13/20	13:15					
13:20		2563.14	03/13/20	14:05					
14:05	2579.93		03/13/20	15:00					
14:30	2555.07		03/13/20	14:40					
14:45		2552.91	03/16/20	9:30					
15:30	2591.3		03/13/20	15:40					
15:40		2573.46	03/16/20	9:30					

volatile market conditions, thereby generating profitable outcomes. Notably, the four dramatic price plunges that triggered market circuit breakers on 3/9, 3/12, 3/16, and 3/18 were recovered at better prices swiftly. Consequently, banks harvested significant trading profits during the first quarter of 2020. Bank of America, for instance, reported an increase in profit solely attributed to its trading division, with gains of approximately 33% amounting to $1.48 billion. This growth was driven by heightened market volatility and increased client activity (Son 2020a). Goldman Sachs experienced a mixed performance, as losses in debt and equity holdings within their asset management business weighed down their overall results, their trading division surpassed expectations, contributing to a boost in companywide revenue, which reached $8.74 billion (Son 2020b). JPMorgan's trading division achieved remarkable success, with revenue soaring by 32% to reach a record-breaking $7.2 billion (Son 2020c). For Citigroup, equity-trading revenue also experienced a significant surge, jumping by 39% to $1.2 billion (Imbert 2020).

In contrast, a smoother market environment may pose challenges for market makers. For instance, Goldman Sachs attributed its underwhelming trading performance in the first quarter of 2017 to a combination of low trading volume and volatility (Kelly 2017). In our data, during the first quarter of 2017, market makers possessed 163 inventory positions, and 153 of them were unwound within eight trading days, resulting in an average of 2.5 reversals per day, four times lower than the average observed in 2020 and indicating a much smoother market environment.

In the upcoming section, we will demonstrate that the origins of momentum lie in the interactions between liquidity takers and providers. The consistent behaviors of market participants contribute to the development of positive or negative momentum, depending on investors' market views. Conversely, contradictory behaviors bring an end to price trends, paving the way for a transition toward an opposite momentum direction. By analyzing the behaviors of measured NEDs and price changes, we can identify signals that indicate the formation, termination, and reversal of momentum.

Results

Momentum signals: formation, persistence, and transition

In stock markets, liquidity-takers place market orders (or executable limit orders), and liquidity providers submit limit orders (Hopman 2007). Since the behaviors of liquidity-takers and -providers determine market price changes, we can analyze their interactions once NEDs can measure the liquidity takers behaviors. Han and Keen (2021) summarized six signals that can identify behavioral interactions and infer future market directions. The following are the six signals.

1. Positive momentum signal. This signal emerges when the ridges and troughs of NED are higher than the previous adjacent ones during market oscillations, like the peaks and valleys of the S&P 500. It indicates optimistic sentiment from both price-takers and price-makers, suggesting a positive market outlook.
2. Negative momentum signal. This signal arises when the ridges and troughs of NED are lower than the previous adjacent ones during market oscillations, mirroring the peaks and valleys of the S&P 500. It indicates a pessimistic sentiment prevailing among most market participants.

Signals 1 and 2 mirror the consistent actions of liquidity-takers and liquidity providers when they hold a shared view of the market. These consistent actions play a role in the development of either positive or negative momentum. The momentum will endure until there is an emergence of conflicting behaviors between liquidity-takers and liquidity providers.

3. An approaching uptrend signal. This signal is triggered when there is a lower trough in NED coinciding with a higher valley in the S&P 500. It signifies that, despite heightened selling pressure from liquidity takers, the S&P 500 level does not decrease proportionally because a significant volume of limit-buy orders is positioned at a level higher than the previous low.
4. A looming downtrend signal. Unlike signal three, this signal arises when the crest of NED is higher than the adjacent ridge preceding it, while the corresponding peak of the S&P 500 is lower than the previous one. This signal implies a situation akin to signal three but in the opposite direction, signaling the potential initiation of a downtrend.

Signals three and four offer insights into the market microstructure, a concept initially addressed by Arrow (1959) as a pivotal factor influencing price adjustments. Signal three arises when there is a concentration of buyers in the order book, while signal four indicates a predominant presence of sellers among liquidity providers. These two signals reveal the presence of the herding effect, a phenomenon documented since the 1990s but lacking conclusive empirical verification (Komalasari et al. 2022). The studies by Gould and Bonart (2016) and Cartea et al. (2018) have illustrated that the price pressure stemming from the market microstructure can adeptly forecast the direction of price movements.

Signal three bolsters positive momentum or halts negative momentum by shaping an uneven market microstructure that exerts upward pressure, resulting in subsequent price increases. Conversely, signal four reinforces negative momentum or terminates positive momentum as the market microstructure generates downward pressure, precipitating a subsequent decline in price. These two signals tend to manifest during prolonged periods of market upswings or downturns, underscoring the substantial impact of the market microstructure on the evolution of momentum in such market conditions.

5. Warning signal at a new market high. This signal occurs when the NED value drops as the market reaches a new high, or when it is lower than the NED value at a previous lower market peak. The inverse movements of the NED value and the S&P 500 indicate that certain liquidity takers initiate selling at market peaks to capitalize on profits.
6. Recovering signal at a new market low. This signal emerges when the NED value rises as the S&P 500 drops to a new low level. The increased NED value suggests that some liquidity takers begin to buy at a lower price, indicating a potential market recovery.

Signals five and six shed light on the behaviors of informed investors who perceive that an ongoing trend should come to a halt. These signals can also be associated with intelligent investors who adhere to Warren Buffett's investment principle: "*Be fearful when others are greedy, and greedy when others are fearful*" (Buffett 1986). Signals five and six serve as warnings for the potential reversal of momentum, indicating that caution may be necessary. However, to confirm the formation and continuation of a new trend, these signals should be accompanied by additional supporting signals.

In summary, signals 1 and 2 arise from consistent actions when investors share the same view of the market future, while signals 3 through 6 emerge from contradictory behaviors of liquidity takers and providers. These six signals collectively offer predictive power across various timeframes, ranging from intraday fluctuations to long-term trends. Han and Keen (2021) detailed the utilization of these signals during market crises in 2000, 2008, and 2020. For added emphasis, the subsequent sections will depict the precision of these signals in pinpointing price momentum formation, continuation, and transition periods during the 1999–2023 timeframe, further validated by examining the warning signals preceding the 1987 Black Monday event.

Price momentums dynamics: 1999–2023

In scholarly discussions, the effectiveness of momentum has waned since 2000, with momentum investing experiencing a complete disaster in 2009 (Grein 2011; Dierkes and Krupski 2022; Daniel and Moskowitz 2016; Dolvin and Foltice 2017; Hwang and Rubesam 2015; Bhattacharya et al. 2017; Hou et al. 2020). The instability of momentum profits stems from the rigidity of fixed rankings and holding periods derived from statistical optimization during a sample period, which may not translate effectively in out-of-sample scenarios.

In this section, we illustrate the period variation of momentum formation, sustenance, and transition throughout 1999–2023 by employing signals generated from the

Samuelson model. Optimal profits for the momentum strategy can be achieved by following the provided signals.

Figure 3 is the monthly chart showing S&P 500 (candle bars) and NED (hollow circles) from 1999 to 2011. The initial signal 5 materialized in July 1999 when S&P 500 reached a new peak, accompanied by a decrease in NED from 52 to 27% and succeeded by a two-month decline in S&P 500. The downward trajectory ceased in October when signal 3 indicated a clustering of limited buy orders, leading to the resumption of positive momentum.

In March 2000, a subsequent signal 5 emerged as S&P 500 hit a record high of 1552.87, despite NED being only -35%, suggesting that most liquidity takers were selling at the new market peak. Sensing the sentiment, liquidity providers began placing more limit-sell orders, as evidenced by signals 4 in May and August, marking the end of positive momentum. The market shifted to negative momentum since October 1999, confirmed by four signal 2s in November 2000, March and September 2001, and July–October 2002. Additionally, four signal 4 occurrences in December 2000, June 2001, March 2002, and January 2003 indicated the sustenance of negative momentum. Signal 1 in March 2003 marked the end of the negative price momentum and signaled the beginning of a positive momentum.

As signaled by the alternating appearance of signals 1 and 3, the positive momentum endured until October 2007, when signal 5 suggested a possible culmination of the upward price trend and an impending shift to negative momentum. This transition from positive to negative momentum was subsequently affirmed by signal 2 in January 2008 and a signal 4 in May 2008. The downward momentum persisted until early 2009, marked by signal 6 occurrences in February and March, signaling the conclusion of the negative momentum phase. This raises two inquiries. Firstly, can we ascertain the onset of negative momentum before the end of January 2008? Secondly, when can we confidently identify the shift from negative to positive momentum in early 2009? Daily charts can provide a more immediate depiction of momentum transitions, as illustrated in Figured 4 and 5.

Figure 4 displays, on October 11, a noteworthy signal 5 as S&P 500 reaches an all-time high of 1576.09, accompanied by a sharp decrease in NED from 75 to − 32%, indicating substantial selling activity at the market peak. Signal 2 follows in the subsequent week, and signal 4 on October 29 signals a shift in the market microstructure, leading to

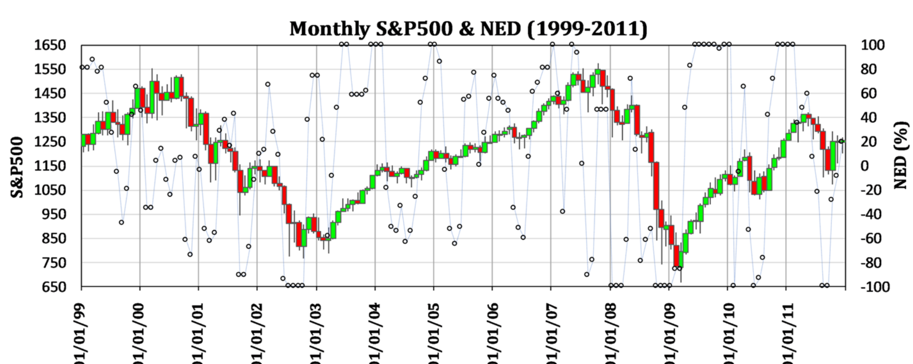

Fig. 3 Monthly chart of S&P 500 and NED from 1999 through 2011

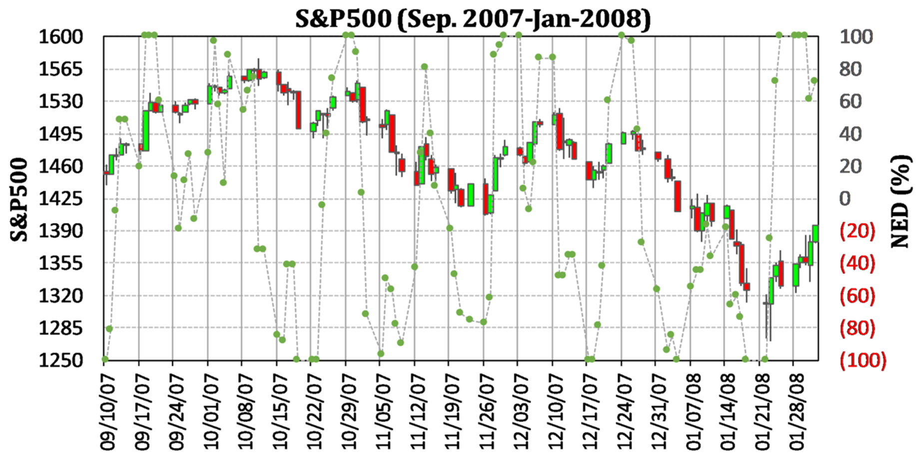

Fig. 4 Daily chart of S&P 500 index (candle bars) and NED (open circles) from September 2007 to January 2008. Labeled days represent Mondays of each week

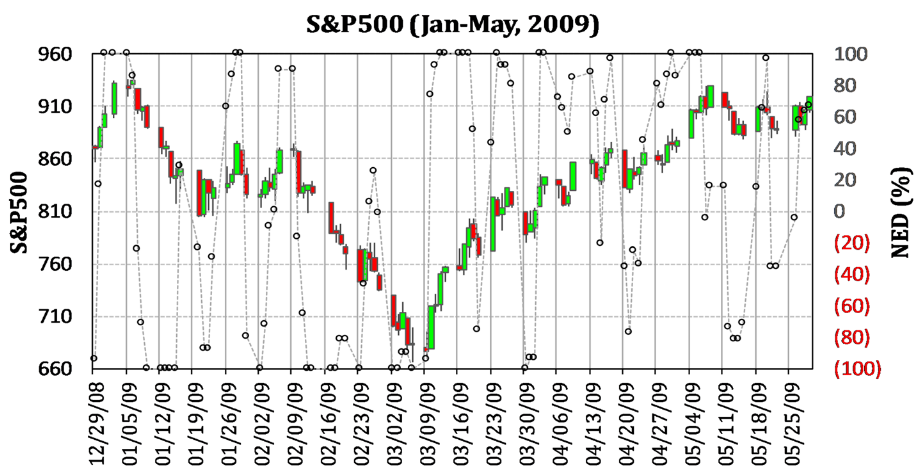

Fig. 5 Same as Fig. 4, but from January to May 2009

downward price pressure. The timing of the momentum transition is identified on the daily chart three months earlier than indicated on the monthly chart.

Figure 5 depicts the early 2009 transition from negative to positive momentum. Although a signal 6 on the monthly chart on February 28th hinted at a potential end to negative sentiment, the daily chart revealed lingering downward pressure through a signal 4 on February 26th, leading to further market decline in early March. The first confirmation of the momentum shift came on March 11th with a signal 1, followed by additional confirmations on March 20th (signal 1) and March 30th (signal 3).

The positive momentum started from March 2009 continued for more than 10 years due to the low interest rates (Leonard 2022) as shown in Fig. 6.

Alternative signals 1 and 3 are indicators of sustained positive momentum at market lows. For example, signal 3 observed at the close of August and September 2011 marked the resolution of a 15% market decline. Another instance occurred during the August 2015 slump when signal 3 arrested the downturn. In the scenario of a 15% drop in the

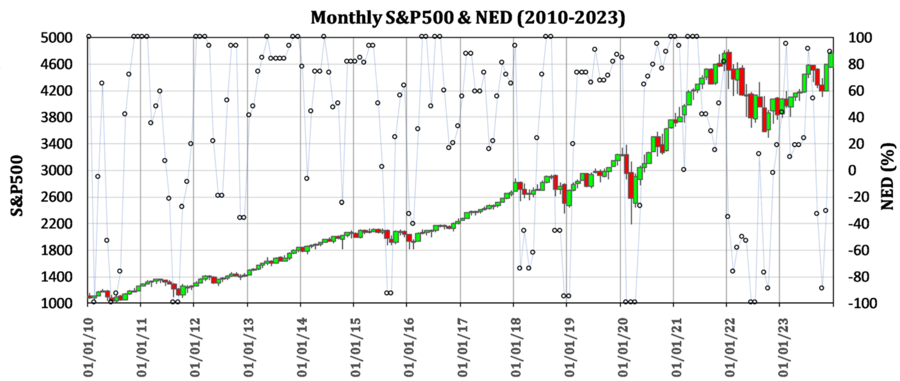

Fig. 6 Monthly chart of S&P 500 (candle bars) and NED (open circles) from 2010 through 2023

fourth quarter of 2018, a year-end signal 2 on both monthly and daily charts hinted that the downturn persisted. However, as early as January 4, 2019, a signal 1 in the daily chart (not displayed here) suggested the conclusion of the downturn. The rapid shift between positive and negative momentum in February and March 2020, triggered by the COVID-19 pandemic, demanded the resolution offered by daily charts, as illustrated in Figs. 3 and 4 of Han and Keen (2021). For the 2022 decline, the monthly chart registered signal 2 in January and June, followed by signal 6 in October, indicating the potential end of negative momentum. Finally, signal 1 in March 2023 confirmed the transition to positive momentum. Consistent with previous observations, daily charts provide valuable signals for momentum shifts. Signals generated at the end of the month in the monthly chart are frequently too tardy for adapting momentum strategies. For instance, on January 4, 2022, when the S&P 500 hit a new high of 4818.62, a significant signal 5 (NED − 0.11) appeared on the daily chart (not displayed here), indicating the end of positive momentum. Shortly after, on January 13, signal 4 emerged, confirming downward price pressure and the beginning of negative momentum.

Analyzing monthly charts over the past 25 years reveals that momentum duration and transition are highly irregular and rarely coincide with month-ends. The observed irregularity in momentum phases aligns with the random walk theory's proposition of unpredictable market movements. Consequently, momentum strategies based on fixed ranking/holding periods derived from monthly returns may not be optimal, potentially leading to significant losses during volatile periods with rapid shifts in momentum.

Warning flags before Black Monday, 1987

On October 19, 1987, the Dow Jones Industrial Average experienced a staggering 22.6% decline, while the S&P 500 slumped by 20.46% in a single day. This catastrophic event led to significant financial losses and triggered a wave of panic-driven selling among investors. Extensive exploration into the causes of the 1987 crisis has been conducted (Waldrop 1987; Metz 1988; Amihud et al. 1990; Bates 1991; Soros 1988; Harris 1989; Lehn 1989; Jüttner 1989; Roll 1989; Wigmore 1998; Bogle 2008; McKeon and Netter 2009; Bernhardt and Eckblad 2013; Henriques 2017; Diks et al. 2019), with one notable absence being the economy's fundamentals (Glaberson 1987; Cutler et al. 1989; Bernanke 1990). The reasons behind the 1987 stock market crash remain a topic of ongoing debate. The Presidential Task Force, spearheaded by Nicholas Brady, pinpointed takeover tax legislation as a primary instigator (Brady 1988), a stance corroborated by the compelling evidence put forth by Mitchell and Netter (1989). However, Eugene Fama (1989) contended that the crash was a rational reaction to fundamental changes in economic expectations, thereby deeming the conclusions of the Brady Report inconsequential. Robert Shiller (1988) argued that investor awareness of the possibility of a crash triggered the observed cascading selling pressure associated with portfolio insurance. Their contrasting views raise two key questions: Is there evidence to support a shift in investor expectations prior to the crash? What factors might have led investors to alter expectations and become aware of the possibility of a market crash?

We address these questions by showcasing how investor sentiment shifted from optimism to fear weeks before the Black Monday market crash. The signals provided by the extended Samuelson model identified this transition in investor expectations with time. Regarding the suggested influence of takeover tax legislation as outlined in the Brady Report, we demonstrate that its impact could be either positive or negative, depending on the prevailing sentiments, aligning with Fama (1989) and Shiller (1988). Additionally, we offer a potential explanation for the cause that prompted investor shifting expectations in 1987. Instead of employing a weighted average of constituent NEDs, we directly calculate NED for the S&P 500 in this section, ensuring the robustness of our findings when using the same methodology for individual stocks.

The chart in Fig. 7 shows the S&P 500 and NED monthly performance from 1985 to 1990. Signal 1 in December 1985, March 1986, and the first quarter of 1987 indicate both liquidity providers and takers share an optimistic view of the future market. The repeated signals 3 in September 1985, 1986, and May 1987 reflect bullish sentiment from liquidity providers who placed significant buy orders at specific prices (limit orders), preventing price drops even when NED hit lows. Signal 5 appeared in July 1985, August 1986, and 1987, coinciding with declining NEDs despite peaks in the S&P 500, indicating selling activity at market highs by informed investors. Interestingly, while the 1985 and 1986 Signal 5s were followed by Signal 3, indicating liquidity providers' optimism dominated,

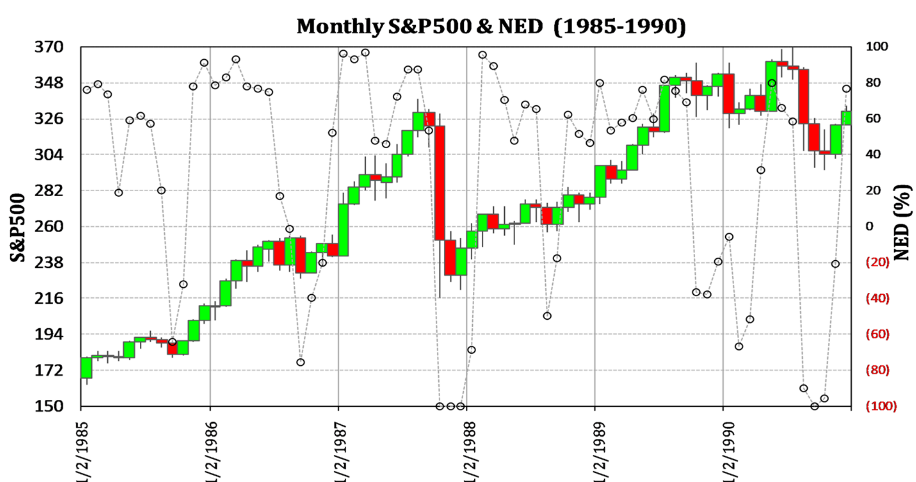

Fig. 7 Monthly chart of S&P 500 and measured NED for 1985–1990

the 1987 Signal 5 in August preceded the October market crash, revealing a sudden shift of investor anticipations of the future market. We can conclude from Fig. 7 that the investor expectation shifted between August and October 1987. Next, we will examine weekly and daily charts for more precise timing of the sentiment transition.

Figure 8 is the weekly chart from 1985 through 1987. Like Fig. 7, signal 5 s are often followed by signal 3, from 1985 through March 1987, suggesting liquidity providers firmly view the future positively. The sentiment shift emerged when a signal 5 in the week of April 6 led to a signal 4 in the week of May 4. Although another signal 3 in the week of May 18 sustained market momentum, it hints at a perspective shift among some liquidity providers who placed large limit-sell orders. The bullish market phase concluded when two consecutive signal 5 s in the weeks of August 17 and 24 were followed by a signal 4 in the week of September 28, three weeks before the Black Monday crash. Figure 8 shows that unlike the sudden shift between August and October suggested by Fig. 7, the positive investor expectations started to weaken in April, and the bull market ended at the end of September 1987 when a strong signal 4 followed signal 5, suggesting that liquidity providers joined liquidity takers to sell. Before explaining why signal 4 in September reflects a broader shift towards a passive outlook on the market's future than the one in May, let's examine the role of takeover tax legislation in triggering the Black Monday crash.

Mitchell and Netter (1989) provided strong evidence for the proposition that the anti-takeover legislation triggered the Black Monday crash by the Presidential Task Force (Brady 1989, often referred to as the Brady Report). They argued that the announcement on the evening of October 13, 1987, regarding this legislation led to a market decline of over 10% during October 14–16, an unprecedented occurrence since May 13–14, 1940, after German troops breached French defenses during World War II. This three-day decline altered investor sentiment and strategies, ultimately contributing to the Black Monday crash (Jacklin et al. 1992; McKeon and Netter 2009). However, it's worth noting that there had been Congressional proposals regarding anti-takeover legislation for several years before 1987. An almost identical bill to that adopted in October was introduced in the House Ways and Means Committee on July 23, 1987 (Mitchell and Netter

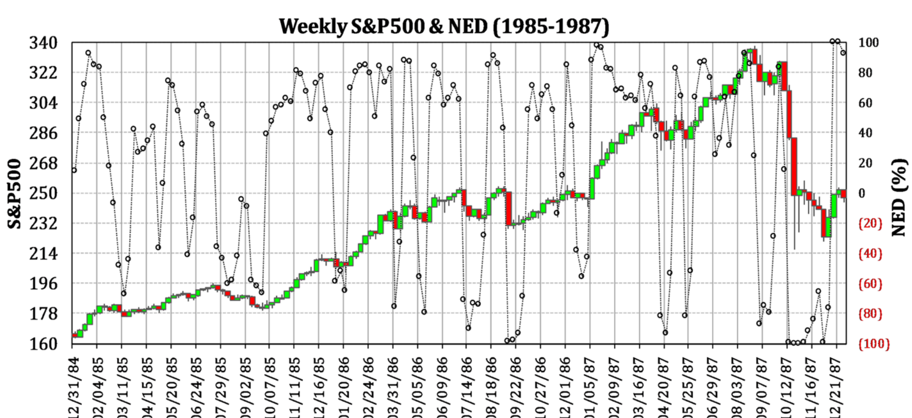

Fig. 8 Weekly chart of S&P 500 and measured NED for 1985–1987

1989). However, the legislation did not disturb the market before 1987 and even resulted in a market upsurge after July 23, as illustrated in Fig. 9.

Figure 9 depicts the daily chart for the second half of 1987, showcasing alternating signals 1 and 3 observed from July to mid-August that sustained the prevailing market optimism since May 1987, as illustrated in Fig. 7, resulting in new market highs. The market responded to the bill introduced on July 23 with a signal 3, indicating significant limit-buy activity that drove the S&P 500 level up by 9% until October 14, when two consecutive signal 5 s temporarily halted the surge. The fact that the identical proposed legislation bill elicited opposite market responses in July and October 1987 suggests that it's not the nature of the news but rather investor sentiment that predominantly influences market reactions. This phenomenon is a recurring theme throughout market history. We'll continue with our analysis of the signals in Fig. 9 and demonstrate later that the announcement of the legislation bill on October 13th occurred after the market sentiment had already turned extremely pessimistic.

The two consecutive signal 5 s on August 13th and 14th were followed by a signal 3 on August 18th, indicating a return to optimism. However, this uptrend was short-lived. The market peaked on August 25th, only to be met with another signal 5, triggering a 7% decline. The recurrence of signal 5 s in the daily chart was mirrored in the monthly chart (Fig. 7), revealing a flat NED in August despite a 3.5% gain in the S&P 500. Continuous selling actions at market highs by liquidity takers conveyed a message to liquidity providers, prompting a shift in their outlook on the market's future. As a result, two signal 4 s emerged in September, indicating the placement of large limit-sell orders, which led to signal 4 in the weekly chart (Fig. 8) at the end of September. Therefore, the daily chart reveals that liquidity providers shifted to a pessimistic sentiment in early September, preceding the timeframe suggested by the weekly chart. The monthly chart (Fig. 7) recorded the prevalent pessimistic sentiment with a decreased NED (0.48) in September and decreased sharply in early October. The monthly NEDs in early October are October 1: 0.46, October 2: 0.47, October 5: 0.47, October 6: 0.28, October 7: 0.27, October 8: 0.15, October 9: 0.06, and October 12: − 0.66. Given that monthly NEDs reflect sentiment over a longer

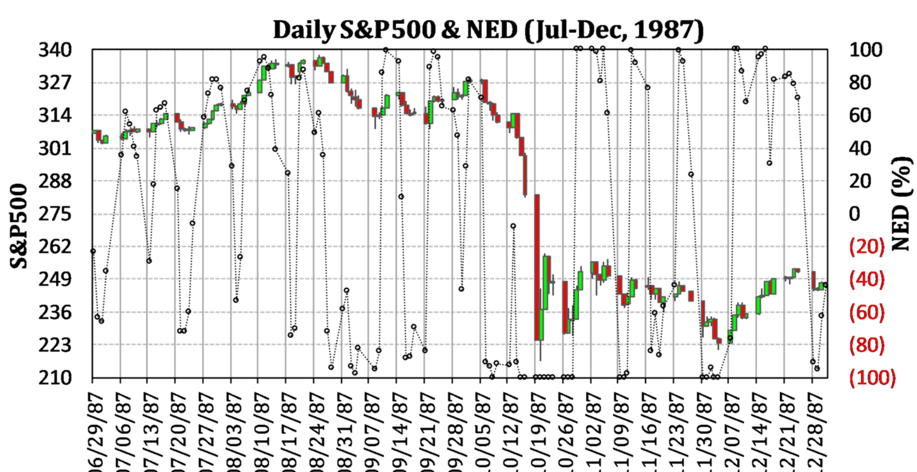

Fig. 9 Daily chart of S&P 500 and measure NED from July through December 1987

period than weekly and daily NEDs, the observed rapid decline in monthly NEDs every day in early October suggests a plunge in market anticipations. On October 13, ESM released a strong signal 4, with NED at − 0.33 and the S&P 500 at 314.53, compared to NED at − 0.96 and the S&P 500 at 319.34 on October 8th, indicating heavy downward price pressure due to large limit sell orders from wide-spread pessimistic anticipation of the future market. The announcement of the proposed anti-takeover legislation came after the down-pressured market closed.

The legislation announcement in October occurred when the market sentiment had shifted to pessimism, contrasting sharply with the euphoric sentiment in July. This disparity elucidates the divergent market reactions to the same legislative news. The variance in monthly NED between early October and July further clarifies the different outcomes of weekly signal 4 s in May and September. The observation above underscores the necessity of incorporating information from various time-frames, including daily, weekly, and monthly data, when analyzing market behaviors. We will outline our approach to addressing this need after introducing a proposed hypothesis regarding the trigger for the sentiment shift preceding Black Monday.

Having demonstrated that the shift in market anticipation preceded the 1987 crash, consistent with findings by Fama (1989) and Shiller (1988), a pertinent question arises: What prompted investors to recognize the market's overvaluation and anticipate a possible crash? Fama (1989) answered this question, "*I do not know. But I am not alone in my ignorance, and it is not special to the October experience*" because "*there is no way*" to know the fundamental values. Unfortunately, his response overlooked the role of ongoing evaluation by skilled investors. Astute value investors meticulously analyze fundamental factors, and their insights are highly respected in the market, suggesting some level of predictability might exist beyond mere chance.

In light of this, we propose examining the timing of Warren Buffett's 1986 annual report (Buffett 1986), released on February 27, 1987, just weeks prior to the onset of the widespread selling frenzy. This report contained two elements that warrant attention:

1. Buffett's famous quote, "*…simply to be fearful when others are greedy and to be greedy only when others are fearful*," encourages selling during periods of excessive market optimism.
2. The report noted that "*euphoria prevails*" in the market at that time, with "*the rewards to owners of businesses becoming gloriously uncoupled from the plodding performances of the businesses themselves. Unfortunately, however, stocks can't outperform businesses indefinitely,*" suggesting an overvalued market and an impending downturn.

Warren Buffett, a towering figure in value investing due to his success and devotion to Benjamin Graham's principles, wields significant sway over investor sentiments. The immense popularity of the quote from this annual report exemplifies his profound influence on a broad range of investors and their market behaviors, especially right after he presented the report in early 1987.

Table 3 Eight market states

	1	2	3	4	5	6	7	8
Monthly NED	N	N	N	N	P	P	P	P
Weekly NED	N	N	P	P	N	N	P	P
Daily NED	N	P	N	P	N	P	N	P

N, Negative; P, Positive

Different market states[4]

We have shown that valuable insights into the overall market condition and future direction stem from examining NEDs across various timeframes. Combining NEDs from different time scales provides a comprehensive snapshot of market states. Following this approach, we've been able to categorize market conditions into eight distinct states, as detailed in Table 3.

A negative NED indicates more market-sell orders than market-buy orders in the transactions, while a positive NED suggests the opposite. State one represents a scenario where selling dominates across all time scales, while state eight signifies dominant buying transactions in daily, weekly, and monthly horizons. The remaining six states fall between these two extreme states. The sequence of states takes into account the lasting impact of NEDs on price changes over longer time periods. In the short term, we expect that the S&P 500 level will exhibit a proportional relationship with the market states. However, exceptions can occur because the behavior of liquidity takers is not the sole driving force behind price changes. The behaviors of liquidity providers also contribute to market dynamics and can lead to deviations from the expected proportional relationship.

Table 4 lists the average S&P 500 level for each market state over 25 years (1999–2023). The 25-year average S&P 500 for each market state increases with the state level, suggesting that the market states are good indicators of the market conditions. This relation holds for all individual stocks we tested and aligns with the general market principle that more buyers drive prices up, and more sellers pull the market down.

A significant challenge in contemporary risk management is the ambiguity surrounding the concept of risk (Hubbard 2020; Hopkin and Thompson 2022). This confusion stems from the widespread belief, rooted in Bachelier's random walk theory (1900) and reinforced by Fama's efficient market hypothesis (1970), that market movements are inherently random and unpredictable. To effectively define and measure the risk for financial loss, we must understand two key factors: (1) the likelihood of a market decline, and (2) the current market level. Unfortunately, these factors are difficult to ascertain under the assumptions of the random walk theory and the efficient market hypothesis, which posit that market prices reflect all available information and are unpredictable.

The extended Samuelson model provides the two factors by signifying potential market declines through signals five and four and identifying market conditions by eight market states. This information enables a more accurate definition and measurement

[4] The idea of categorizing market conditions into different states is inspired by Zuckerman's book "***The Man Who Solved the Market: How Jim Simons Launched the Quant Revolution***."

Table 4 Average S&P 500 level for each market state over 25 years (1999–2023)

	1	2	3	4	5	6	7	8
1999	1294.38	1312.77	1335.95	1360.03	1305.95	1308.70	1324.28	1346.23
2000	1364.10	1369.85	1434.07	1447.57	1421.00	1439.97	1449.86	1478.04
2001	1154.50	1152.75	1202.42	1200.28	1191.79	1209.81	1233.17	1267.29
2002	900.47	927.00	911.98	907.68	1042.93	1081.55	1089.05	1071.23
2003	810.32	831.90	874.01	885.69	913.97	955.08	1000.86	1013.50
2004	1095.52	1102.74	1125.19	1125.49	1124.47	1129.01	1161.15	1162.46
2005	1174.99	1177.61	1181.81	1196.85	1202.91	1210.70	1226.20	1234.47
2006	1253.48	1264.66	1278.28	1287.98	1302.03	1314.45	1327.29	1340.79
2007	1420.27	1442.19	1468.94	1485.46	1471.13	1505.36	1481.64	1494.14
2008	1181.95	1139.42	1172.22	1240.60	1344.55	1335.24	1388.99	1407.50
2009	780.24	802.47	843.15	834.39	953.19	989.12	997.67	1008.72
2010	1072.70	1093.42	1105.50	1128.44	1132.80	1188.23	1190.49	1188.06
2011	1176.24	1194.49	1210.57	1227.77	1297.12	1311.37	1313.99	1315.06
2012	1339.36	1369.61	1367.06	1382.00	1379.25	1402.89	1388.76	1375.39
2013		1462.75		1459.52	1642.60	1641.23	1653.77	1647.54
2014	1829.07	1876.46	1840.59	1889.03	1904.49	1929.91	1943.12	1956.32
2015	1900.44	1956.90	1935.02	2017.54	2054.20	2073.82	2086.40	2105.61
2016	1898.50	1900.69	1903.94	1962.21	2082.71	2131.36	2144.09	2150.88
2017					2407.91	2422.10	2459.02	2455.87
2018	2620.80	2681.74	2700.25	2738.19	2764.49	2758.23	2846.43	2841.04
2019		2522.79	2669.80	2688.50	2874.15	2919.05	2963.76	2984.30
2020	2641.87	2718.12	2861.30	2875.63	3242.14	3276.38	3429.53	3406.48
2021	4341.76	4133.12	3913.06	4009.68	4288.61	4308.90	4255.41	4324.08
2022	4041.70	4113.21	4138.83	4088.23	4042.12	4108.05	4337.48	4234.68
2023	4233.40	4319.92	4272.25	4479.10	4198.80	4124.11	4266.88	4317.18
Average	**1796.64**	**1827.74**	**1858.41**	**1871.62**	**1943.41**	**1962.99**	**1998.37**	**2005.13**

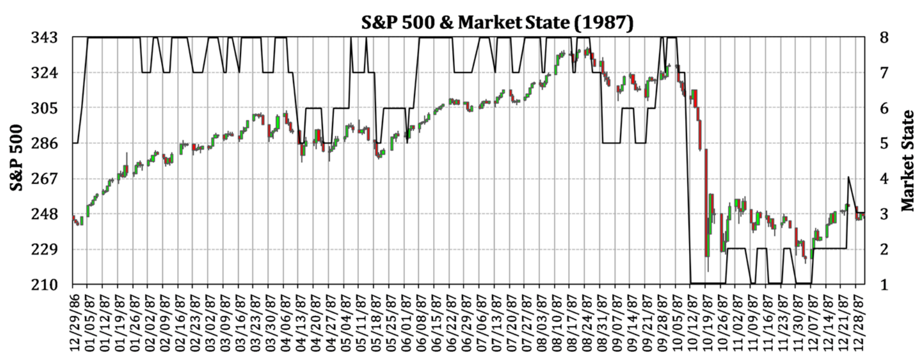

Fig. 10 S&P 500 and market state for 1987

of risk. Additionally, the model can determine the thresholds between different market states, allowing us to anticipate market shifts as prices approach these critical points. The eight states of the financial market are analogous to the four seasons in weather patterns. Although temperature fluctuations occur within each season, we can anticipate a seasonal change as the Earth approaches a specific position in its orbit. However, unlike the smooth and regular shifts of the four seasons, changes in the market state have no fixed sequential patterns and can involve dramatic shifts during market crises. The ability to anticipate these state changes, combined with the six signals, constitutes the unique strength of the extended Samuelson model in forecasting market direction and assessing risk. In the following, we will demonstrate that the six signals remain valid across the eight market states.

The market state chart for 1987, shown in Fig. 10, combines the Normalized Excess Demand (NED) values for monthly, weekly, and daily horizons. The overall trend outlined in the monthly NED chart remained intact but with more detailed information. In Fig. 7, the monthly NED for October 1987 reads − 1. However, this value only represents the last day of the month and cannot be considered representative of every day of October.

Analyzing the market state chart, it's evident that the monthly NED maintained positivity from the year's onset until October 12, when it swiftly transitioned to negativity within eight trading days, as detailed in the preceding section. Given that the monthly NED's direction mirrors market sentiments—optimistic or pessimistic—over an extended period, this abrupt switch signals a significant concern, indicating a drastic shift in market sentiment and foreshadowing the Black Monday crash one week later.

It is important to emphasize that on October 12, the S&P 500 closed at 309.39, representing a remarkable 37.6% increase compared to the S&P 500 closing level of 224.83 on Black Monday. Taking appropriate action at the close of October 12 would have prevented a substantial investment loss.

The NED characteristic of the weekly chart also presents in the market state chart with timely updates because the weekly NED value can change any day of the week in the market state chart. In Fig. 8, we observe signal four in the weeks beginning on May 4th and September 28. Examining Fig. 10, which corresponds to the same two weeks, we find that signal four was present on May 5 to 7, and 14, as well as on October 1, 2, and 5. The market state gradually declined from 8 to 7 on October 6, when the daily NED turned negative. Subsequently, it decreased to state 5 on October 9, when the weekly NED became negative. Suddenly, the market state dropped from 7 to 1 on October 12th, when both the weekly and monthly NED fell below zero. As a result, the earliest formation of signal four occurred on October 6th, and solidified on October 9th when the S&P 500's closing levels were 319.22 and 311.07, respectively, representing substantial increases of 42% and 38% compared to the closing level of 224.83 on Black Monday. Exiting the market on either of these days would have resulted in significant loss prevention.

Now, let's delve into the signal four observed in May, which did not result in a market crash but rather ushered in a wave of surges until the end of August. The crucial question is whether exiting the market based on this signal would have caused significant profit loss by missing out on the subsequent market surge in the following months.

Let's begin by examining the formation of signal four on May 8, when the market state decreased from level 8 to 7, and the S&P 500 closed at 293.37, lower than that at the previous state 8. As a measure against the danger of a market crash anticipated after the signal, we decided to exit the market at the close of that day. Subsequently, the market experienced a gradual slide, leading to a further reduction in the market state to level 5 when the weekly NED turned negative on May 18th. The market state remained at level 5 for four consecutive days.

However, on May 22, the market state rose to level 6, and the S&P 500 closed at 282.16, forming signal three, indicating an entry signal, as it implies an upward price pressure in the market microstructure driven by the behaviors of liquidity providers. Following this signal, we reentered the market at the close of May 22, capitalizing on the surging trend that propelled the market to its peak.

In summary, implementing the signal-based trading strategy would have effectively shielded investments from substantial losses. Timely exits upon signal four and re-entries at signal three allowed for capital preservation during downturns and opportunistic capture of upswings.

The behavior chart classifies the behavior of liquidity takers into eight states based on the NED signs observed on monthly, weekly, and daily scales. This categorization retains signals that are valuable for making informed decisions. However, we note that signals five and six, which reflect the behaviors of informed investors comprising a smaller portion of market participants (Elder 1993; Drakoln 2008; Gillham 2018), are absent from the behavior chart as there are no NED sign changes associated with them. One notable exception occurred when signal five appeared in the behavior chart on 10/11/2007, coinciding with the S&P 500 reaching its all-time high of 1576.09. On the same day, the daily NED experienced a significant drop from 0.75 to − 0.32, causing a market state change from level 8 to 7. After that day, it took five and a half years for the S&P 500 to recover and reach this level again, finally achieving it on April 10, 2013.

In the case of the 1987 market crash event, we observe that the monthly signal 5 at the end of August (Fig. 7), the weekly signal 5 at the end of the week of August 24th (Fig. 8), and the daily signal 5 on August 24th, October 2nd, and 5th (Fig. 9) provided an alarming message earlier than that from the behavior chart. However, all these signals are missing from the behavior chart because the decreased NEDs remained positive, so the behavior level did not lower to form signal 5. Given that these signals serve as early warnings, signaling potential issues and demanding attention, it is advisable to consider the NED charts at various scales alongside the behavior chart when making informed decisions. By examining the NED charts at different scales, we gain a more comprehensive understanding of market dynamics and can better anticipate and respond to emerging trends and potential risks.

Categorizing the market into various states is not a novel idea in financial market research. Previous studies by Cooper et al. (2004) and Muga and Santamaria (2009) have explored the connection between the profitability of momentum strategies and the existing upward or downward market states. Cornell (2018), in an invited editorial comment, proposes an alternative hypothesis to the Efficient Market Hypothesis (EMH) by suggesting viewing market noise (Black 1986) as constant state-dependent bubbles and crashes. Cornell supports this hypothesis with experiments conducted by Smith et al. (1988).

Jim Simons, the renowned founder, and manager of the Medallion hedge fund recognized that the market exhibits eight distinct states and capitalized on this understanding (Zuckerman 2019). Unlike most other fund managers, Simons and his colleagues at Medallion did not focus on fundamental factors such as earnings, dividends, and cash flows when making trades. Remarkably, the Medallion fund achieved an extraordinary average annual return of 66% for more than 30 years since its launch in 1988. It notably never experienced a negative return year, even during market crises, consistently outperforming the market with exceptional success.

The exceptional performance of Medallion and the widespread underperformance of most fund managers underscore the notion that relying solely on fundamental factors for investment decisions may not be the most appropriate approach. Market psychology (Kahneman and Tversky 1979; De Bondt and Thaler 1985), rather than economic factors or intrinsic values, significantly influences the decision-making and behaviors of traders, thereby influencing market prices (Cornell 2016). This assertion is supported by the inherent difficulty in accurately determining asset intrinsic values (Fama 1989; Damodaran 2012; Graham and Dodd 2008; Greenwald et al. 2010; Shiller 2015).

Pre-crisis foresight from numerous scholars and fund managers, fueled by insightful fundamental analysis, fell short of translating into substantial profit opportunities. While their identification of flawed fundamentals proved prescient for the 2000 and 2008 downturns, the market's continued surge for several years prior posed a challenge for capitalizing on their insights. As documented by Cassidy (2002), Lewis (2010), and Zuckerman (2009), the majority struggled to generate significant returns and even faced losses, with only a select few demonstrating successful market navigation during these volatile times.

Discussion and conclusion

The sustained ability to generate abnormal profits using the momentum strategy contradicts the weak form of the Efficient Market Hypothesis (EMH). However, the strategy's inconsistent performance, including substantial losses, has made it unreliable. This paradox—profitability coexisting with unreliability—prompted us to investigate further into its underlying reasons. Through literature review, we pinpointed the out-of-sample problem in momentum strategies, stemming from fixed ranking/holding periods determined by statistical analyses. While statistical methods are powerful for analyzing past market phenomena, their inherent limitation lies in their inability to uncover the underlying causes driving these patterns (Say 1821; Freedman 1987; Xie 2011), which becomes problematic when predicting future movements, as statistical approaches assume that past patterns will repeat themselves. However, this assumption often fails when the underlying causes evolve with time, resulting in the out-of-sample problem even for advanced machine learning techniques (Beutel et al. 2019). This discrepancy between past and future data significantly undermines the reliability of statistical methods for future predictions.

The literature also highlighted promising solutions, i.e., the dynamic price adjustment model by Paul Samuelson, the concept of price-makers from Ragnar Frisch, and the role of market microstructure in regulating market directions from Kenneth Arrow. These ideas culminated in the extended Samuelson model, which incorporates the strengths of all three. This dynamic model goes beyond statistics by establishing a causal link between price movements and investor behavior, generating real-time signals on market microstructure evolution. These signals predict future market direction. Our back testing over 25 years demonstrates the model's effectiveness in identifying momentum formation and transition points. More importantly, the model provided warnings weeks before the 1987 crash, aligning with our previous paper's findings on predicting the

2000, 2008, and 2020 crises (Han and Keen 2021). These results suggest a paradigm shift in financial economics, moving from static statistical methods towards dynamic models for understanding market fluctuations, especially when anticipating crises.

Financial economics has made considerable advances in understanding the influence of various factors on market movements, including both rational and irrational investor behavior (e.g., Klein 1946; Marschak 1950; Becker 1962; Fama 1970; Posner 1997; Thaler 2015) and information asymmetry (e.g., Kyle 1985, 1989; Admati and Pfleiderer 1988; Holden and Subrahmanyam 1992; Foster and Viswanathan 1993, 1996; Ivanistsky and Tatyannikov 2018; Back et al. 2018). However, due to its inherent limitations, traditional statistical models struggle to account for the evolution of these factors over time, limiting their ability to explain market fluctuations and predict major financial crises.

One limitation of static theory is its instantaneous shift between situations, viewing them as alternatives rather than sequential, as seen in the dynamic approach. As a result, static analyses are *timeless,* depicting what would happen in the long term based on assumed conditions that seldom persist over extended periods (Frisch 1992). This characteristic of the statistical approach limits its ability to explain short-term market fluctuations, treating them as random, unrelated movements. Examples include the "*instantaneous price adjustment*" (Hicks 1939) and the idea that "*intrinsic value is instantaneously reflected in actual prices*" (Fama 1965). The transition from a statistical to a dynamic approach is inevitable in the historical evolution of science, as Joseph Schumpeter (1954) observed: "*…in any field of scientific endeavor, static theory has historically preceded dynamic theory for obvious and sound reasons—static theory is simpler to develop, its propositions easier to prove, and it appears closer to (logical) essentials. The history of economic analysis is no exception.*"

The extended Samuelson model offers a dynamic solution to this theoretical gap by establishing a causal link between investor behavior and price movements. Through real-time monitoring of aggregate investor actions, the model reveals the behavior of informed traders and detects changes in market microstructure driven by herding effects, enabling it to forecast impending market crises.

Figure 11 illustrates how the extended Samuelson model (rectangular frame) bridges the gap between the diverse ways investors might react to information (left to the frame) and the resulting market outcomes (right to the frame). Behavioral finance research has long recognized the impact of sentiment and emotions on investor decision-making, dating back to the 1930s (Keynes 1936; Tversky and Kahneman 1974; Thaler 2015; Shiller 2019). Over the past few decades, scholars have developed various methods for measuring sentiment (Barberis et al. 1998; Daniel et al. 1998; Baker and Wurgler 2006; Hong and Stein 2007; Shefrin 2008; Engelberg and Parsons 2011; Yang et al. 2017; Sul et al. 2017; Siganos et al. 2017; Gardini et al. 2022). While these studies can establish a general

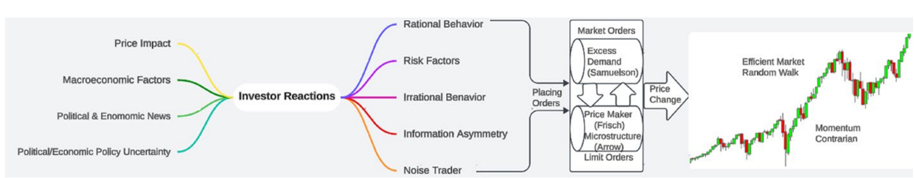

Fig. 11 Deconstructing price fluctuations: a stock market flowchart

causal link between sentiment and stock returns, sentiment as an emotion, is a precursor to investor behavior and does not directly cause price changes. Investor actions, such as buying or selling, are the primary drivers of market fluctuations. The extended Samuelson model presents a dynamic approach by continuously monitoring the aggregated order placements of investors, whether buying or selling, as indicative of their collective actions, rather than emotions, to information. Through this model, signals 5 and 6 unveil the activities of informed traders, while signals 3 and 4 detect changes in market microstructure due to herding effects. This real-time insight into the combined reactions enables a quantitative understanding of how they influence market outcomes.

Although the extended Samuelson model incorporates causality, its limitation is the reliance on accurate NED measurements. Direct evaluation of NED accuracy is impossible due to lack of data, leaving performance in practical applications as the sole validation method. We assessed the model's effectiveness across intraday and interday by revealing market makers' inventory positions. We validated its long-term efficacy by analyzing the timing of momentum formation, continuation, and transition processes over 25 years (1999–2023). Notably, the model accurately signaled imminent crashes in 1987, 2000, 2008, and 2020, followed by timely recovery signals. We acknowledge the need for further validation through additional market events. As a subsequent paper demonstrates, the model issued clear warnings before various noteworthy downturns, including the Kennedy Slide of 1962 (Everitt 1963) and flash crash of 1962 (Zweig 2010), the 1969–1970 recession (Fabricant 1972), the 1973 oil crisis (Zarnowitz and Moore 1977), the mini crash of October 13, 1989 (Gemmill and Saflekos 2000), the aftermath of the Chinese stock market collapse in 2015 (Xu et al. 2019), the Brexit referendum in 2016 (Breinlich et al. 2018), the year-end market slump in 2018, and the 2022 stock market decline.

Why can the extended Samuelson model consistently provide timely signals before major market downturns? Financial literature explores a multitude of factors that contribute to market crises, encompassing regulatory failures (Davies 2010), rational shifts in expectations (Roll 1988), investor overreactions (Seyhun 1990), asset overvaluations (van Norden and Schaller 1996), specific legislative changes (Delossantos 2023), excessive reliance on credit rating agency (Coffee 2009), and amplified systemic instability (Shu et al. 2021). Despite the diverse underlying causes, all major market downturns share a common prerequisite: significant downward price pressure due to a shift in market microstructure caused by widespread selling triggered by herding behavior, resembling the gathering of thick black clouds preceding a thunderstorm. The Extended Samuelson Model (ESM) not only identifies periods of significant downward pressure (Signal 4) but also indicates when informed investors act before the microstructure shifts (Signal 5). The advantage of the ESM lies in its ability to provide actionable signals weeks in advance, a stark contrast to traditional methods that offer vague warnings or uncertain timeframes even from astute experts. For instance, Alan Greenspan's warning of "*irrational exuberance*" (Shiller 2015) four years before the dot-com bubble burst in 2000 or Warren Buffet's criticism of derivatives as "*financial weapons of mass destruction*" (Buffet 2002) five years before the subprime mortgage crisis started in 2007–2008.

Another application of ESM is to offer a fresh perspective on the asset price booms and busts, often referred to as bubbles and crashes, a phenomenon that has intrigued economists for generations (Frisch 1934; Kuznets 1940; Kindleberger and Aliber 2005; Goldfarb and Kirsch 2019; Quinn and Turner 2020). The explanations range from money supply inflation (Schulak and Unterkofler 2011; Rothbard 1963), to market psychology (Mackay 2008), market fundamentals (Garber 1990), and the complex interplay between these factors (Quinn & Turner 2020). Yet, identifying and predicting the emergence of bubbles remains a formidable challenge (Engsted 2016). Eugene Fama famously denies their existence: "*What's the bubble? The up? The down? The subsequent up?*" (Chicago Booth Review 2016). By focusing on the underlying dynamics of investor behavior, the ESM has the potential to shed light on bubble formation and bust. Shifting from historical data analysis, the ESM directly examines real-time market behavior, offering early signs of order imbalances that could precede a bubble and crash. Boom and bust phases emerge when investors, united in their optimism or pessimism, engage in harmonized buying or selling, propelling the formation of a positive (boom) or a negative (bust) momentum. The transitions between boom and bust arise when investor behavior becomes dissonant, reflecting divergent views on the future direction.

Compared to the statistically based Efficient Market Hypothesis (EMH), the extended Samuelson model (ESM) demonstrates superior efficacy in explaining market price fluctuations across various dimensions. Here are five key reasons why:

1. **Understanding Price Momentum:** Numerous studies over the past 30 years have shown the existence of price momentum, contradicting the weak form of EMH. The Samuelson model, however, can identify signals that delineate various stages of price momentum, providing valuable insights beyond the limitations of EMH. Accurately pinpointing the inherent irregularity in the timing of momentum's initiation, persistence, and reversal could pave the way for overcoming the limitations of conventional fixed ranking/holding periods, which are susceptible to significant profit reduction and potential crashes.
2. **Fewer Assumptions:** Einstein believed that the "grand aim of all science" is to cover the greatest number of facts with the fewest possible hypotheses (Barnett 1957). Original EMH relies on many unrealistic assumptions (Farmer and Lo 1999; Brown 2011). Factor models adhering to EMH relied on three risk factors (Fama and French 1992) and then five (Fama and French 2015) to explain stock returns. This approach led to the proliferation of a "*factor zoo*" (Cochrane 2011), with Harvey et al. (2019) documenting a staggering 316 risk factors in the literature. In stark contrast, the extended Samuelson model stands closer to Einstein's vision of science. It relies on a single, realistic assumption that market participants drive stock return changes.
3. **Predicting Market Downturns:** While EMH asserts that predicting market collapses is impossible, the extended Samuelson model has effectively generated signals foreseeing significant downturns in 1987, 2000, 2008, and 2020, as demonstrated in our paper. The capability to anticipate impending market crashes could assist policymakers in taking timely action to alleviate economic damages, mitigate unemployment rate spikes, and avert societal upheavals.
4. **Explanatory Power:** The ability to explain observed phenomena is the ultimate measure of any theory. EMH, relying on news-driven price changes, can only account for a small fraction of daily price change variances. The extended Samuelson model,

however, can explain all variances through the interaction between liquidity takers and providers.

5. **Testable Model:** Dr. Fama argued that a "*full-blown testable model*" is necessary[5] to supplant EMH (Chicago Booth Review 2016). The extended Samuelson model fulfills this requirement, offering a robust alternative to the limitations of EMH.

The assumption of rational investor behavior in EMH has faced heavy criticism (Grossman and Stiglitz 1980; Milgrom and Stokey 1982; Black 1986), and spurred the development of BFT price models that incorporate irrational or "*noise*" traders (see Gupta et al. 2023 for a review). Noise trading models (e.g., Kyle 1985; Glosten and Milgrom 1985; Admati and Pfleiderer 1988; De Long et al. 1990) can effectively explain excess market volatility, a phenomenon that challenges EMH. However, these models have limitations when it comes to real-time market monitoring and predicting future directions. The key challenge lies in the difficulty of accurately measuring critical parameters within the models. For instance, the illiquidity (λ) in the Kyle (1985) and Admati and Pfleiderer (1988) price models relies on factors like the number of informed traders and the variance of uninformed trades (Brennan and Subrahmanyam 1996; Chordia et al. 2009). Similarly, the De Long et al. (1990) price model requires information on the proportion of noise traders (μ) in the market, the "*bullishness*" of noise traders (ρ^*), and the coefficient of absolute risk aversion (γ). Unfortunately, this information can only be estimated retrospectively using statistical methods. For example, Brennan and Subrahmanyam (1996) estimated Kyle-λ by regressing the monthly average price and transaction size from 1984 to 1991 for different portfolios. Ahmed (2019) estimated the parameters μ, ρ^*, and γ in the De Long et al. (1990) model using monthly S&P 500 index data, real per capita personal consumption data, and monthly population data from 1981 to 2018. The information obtained from past data (retro-regressed information) isn't reliable for predicting what will happen in the future because of limitations in applying past patterns to new situations (out-of-sample problem). In essence, while noise trading models offer valuable insights into market behavior, their practical application for market monitoring and prediction remains limited due to the difficulty of real-time measuring key internal factors.

In contrast, the extended Samuelson model can measure excess demand in real-time and generate signals that indicate potential future market directions. Additionally, the eight market states outlined in the paper contribute to the progression of risk assessment and management, an area where the scientific foundation remains fragile (Beder 1995; Nawrocki 1999; Taleb 2007; Fox 2009; Dionne 2013; Aven 2016). From a practical application standpoint, rather than focusing on mathematical convenience, risk should refer to the potential for financial loss. The extended Samuelson model evaluates the risk by combining the signals with the proximity of the current price to a threshold provided daily by the ESM that could trigger a state transition. For example, shortly before the Black Monday crash of 1987, the model warned on October 9 that after a "*signal four*" indicating downward pressure and three consecutive days of decline, the day's low level

[5] EMH itself is deemed a non-testable hypothesis due to the joint-hypothesis problem (Fama 1991; Farmer and Lo 1999). However, the momentum phenomenon falsified the weak form of EMH.

had almost reached or exactly matched the monthly and weekly thresholds,[6] suggesting that the market was poised to plunge from state seven to state one, teetering on the brink of a cliff. As expected, the market nosedived to state one on the next trading day, October 12, initiating the chain reaction that ultimately led to Black Monday on October 19 (see Fig. 10). This approach to risk assessment offers more practical relevance than simply assuming historical variance can predict the future found in extant literature (Markowitz 1952, 1959, 2010; Rocco 2014) that often fails to foresee the emerging danger (Sholes 2000, Jorion 2006; Stulz 2008; Bouvard and Lee 2020).

Fama (1989) acknowledged the inadequacy of current frameworks and models in finance and economics to effectively predict how markets anticipate future business conditions and translate these expectations into stock prices. He also highlighted the difficulty distinguishing between rational and irrational investor behavior, given the elusive nature of intrinsic security values. Barberis and Thaler (2003) echoed the limitations of existing theories in explaining market fluctuations. They concluded, "*First, we will find that most of our current theories, both rational and behavioral, are wrong. Second, substantially better theories will emerge*." Inspired by the intellectual legacy of Nobel Prize laureates Paul Samuelson, Ragnar Frisch, and Kenneth Arrow, the extended Samuelson model emerges as a promising avenue in financial economics. This model offers a potential alternative approach within the ongoing debate on the Efficient Market Hypothesis and market predictability, complementing other efforts in the literature (Mandelbrot and Hudson 2006; Kristoufek 2013; Lo 2017; Cornell 2018; Shiller 2019; Spulbar et al. 2021; Bocher 2022; Nyakurukwa and Seetharam 2023). Our findings are from limited evidence, and further research is necessary before drawing any definitive conclusions.

Abbreviations

BFT	Behavioral Finance Theory
CFTC	Commodity Futures Trading Commission
EMH	Efficient Market Hypothesis
ESM	Extended Samuelson Model
FOMC	Federal Open Market Committee
NED	Normalized Excess Demand
SEC	Securities and Exchange Commission

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Author contributions

QH: Conceived and designed the experiments; Performed the experiments; Contributed analysis tools and data; Analyzed and interpreted the data; Wrote the paper.

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Availability of data and materials

The data will be made available upon reasonable request.

[6] To avoid the data snooping bias, thresholds are established using historical data collected before October 9.

Declarations

Competing interests
The data will be made available upon reasonable request. The author affirms no competing financial interest. Additionally, this research has not received financial support from any agency.

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